Exploring Perceived Risk and Digital Ethics Affecting Consumer Experiences and Decision-Making in Smart Retailing.

Student: Edem Kofi Boni

Supervisor: Dr. Asieh Hosseini Tabaghdehi,

A thesis submitted to the Brunel Business School, Brunel University London, in partial fulfillment for an award of degree of Doctor of Philosophy (PhD)

May 2024

Keywords

Consumer Experience; Digital Ethics; Digital Well-being; Perceived Risk; Smart Retailing

Abstract

Smart technologies, such as artificial intelligence (AI), the Internet of Things (IoT), and virtual reality (VR), are transforming the retail industry by reshaping consumer interactions and enabling personalised, enhanced shopping experiences. These advancements, while revolutionising operational efficiency and consumer engagement, also raise critical challenges related to ethics, privacy, and perceived risks, significantly influencing consumer trust, satisfaction, and behaviour. Despite the increasing integration of smart technologies in retail, limited research has explored how constructs such as perceived risk, trust, and digital ethics collectively impact consumer behaviour. This study addresses this gap by introducing and empirically validating the constructs of "smart consumer experience," "smart satisfaction," and "digital well-being," offering a comprehensive framework to understand consumer engagement in smart retailing.

This research employs a quantitative approach, collecting survey data from over 500 respondents to examine consumer interactions across pre-purchase, purchase, and post-purchase stages. Using structural equation modelling (SEM), this study investigates the relationships among perceived privacy concerns, fairness, risk, trust, satisfaction, purchasing behaviour, e-loyalty, and digital well-being. Findings reveal that perceived fairness and privacy concerns significantly influence trust, which mediates their impact on smart satisfaction and e-loyalty. Notably, while smart satisfaction enhances consumer engagement and e-loyalty; however, its direct effect on purchasing behaviour remains complex and requires further exploration. This study highlights the reciprocal relationships among trust, smart satisfaction, and digital well-being, underscoring their collective importance in shaping positive consumer experiences. By addressing key barriers such as trust,

perceived risk, and ethical concerns, this research contributes to the growing discourse on digital transformation in retail. The findings provide actionable strategies for stakeholders, including enhancing transparency in data usage, integrating fairness into algorithmic processes, and designing consumer-centric technologies to promote digital well-being. These insights are critical for retailers, policymakers, and technologists striving to optimise consumer engagement while fostering ethical accountability in smart retailing.

In addition to the retail sector, the implications of this research extend to other industries, such as healthcare, education, and finance, where smart technologies are increasingly being adopted. This study provides a robust empirical foundation for understanding how ethical considerations and digital transformation intersect to shape consumer behaviour, trust, and satisfaction. By bridging critical gaps in the literature and offering practical guidance, this research advances academic knowledge and equips stakeholders to navigate the complexities of ethical and sustainable technology adoption in an increasingly digital world.

Table of Contents

List of Figures

List of Tables

List of Abbreviations

Abbreviation(s)	Explanation(s)
AI	Artificial Intelligence
IoT	Internet of Things
VR	Virtual Reality
AR	Augmented Reality
MR	Mixed Reality
ML	Machine Learning
ATM	Automated Teller Machines
GPS	Global Positioning System
5G	Fifth Generation Technology

Declaration

I, Edem Kofi Boni, declare that the ideas, research work, analyses, and conclusions presented in this research thesis are solely and completely my own independent work, unless otherwise acknowledged. I am submitting this thesis to partially fulfil the requirements for the Doctor of Philosophy degree at Brunel University London, United Kingdom.

Signature: Edem Kofi Boni

Date: 05/05/2024

Acknowledgements

The writing and completion of this thesis undoubtedly bear the imprint of myriad intellectual contributions and guidance from my supervisory team, colleagues, friends, and family. I extend my profound gratitude to each of them for investing their time in thoughtful discussions, debates, and critiques. This collective effort has greatly influenced the scope and clarity of the concepts imprinted in this work. I am profoundly thankful to the Almighty God for guiding me through this pursuit of knowledge and enabling me to successfully complete this doctoral thesis. I would like to extend my deepest appreciation to my principal supervisor, Dr. Asieh Hosseini Tabaghdehi, for her wisdom, deep knowledge, guidance, and unwavering support, which have been crucial in shaping my research direction and journey. Her counsel, encouragement, and patience have been a source of motivation for me during challenging times, and I truly appreciate her mentorship. On days when I felt disheartened, she provided a simple yet powerful reminder to “keep pushing.” I am truly grateful for the thoughtful messages, calls, meetings, timely reminders, and invaluable career guidance she has provided. I am also extending my heartfelt thanks to my wife, Elizabeth Boni, my children, Selorm and Seyram Boni, Miss Saranya Sriskantharasa, and Mrs.Yvonne Menka-kpatakpa, Mr. Senyo and Mrs. Pauline Gati, Mrs. Rebecca Asima, Kwami Boni (Dad), Beatrice Boni (Mum), Dela Boni (Brother), Esi Boni (Sister), Eli Asiam (Sister), and the rest of my extended family and church community for their unwavering support, love, and understanding. Your encouragement, patience, and sacrifice have been a constant source of strength and motivation. To my friends and colleagues who have shared the challenges and triumphs of this academic journey, you have provided me with camaraderie and encouragement. To all my friends, coworkers, and acquaintances who have been with me through the ups and downs of this adventure, I truly appreciate your company and encouragement. I want to express my thanks to everyone who has played a part, small or large, in helping me finish this research. Your support and faith in me have played a role in my reaching this academic achievement. This thesis symbolises our combined efforts and perseverance.

Chapter 1: Introduction

The rapid advancement of smart technologies has significantly transformed industries globally, with the retail sector undergoing profound changes. These technologies have redefined how consumers interact with businesses, offering personalised and efficient experiences that reshape the consumer journey and disrupt traditional business models. The COVID-19 pandemic further accelerated these transformations, compelling retailers to adopt smart technology solutions to meet evolving consumer demands and ensure operational continuity (Guha *et al.*, 2021; Shankar *et al.*, 2021). Innovations such as Amazon Go, one-click ordering, and personalised recommendations illustrate this shift, demonstrating how smart technologies can revolutionise retail operations while redefining competitive strategies (Shankar, 2019; Grewal, Gauri, Roggeveen, *et al.*, 2021; Shankar *et al.*, 2021; Manis and Madhavaram, 2023). Smart technologies, defined as devices or systems embedded with algorithms capable of collecting, processing, and intelligently responding to data, underpin these advancements (Goddard et al., 1997; Grewal, Noble, et al., 2020; Riegger et al., 2022). Core technologies, such as artificial intelligence (AI), the Internet of Things (IoT), virtual reality (VR), augmented reality (AR), mixed reality (MR), and machine learning (ML), are increasingly being integrated into retail processes to optimise business operations and enhance consumer experiences. The necessity of these technologies became particularly apparent during the COVID 19 pandemic, as brick-and-mortar retailers rapidly transitioned to digital solutions, such as online ordering, click-and-collect services, and robot-assisted operations, to remain competitive (Allal-Chérif, Simón-Moya and Ballester, 2021; Guha *et al.*, 2021; Shankar *et al.*, 2021; Chen and Chang, 2023).

Retailers that leverage advanced data-driven capabilities have demonstrated greater adaptability to volatile shifts in consumer behaviour (Shankar *et al.*, 2021; König, Hein and Nimsgern, 2022; Marder, Angell and Boyd, 2023). However, the integration of smart technologies also presents significant challenges. Concerns regarding data privacy, perceived risks, and ethical dilemmas have grown as the extensive use of consumer data for personalisation raises anxieties about security, fairness, and digital well-being (Varadarajan *et al.*, 2010; Bleier, Goldfarb and Tucker, 2020; Martin and Palmatier, 2020; Martin *et al.*, 2020; Abuljadail *et al.*, 2023; Xu, Jia and Tayyab, 2023). Despite the growing adoption of smart technologies, existing research has predominantly focused on operational efficiencies and consumer management rather than the deeper psychological and ethical dimensions of such advancements. Constructs such as "smart consumer experience," "smart satisfaction," and "digital well-being" are underexplored, particularly their interplay with consumer trust, engagement, and loyalty.

Furthermore, existing frameworks like the theory of planned behaviour (Roy *et al.*, 2017) and the unified theory of acceptance and use of technology (Zhani et al., 2022) often neglect the nuanced effects of these constructs on consumer engagement and satisfaction in retail contexts. This research addresses these gaps by examining the consumer journey across the pre-purchase, purchase, and post-purchase stages to provide a comprehensive understanding of the factors influencing consumer behaviour in smart retail environments. It also incorporates emerging ethical concerns, such as fairness in data use and the promotion of digital well-being, to address the broader implications of smart technology integration. This study proposes a conceptual framework that extends the existing literature and provides actionable insights into consumer engagement in smart retailing.

This study contributes to the academic literature by introducing and empirically validating novel constructs such as "smart consumer experience," "smart satisfaction," and "digital well-being." This study highlights the reciprocal relationships among trust, satisfaction, and digital well-being, demonstrating their collective role in shaping consumer engagement and loyalty. These insights also have significant practical implications. For example, retailers can enhance transparency in data usage, integrate fairness into algorithmic processes, and design strategies to promote consumer digital well-being. Policymakers and technologists can leverage these findings to foster trust and loyalty, address ethical concerns, and optimise consumer experiences in smart retailing environments. This chapter introduces the study's background, research gap, and objectives. Section 1.1 discusses the theoretical foundation of smart retailing, focusing on its ethical and psychological dimensions. Section 1.2 outlines the research objectives and questions, and Section 1.3 describes the quantitative methodology used in this study. Section 1.4 highlights the theoretical and practical contributions of the research, and Section 1.5 provides an overview of the thesis structure, guiding the reader through the subsequent chapters.

1.1 Background

A considerable amount of literature has been published on the mass revolution in global industries that has occurred in the age of digital transformation. The emergence of new-generation smart technologies like big data (BD), the Internet of Things (IoT), artificial intelligence (AI), virtual reality (VR), augmented reality (AR), mixed reality (MR), and machine learning (ML), is transforming the human-machine interaction pattern (Guha *et al.*, 2023). Smart technology has become an increasingly common feature in all spheres of our lives, from critical areas, such as healthcare, retailing, agriculture, law enforcement, and banking, to the mundane, such as dating (Cath, 2018; Shankar *et al.*, 2021; Mancuso, Messeni Petruzzelli and Panniello, 2023). Cumulatively, deep learning algorithms have evolved to enhance consumer experiences in the ever-dynamic digital era. Whilst these algorithms enhance business processes, business management researchers continue to investigate the effects of smart technologies on consumers and other stakeholders in increasingly automated and interconnected business environments (Huang and Rust, 2018; Ferreira *et al.*, 2021).

In recent years, academic scholars and practitioners have taken a keen interest in the prospects and perils of smart technology, which has captured substantial interest across a wide array of retail scholarships (for example, Davenport et al., 2020; Guha et al., 2021; Shankar et al., 2021). Such smart technologies, including AI, are considered to be one of the most promising new technologies with high processing power and the ability to mimic intelligent human behaviour(s). Cumulatively, deep learning algorithms have evolved to enhance consumer experiences in the ever-dynamic digital era. These algorithms enhance business processes; however, business management researchers continue to investigate the effects of smart technologies on consumers and other stakeholders in increasingly automated and interconnected business environments.

In the retail context, smart technology has augmented dramatic shifts, created significant disruptions in retail environments, and is increasingly being adopted by smart retailers. In some cases, retailers deploy smart technology, such as robots, to enhance efficiency by streamlining non-consumer-facing functions (e.g., forecasting demands, automated inventory management, and consumer sentiment analysis) and reducing the likelihood that retail employees performing these tasks. In other cases, these robots directly perform consumer-facing tasks (e.g., interacting with consumers, providing recommendations, and providing promotional information, including product information, or providing a platform for retail cooperatives to perform consumer-facing tasks to enhance the consumer experience. Such tasks are the driving force behind the ongoing and significant changes in the retail sector (Shankar, 2018; Cukier, 2021; Shankar *et al.*, 2021). The influence of smart technology on retailing is expected to be substantial, as retailers who fail to adopt the technology are likely to fail. For example, smart retailers , such as Amazon have redefined the consumer shopping experience and displaced many brick-and-mortar retailers with technology-driven innovations like one-click ordering, personalised recommendations, smart speakers, and anticipatory shipping (Xiao and Benbasat, 2007; Nichols, 2018; Shankar, 2019; Shankar *et al.*, 2021; Del Vecchio, Secundo and Garzoni, 2023).

Following the COVID-19 pandemic, the role of smart technologies has taken on an even more dramatic leap, and the use of retail technologies has dramatically increased. Many brick-and-mortar retailers were forced to close their physical stores and transition more quickly to technology-based solutions like online ordering and fulfilment, click-and-collect, and robot-assisted operations, because shelter-in-place and lockdowns intended to stop the spread of the coronavirus impacting shopping trends, which experienced dramatic week-to-week or day-to-day changes (Shankar *et al.*, 2021; Gupta, Gaurav and Panigrahi, 2023). It became evident that retailers equipped with instant access to data had a significant advantage, enabling them to make better-informed decisions and investments than retailers that rely on outdated information. The COVID-19 pandemic and government restrictions have led to a rapid surge of digitalisation in shopping activities and impacted a drastic shift in consumer behaviour. Although the phenomenon of technology-dependent shopping is sensational, the subtle motivations behind it remain to be explored. To keep up with the volatile shifts in consumer shopping behaviour during this extraordinary period, brands and retailers must leverage various technological advancements to remain relevant. A well-known example of this is the use of mobile global positioning system (GPS) tracking, which provided real-time updates on store traffic. By employing such technology, retailers could adapt their strategies swiftly and effectively (Delgado, 2020; Shankar *et al.*, 2021; Gupta, Gaurav and Panigrahi, 2023).

As a consequence of this radical transformation of the retail environment due to the use of smart technology and its growing popularity among consumers, it has prompted more recent arguments for the need for retailers to better understand the impact of these technologies on the consumer (Guha *et al.*, 2023). The unique attributes of smart technologies are expected to stimulate consumer engagement (McLean et al., 2021), foster the practical usefulness and enjoyment of the consumer's shopping experience (Nikhashemi *et al.*, 2021), and has a positive effect on brand valence, as well as purchasing intentions (Loureiro, Guerreiro and Tussyadiah, 2021). However, empirical evidence must be strengthened to further support these discussions and provide much-needed recommendations and guidelines to various stakeholders. This is because as consumers begin to encounter smart technology-enabled retail products and services, there have been concerns regarding consumer adoption, perceived digital ethical challenges, and their psychological reactions towards smart retail technologies and platforms. Therefore, exploring the factors that contribute to consumers' perceived fairness, satisfaction, experiences, and loyalty with smart retail technologies and platforms remains of significant research significance. Academics and other stakeholders have already established the pressing need for research on various aspects of smart retail technologies (Chen and Chang, 2023). Previous studies have demonstrated how smart technological advances influence perceived ease of use, usefulness, and attitudes towards brands (e.g., Lee, 2018). Thus, consumers expect benefits to result in purchase intention using smart technology in retail (e.g., Dacko, 2017), and how smart retail platforms expedite consumer decision-making processes (e.g., Nawres et al., 2024). However, what is not yet clear is the precise influence of smart technologies on consumers and retailingremains uncertain, primarily because of their evolving nature.

From a strategic retailing perspective, existing studies have proposed strategic frameworks for effectively managing smart technologies and platforms and explored their implementation within smart retail platforms (Grewal *et al.*, 2023). However, a notable thread across these studies is the frequent attempt to apply insights from conventional information technology, such as computers and the Internet, to the use of smart technology in retail contexts. Furthermore, according to Loureiro, Guerreiro and Tussyadiah (2021), these studies primarily focused on either the product or the consumers, paying little attention to the deeper connections, development, and interpersonal interaction between smart retail environments and consumers. For example, McLean and Wilson (2019) argued for the need for research to explore and establish causal links between the attributes of smart retail platforms and shopping engagement. Fan et al. (2020) supported this assertion, agreeing that a major concern in the field is the ambiguous relationship between smart technology in retail, consumer value perceptions, and consumer engagement. This calls for research to address the knowledge gap regarding the impact of smart technology adoption on consumers' attitudinal and behavioural outcomes. Specifically, there is an urgent need to explore and establish a deeper understanding of the unique characteristics and features of smart retail technology and platforms, such as how interactivity and augmentation influence consumer behaviour, consumer perceptions (digital ethics and risk), and how these shape smart shopping experiences, satisfaction, and loyalty. Similarly, it has been difficult to develop a unique and widely accepted concept of smart retailing (Rese, Ganster and Baier, 2020; Loureiro, Guerreiro and Tussyadiah, 2021; Chen and Chang, 2023). This indicates that consumer engagement within smart retail environments and its implications must be better understood to improve the operational effectiveness and consumer acceptance of smart retail.

As more retailers shift a substantial portion of their retail operations online and use smart technology, either voluntarily or because they must, to avoid going out of business, consumers are becoming more involved with smart technology-enabled retail, and ethical concerns regarding consumers' engagement with smart technology-enabled retail environments have grown (Agag, 2019; Yang *et al.*, 2019; Ferreira *et al.*, 2021). Social scientists have studied this, which has sparked debates regarding the ethical and legal implications of using these technologies. The ethical and social consequences of smart technology-enabled retail environments have risen to the forefront of public, political, and research agendas (Shankar *et al.*, 2010; Grewal *et al.*, 2016a; Martins *et al.*, 2019; Ryu and Park, 2020). For example, sending location-based advertising messages through smart devices is becoming more common; however, little is known about its impact and how consumers react to such personalised advertising messages, including the disclosure of their personal data. This is because location-based advertisement messages track consumers' actual geographic locations; as a result, they generate debates about privacy concerns and consumers' general digital well-being and may hinder their adoption of these technologies. For example, in 2019, consumers were concerned about how businesses used the data they collected, with more than 70% expressing their concerns (Martin and Palmatier, 2020). Further studies established that avatars on websites and AI-empowered chatbots enhance consumers' interactions and shopping value and are just as efficient as skilled workers. On the other hand, when consumers became aware before the start of their interaction that they were chatting to a chatbot, the effectiveness of the use of the chatbot dropped by about 80% (Wang *et al.*, 2007; Fu *et al.*, 2020; Martin and Palmatier, 2020). Despite the potential benefits of using smart technology in retail, research has shown that it also can cause harm, including bias (Miller and Hosanagar, 2019). Today, retailers can capture and manipulate consumer data for less cost, thanks to rapid technological advancements. As a result, new knowledge flows emerge that may pose a threat to user privacy as data are introduced into new contexts. This alarming situation raises many questions in everyone’s minds, especially about how retailers should immediately respond to these ethical concerns (Miller and Hosanagar, 2019; Bleier, Goldfarb and Tucker, 2020). According to Cath (2018), the lack of unified governance guidance on their use and legal ramifications further raises doubts about the interplay between law, ethics, and technology in regulating smart technology-enabled retail environments, which are more crucial than ever. To address these shortcomings, this study’s main goal is to extend the initial insights developed in the extant literature and contribute further to the impact of the use of smart technology in retail and on consumers.

1.1.1 Consumer Behaviour in Smart Retail Environments

As discussed above, advancements in smart technological retail solutions, digital retail transformation, and the emergence of multi-channel retail modalities have profoundly shifted the way consumers engage with and interact with smart technology-enabled products, services, and digital platforms. A prominent trend is the increasing autonomy of consumer-facing smart retail technologies. Chatbots, humanoid robots, and drones are just a few examples of technologies capable of autonomous actions (Sohn, 2024). Notably, the integration of smart technology in retail offers retailers several benefits, including enhancing operational efficiency, enriching consumer experiences through the provision of nuanced insights into consumer needs and preferences, and the development of innovative consumer services. Major retail outlets like Amazon, Sainsbury’s, Morrisons, and Tesco exemplify this trend through their unmanned 24/7 online shopping, which ultimately influences consumer behaviour (de Bellis and Venkataramani Johar, 2020).

Several recent studies (e.g. Martins et al., 2019; Guha et al., 2021, and 2023) have brought to light the transformative impact of smart technology-enabled retail platforms and environments. These smart technology-enabled platforms have demonstrated their ability to perform tasks autonomously during shopping, streamlining the consumer experience and catalysing significant shifts in consumer behaviour. For example, these platforms can seamlessly integrate selected shopping items into consumers' shopping apps, revolutionising traditional checkout processes. However, given the disruptive nature of such technologies, recent scholarly evidence (e.g., de Bellis and Venkataramani Johar, 2020; Pentz, du Preez , andSwiegers, 2020; Kamoonpuri and Sengar, 2023) suggest that consumers exhibit hesitancy in adopting them due to perceived risks associated with these smart technologies, thereby impeding their widespread acceptance. Similarly, recent research has theorised that smart retail technologies involve several factors that might inhibit their adoption by consumers (Bellis and Venkataramani Johar, 2020). This development underscores the high awareness among smart retailers, who have never been more conscious of the value of understanding consumer experience and behaviour within smart retail settings. In recent years, scholars (Mauri *et al.*, 2024) explored various approaches to understanding the complexities of consumer behaviour because modern consumers are driven by dynamic cross-channel consumer journeys rather than following a linear path to purchase. Understanding this dynamic shift is pivotal, particularly when evaluating consumer experience and purchasing behaviour within smart technology-enabled settings (Mauri *et al.*, 2024).

Despite the prevalence of scholarly efforts to understand, researchers (e.g., van Esch, Cui and Jain, 2021; Cui, van Esch and Jain, 2022; Malhotra and Ramalingam, 2023) argue that extant literature still lacks a systematic and empirically validated understanding of the factors inhibiting consumers' adoption of smart technology-enabled services, which is considered a limitation in the existing works on the subject. Given the growing scepticism among consumers towards anthropomorphized products, services, and platforms. Perceived risk, as argued by Sohn (2024) is a key factor driving this scepticism, which may influence consumers attitudes, experiences, satisfaction, and loyalty towards smart technology-enabled retail environments. Against this background, the present study explores the inhibitors, constituents, and consequences of associated with consumer digital ethics, risk, and experience of smart retail technologies, employing the theory of affordance (Gibson, 1977) as its guiding framework.

1.1.2 Consumer Experience

One of the key strategies for the sustainable success of the retail sector mainly involves retailers understanding their consumers and products at their best ability. A critical reflection of consumer behaviour and concerns within smart retail settings underscores the need to broaden the empirical scope beyond established contexts. In addition, it put emphasis on the necessity of refining the focus to explore deeper consumer experiences in smart technology-enabled retail environments. Consumer experience, a pivotal research domain in smart retailing, plays an important role in shaping the competitive edge of smart retailers (Grewal, Levy and Kumar, 2009; Grewal, Roggeveen and Nordfält, 2017; Homburg, Jozić and Kuehnl, 2017a; Guha et al., 2023). The theoretical concepts encompass various facets, including cognitive, emotional, physical, sensorial, and social elements, which mark consumers' direct or indirect interactions with smart retail products and services (Keyser et al., 2015; Chaney, Lunardo and Mencarelli, 2018; Hassenzahl, Burmester and Koller, 2021). These can be negative or positive, for example, satisfaction, anger, regret, outrage, joy, or surprise. A related stream of research has shown that consumers attain such experiences by actively engaging and interacting with smart retail technological solutions, products, or services, whether in-store or online (de Oliveira Santini *et al.*, 2018; Becker and Jaakkola, 2020; Sheth, Jain and Ambika, 2023; Desveaud, Mandler and Eisend, 2024). For example, in a smart technology-enhanced fashion retail setting, consumers experience a seamless fusion of physical and digital platforms. Through smart displays, kiosks, and virtual showrooms, clothing collections are showcased in an interactive and informative manner. These smart displays offer extensive details about clothing products, including features, colours, sizes, prices, and availability. Consumers can easily interact with a smart display to compare different options and, in certain cases, simulate clothing product usage in different scenarios using smart mirrors to assess suitability. This comprehensive approach encompasses tangible retail elements, such as physically examining and trying on the clothing items, as well as intangible requirements, such as obtaining information and simulating environmental circumstances (i.e., weather conditions) via digital means. Such integration of smart technology not only enriches the shopping experience and empowers consumers with enhanced decision-making capabilities. This contrasts sharply with traditional retail settings, where consumers typically rely on physical catalogues or in-store fitting rooms for similar assessments. This distinction is further exemplified in recent studies (Banik and Gao, 2023) on consumer experience, which indicate that this omni-touchpoint interaction and approach allows consumers to customise product experiences in real time without the need for prior technological expertise. Despite these significant technological advances witnessed in recent years, it remains important to acknowledge that consumer experience research with these smart technology-enabled products is still in its infancy, as noted by recent scholarly contributions (e.g., Grewal et al., 2023; Benoit et al., 2024). These studies underscore the pressing need for further exploration and understanding in this evolving domain, where there is a shift from traditional retail towards smart technology models despite consumer scepticism towards the smart platforms due to concerns, including perceived risk and digital ethics. Similarly, extant literature (e.g., Shankar, 2018; Martins et al., 2019; Guha et al., 2021, 2023; Grewal et al., 2023; Benoit et al., 2024) indicates a growing trend among smart retailers to embrace and integrate smart technological solutions (e.g., chatbots, cashier-less systems, and drones) into their services, echoing the gradual shift from traditional retail cooperative-driven service delivery models towards smart technology-driven ones. This phenomenon has been widely documented in the literature (e.g., Shankar, 2018; Davenport et al., 2020; Guha et al., 2021), and scholarly evidence (e.g., Grewal et al., 2023; Benoit et al., 2024) indicates that the adoption of smart technology is on the rise, promising to revolutionise the shopping experience. However, while forecasts depict exponential growth, the reality of implementation has been characterised by trials, revisions, and slow rollouts. For instance, the highly anticipated debut of Amazon Go autonomous stores, which unfolded at a pace far slower than anticipated. Despite projections of 3000 stores by 2021, only around 40 such establishments currently operate, confined to the United States and the United Kingdom. Similarly, Dutch retailer Albert Heijn embarked on an autonomous store trial at Amsterdam Schiphol Airport in 2019, only to pivot two years later, reevaluating its concept, location, and target market. The Swiss counterpart Valora encountered a similar fate, initially placing its autonomous store in a bustling train station before relocating to a university campus and subsequently opting for locations near commuter roads (Benoit *et al.*, 2024). These instances underscore a common trend among retailers: an eagerness to embrace smart technology without comprehensive assessment of its purpose or potential impact. The allure of innovation often overshadows the considerations of consumer convenience and business viability. As reflected in existing studies (e.g., Roggeveen and Sethuraman, 2020; Grewal et al., 2023), this enthusiasm must be tempered with a strategic evaluation of smart retail environments and their profound impact on consumer experience, behaviour, and perceptions to ensure sustainable and effective technology adoption. Thus, there is a call for research on how consumers use smart retail technologies (Sohn, 2024). This sentiment is also echoed by Wang et al. (2023)asserted a notable gap in research, specifically regarding the interaction between smart technology-enabled products and consumers. In other words, various studies have explored factors influencing the positive impact of integrating smart technology in retail. Smart retailers benefit from this approach, including enhanced consumer loyalty, stimulated purchase behaviour, increased shopping satisfaction, and augmented perceived value. Nonetheless, a gap exists between smart retail platform capabilities and consumer perceptions, and ethical concerns persist, hindering consumer experience and acceptance.

Recent scholarly discourse, as exemplified by (Adapa *et al.*, 2019), has adopted a consumer-centric approach to explore the antecedents of shopping value perceptions towards smart retail technology. However, these studies have not fully explored the constituents and consequences of the smart consumer experience in retailing, digital ethical concerns that differ from other retail formats, or how consumers perceive digital ethics in these settings. Even though ethical concerns and perceived risks have a large impact on consumers' reluctance to use smart services (Davenport *et al.*, 2020; Guha *et al.*, 2021; Y. Zhang *et al.*, 2024; Zhu, Vigren and Söderberg, 2024). Given the ever-changing dynamism of today's retail environment, where technology holds a prominent position in shaping consumer interactions, it is imperative to acknowledge the influence of consumer engagement on the overall shopping experience. Lemon and Verhoef (2016) in their study, emphasise the significance of understanding consumer behaviour within smart retail settings and dissecting the consumer experience into distinct stages. Despite the prevalence of scholarly efforts, further research is necessary to fully grasp the intricacies of consumer experiences, which indicate a promising avenue for future exploration.

Against this background, this study will explore and contribute to bridging the existing gap in understanding by positing that consumer experiences, ethical perceptions, and perceived risk in smart retail environments extend beyond mere attitudes towards technology. These factors significantly influence consumers' perceptions of value for smart solutions, services, products, and retailers, thereby shaping their intentions to patronise. Addressing these gaps will not only advance scholarly knowledge on consumers' experiences and behaviours in a smart retail environment but also provide insight into the ethical concerns inherent in such a context.

1.1.3 Consumer Engagement

Consumer engagement is a critical factor that determines the success of smart retailers in today's competitive retail setting (Kumar *et al.*, 2019; Chen *et al.*, 2023). Consumer engagement refers to the extent to which consumers contribute value to a retailer (Ho *et al.*, 2022). While direct contributions involve consumers making purchases, indirect contributions (nonpurchase actions), such as referrals, influencing others, and leaving reviews also significantly impact retailers (Kumar and Pansari, 2016; Harmeling *et al.*, 2017; Ho *et al.*, 2022). With the rapid advancement of smart retail technologies, retailers have increasingly implemented interactive and inclusive smart retail environments, substantially enriching consumers' online experiences (Dacko, 2017; Heller et al., 2019; Recalde et al., 2024). For instance, smart retail mobile applications allow consumers to leave reviews, star ratings, and recommendations, upload photos and videos to the retailer's online portals, and even interact and post follow-up questions directly to retailers and other consumers throughout the pre-, during-, and post-purchase stages (Grewal, Roggeveen and Nordfält, 2017; Inman and Nikolova, 2017; Souka, Bilstein and Decker, 2024). The use of smart technology-based interactions between retailers and consumers has become a cornerstone of the twenty-first-century retail setting, driving an extensive volume of research in the field of business-consumer interaction (Vrontis et al., 2017).

Retailers have traditionally used print, radio, television, and major online media to communicate their marketing messages to consumers. However, the efficacy of these old media channels has significantly reduced due to minimal interaction, lower accessibility offerings, and the advent of newer technologies (Dwivedi *et al.*, 2021). To maintain and enhance their market position, retailers have been compelled to adopt initiatives that optimise digital and smart marketing techniques (Naylor, Lamberton and West, 2012; Schultz and Peltier, 2013; Dwivedi *et al.*, 2021). In recent years, research has established that retailers are integrating smart technology in various ways, including the use of augmented reality, AI-driven chatbots, content creation, geo-targeting techniques, and consumer insights (McLean and Wilson, 2019; Fotheringham and Wiles, 2022). The use of conversational smart technologies, such as chatbots, for example, has exploded in recent years, with evidence indicating that their use for automated self-service will only grow (Fotheringham and Wiles, 2022; Rizomyliotis *et al.*, 2022).

For retailers to be able to engage consumers successfully, Hilken et al. (2017) and Ho et al. (2022) argues in their study that the experience within a smart retail service channel, such as smart shopping applications, should mimic "real" shopping to effectively engage consumers. The spatial presence experience, defined as the feeling of realism or "being there," is a key element in explaining consumers' active engagement and behaviour with smart retailers through smart technology-enabled retail platforms or environments (Hilken *et al.*, 2017; Ho *et al.*, 2022). Scholars (Fotheringham and Wiles, 2022) predict that smart retailers will invest more, around £7.5 billion, on smart technologies such as chatbots by 2024, up from an estimated £2.3 billion in 2019, with smart retail technologies like chatbot consumer service expected to be one of the largest and fastest-growing market segments. However, despite the growing expenditures in this domain, the impact of smart technology on consumer engagement, experience, and purchasing behaviour remains ambiguous both in the literature and in practice and needs exploring. It is broadly acknowledged that when consumers experience a sense of spatial presence, they tend to disregard the technology-mediated nature of the smart retail environment, resulting in an online shopping experience that feels as authentic and real as it is in a brick-and-mortar environment (Hilken et al., 2017; Recalde et al., 2024). Although existing literature advocates the strong relationship between consumer experience and engagement in both physical and online environments (Yu, Zhang and Liu, 2018; Davenport *et al.*, 2020; Benoit *et al.*, 2024), Extant research has shown that it has not fully identified the essence of smart experience in a smart technology-enabled retail environment, nor has it empirically examined how this experience enhances consumer engagement and purchasing behaviours within smart retail environments (Ho *et al.*, 2022).

Today, as online shopping environments have increasingly integrated smart technologies with immersive capabilities, a new mode of experience has emerged where consumers feel physically present within virtual shopping environments (Hollebeek et al., 2020; Arghashi and Yuksel, 2022; Y. Zhang et al., 2024). The significance of these smart technology-enabled environments for both retailers and consumers has become evident. However, the existing literature examining the mechanisms that formulate such experiences in smart retail contexts remains sparse (Ho *et al.*, 2022). A review of the literature on general online shopping environments suggests that two major media attributes, namely interactivity and vividness, determine consumer evaluation and experience in those environments (Ho *et al.*, 2022; Bin Kim and Jung Choo, 2023).

Drawing upon existing literature, it can be argued that as consumers engage in smart technology-enabled interactive simulations and immerse themselves in sensory-rich smart retail environments, they become fully engaged in smart shopping environments, experiencing something akin to the "real" brick-and-mortar store experience (Giroux *et al.*, 2022; Ho *et al.*, 2022; Song and Kim, 2022). However, there is limited insight into the impact of smart technology on consumer engagement in retail settings, meaning it is still not well understood. Further research is needed to fully understand the implications of smart technologies for consumer behaviour and retailer strategies. In line with Zhu, Mou and Benyoucef (2019) and Xu, Jia and Tayyab (2023) it is arguable that the mechanism by which consumers interact with smart retail platforms is translated into a feeling of spatial feelings leading to consumer engagement and experience within a smart retailing remains underexplored. This study contributes to the retailing literature by developing and investigating a theory-driven, dynamic, and contingent model of consumer engagement and experience in the context of smart retailing.

1.1.4 Consumer Purchasing Behaviour

Reflecting on the existing literature and the discussion above, it is evident that consumer expectations for seamless engagement and demand for smart retailing platforms are steadily rising (Ostrom et al., 2021; Yan et al., 2023). Smart technologies, such as chatbots, smart mirrors or smart shelves, can address this need by providing the speed and convenience demanded by connected consumers. Despite the widely discussed opportunities and challenges of integrating smart technology into retail (e.g., Cukier, 2021; Guha et al., 2021, 2023), there is ongoing scholarly discourse (e.g., Wang et al., 2022; Malhotra and Ramalingam, 2023; Xiong, Wang and Li, 2023; Sohn, 2024) about the constituents and consequences of an effective smart technology-enabled environment, as well as how consumers respond to smart retailing strategies. Unlike traditional brick-and-mortar settings or traditional e-commerce services, where consumers complete their online shopping process via websites where interaction is mostly limited to the user interface of the shopping website and basic features like recommended products based on browsing history, smart technology-enabled retail environments facilitate real-time information exchange between retailers and consumers and the use of advanced technology, allowing for one-to-many communication. In some cases, smart retailers use AI and data analytics to offer highly personalised services based on consumer preferences obtained through this information exchange (Chen, Lan and Chang, 2023; Chen *et al.*, 2024). This enhances consumer engagement and a plays pivotal role in influencing the consumer purchase decision-making process within smart retail settings. In essence, smart retail environments and platforms function as decision-support systems that fundamentally depart from traditional consumer behaviour in retail settings. While smart technology-enabled products and services offer numerous benefits (Stanciu and Rîndaşu, 2021; Nguyen and Llosa, 2023), consumers' perceptions vary, significantly influencing their purchasing behaviour (Martin et al., 2020; Alyahya et al., 2023). Despite scholarly efforts, this area of study remains relatively underexplored because of the rapidly evolving nature of smart retail technologies. Further research in this domain is essential for businesses to effectively adapt to the changing retail landscape and meet the evolving needs and expectations of consumers. In their seminal study of consumer online purchasing behaviour, Dacko (2017) and Nikhashemi et al. (2021) demonstrated that during online shopping, consumers may engage in goal-directed or unplanned product searches, browsing, and other activities such as virtual try-ons and visualisations to compare products and make purchase decisions. A review of the available literature (Banik and Gao, 2023; Chen and Chang, 2023; Moriuchi and Murdy, 2024) suggests that in a smart retail environment, consumer purchasing behaviour is influenced by various factors, including the convenience, interactivity, and personalisation offered by smart technologies. Scholars argue that purchase behaviour is the external embodiment of consumers' internal minds coupled with different attributes of the shopping environment, which are the key factors affecting their purchases. Holtzman (1989), in his study of consumer purchasing behaviour, points out in the extant literature that the consumer decision-making process has three stages: formulation, evaluation, and appraisal. In the context of smart shopping, several models (Howard and Sheth, 1969a; Nicosia and Mayer, 1976; Hawkins, 2019) have attempted to capture consumer purchasing behaviour and classify it into five fundamental stages: shopping need awareness, information search, alternative evaluations, deciding to purchase, and post-purchasing evaluation. Despite extensive academic research efforts and numerous behaviour models (Howard and Sheth, 1969a; Nicosia and Mayer, 1976; Hawkins, 2019) aimed at understanding consumer purchasing behaviour, most studies in the field have primarily focused on consumer behaviour in the broader retail context. As a result, understanding remains limited in smart retail settings. While the literature widely acknowledges the benefits and scope of using smart retail technologies, existing accounts fail to address the contradiction between consumer behaviour in a broader retail context and that in a smart retail context. Previous studies (e.g., Du and Xie, 2020, 2021; Pazzanese, 2020a; Sohn, 2024) have demonstrated that consumers may perceive certain risks and ethical concerns associated with smart retail environments, which impact their behaviour differently compared with traditional retail settings. Du and Xie (2021); Gutierrez et al. (2023); Laradi et al. (2024) sum up more recent arguments against smart technology-enabled retail environments as follows: consumers are concerned about the quality and accuracy of information (like recommendations and personalised ads) they obtain through smart technology-enabled platforms; digital ethical issues like privacy, fairness, and security regarding the collection and use of personal data are at the forefront. Many analysts now argue that understanding consumer purchasing behaviour in a smart retail setting will require retailers and other stakeholders to address these perceived risks while maximising the benefits of smart retail technologies. This approach creates a seamless and enjoyable shopping experience. Sohn (2024), for example, argues that "despite substantial convenience benefits, consumers are reluctant to use these technologies. Empirical insights into the inhibitors of consumer adoption of autonomous retail technologies are lacking. “Against this backdrop, this study explores and contributes knowledge on consumer purchasing behaviour and perceived risk, specifically within a smart technology-enabled retail environment.

1.1.5 The Ethical Concern in Smart Retailing

Products and services enhanced by smart retail technology are gaining popularity in the current marketplace as discussed above. However, consumers have conflicting views on smart technologies because of the various ethical challenges linked to their development and implementation in retail. To gain a thorough understanding of ethical concerns in smart retailing, a myriad approach of consumer, retailer and regulatory differences including compromises must be considered. Academic research on consumer ethics in retailing continues to be a fertile area of inquiry, precisely because these crucial challenges ("ethical concerns") are fraught with persistent conflicts and paradoxes (Lwin, Stanaland and Miyazaki, 2008; Esmark and Noble, 2018; Martin and Palmatier, 2020). Scholarly studies have indicated that for the past decade, smart technologies have been the driving force behind research, in the field of retail and practice, enabling retailers to streamline their operations, better understand consumer behaviour, and ultimately provide more personalised experiences. With the continued advancement of these technologies, it is evident that they will play an even greater role in shaping the future of the smart retail industry (Shankar, 2018; Martins *et al.*, 2019; Shankar *et al.*, 2021).

From predictive analytics to automated inventory management and consumer service, the possibilities for smart technologies in retail are endless, and their impact will undoubtedly be felt for years to come. As such, it is critical for businesses to embrace these technologies and use them to their advantage, in order to stay competitive and meet the ever-evolving needs of their consumers (Dacko, 2017; Nikhashemi *et al.*, 2021; Ho *et al.*, 2022; Hu, Pantano and Stylos, 2023). Most consumers became aware of the power and promise of smart technologies through online platforms, for example, Google and Facebook, as well as retailers such as Amazon (Pazzanese, 2020; Vimalkumar et al., 2021). Smart technologies are now crucial in a wide range of industries, including retail. Their growing use in retail, coupled with the prominence of ethical shopping motives, offers retailers who value their significance a major advantage. However, its game-changing potential to enhance efficiency, reduce costs and expedite research and development has recently been dampened by concerns that these sophisticated systems may cause more harm than benefit (Dacko, 2017). Researchers argue that smart technologies growing appeal and utility are undeniable. However, according to Karen Gordon Mills (a Senior Fellow at Harvard Business School and a leading authority on U.S. competitiveness, entrepreneurship and innovation), these technologies present major areas of ethical concern for consumers, such as digital well-being, privacy, artificial intelligence-bias and discrimination, and perhaps one of the most difficult philosophical questions of the era: the role of human judgement (Pazzanese, 2020; Du and Xie, 2021). The ethical challenges associated with smart technologies in retail have become more profound and require urgent attention (Du and Xie, 2021; Mostaghel and Chirumalla, 2021).

How can security concerns of consumers' digital data shape consumers' trust?

Consumers must examine their trust in the veracity of their provider's recommendation when deciding whether to accept the recommendation to embrace their "risky" service (Maduku and Thusi, 2023). Trust has become a critical component of success within the smart retailing landscape. Trust is one of the 'essential antecedents of interactions with others' (Hollebeek and Macky, 2019). Although a considerable number of prior studies has been conducted on trust in traditional retail, there has been limited empirical research on trust within the smart retail ecosystem (Vazquez et al., 2017). The concept of trust in everyday life is a somewhat sensitive and ever-changing subject based on the circumstances of human life. A consumer will approach a retail shop assuming they will achieve what they went in for and leave the premises satisfied; thus, a sense of trust will rise and (accepting a return) they will expect to return. However, if they have a one-off experience that is negative, psychologically this ends the trust, and the consumer is left questioning their return to the store. Most humans also rely on the trust of their trusted allies for future consumer decisions (Hong and Cho, 2011; Chi *et al.*, 2021; Leung and Seah, 2022). A prototype was designed to measure consumer trust towards interaction with artificially intelligent social robots in service delivery. The studies indicated that trust in interaction is measured by '3 s-order indicators: propensity to trust in robots, trustworthy robot function and design, and trustworthy service task and context' (Chi *et al.*, 2021). The first concept involves building trust with the robot and creating an understanding. The second element is formed by anthropomorphism, robot performance and effort expectancy, and the final indicator relies on the service risk, robot-service fit and facilitating robot-use condition (Chi et al., 2021). More recently, the heavy reliance on smart apps such as Siri and Alexa have introduced a new dynamic to consumer trust (Hasan et al., 2021). The new direction has not just introduced a surge in reliance on artificial intelligence, but also introduced new means of consumer protection loss, mainly consumer privacy. The development of these technologies has wide-ranging implications for retailers, consumers, and academic research. This is because the adoption of these technologies is intrusive and can harm consumer trust despite its benefit (Bruner and Kumar, 2005; Pizzi and Scarpi, 2020; Canziani and MacSween, 2021).

The main issues with digital information transparency and its impact on consumers

As was mentioned in the previous section, consumers are experiencing an era of rapid change as the result of digital transformation, which facilitates interactions between smart technologies, business models, transactions, and a wide range of innovative goods and services. These conversational smart technologies are ubiquitous and gather enormous personal data to create a tailored consumer experience (Vimalkumar *et al.*, 2021). Despite increasing enthusiasm, both practitioners and scholars hold divergent perspectives on smart technology and vehemently debate its value. These technologies also raise severe ethical issues about the acquisition, usage, and storage of their users' personal data. These concerns, according to research, affect the willingness of consumers to embrace these technologies (Agrawal, Gans and Goldfarb, 2018a; Fernandes and Oliveira, 2021a). Previous studies has indicated that in the modern multifaceted retail environment (Grewal, Roggeveen and Nordfält, 2017), consumers, regardless of their background, belong to a unique segment within the rapidly emerging digital era. Retailers rely on these segmentations (i.e., ethnic, demographic, psychographic, geographic, and behavioural), to identify and improve their effectiveness to deliver more targeted and valuable offerings to drive consumers to make a purchase (Shankar and Balasubramanian, 2009; Grewal et al., 2016; Grewal, Roggeveen and Nordfält, 2017; Davenport et al., 2020). Despite the growing support for these segmentations in retail, they are susceptible to questions of stereotypes and fairness. Given that technology acceptance is one of the most essential steps for retailers to attain future success, segmentation, when done unethically, can lead to the risk of perpetuating stale stereotypes and alienating consumers more than it attracts them (Lutz and Newlands, 2018; Kipnis *et al.*, 2019; Mora Cortez, Højbjerg Clarke and Freytag, 2021). According to research, the lack of relevance might make such measures seem more obnoxious, and consumers may see persistent recording of their location and behaviour as an invasion of their privacy (Martin and Palmatier, 2020; Pizzi and Scarpi, 2020).

1.1.6 Digital Information and Consumer Harm

Consumers are increasingly expecting to obtain instant, seamless, and memorable online shopping experiences when utilising smart technologies and digital shopping platforms (Dacko, 2017; Inman and Nikolova, 2017; Gauri *et al.*, 2021). As a result, retailers are continually developing strategies to meet and satisfy consumers' experience demands by using smart technologies, including artificial intelligence (Fanderl *et al.*, 2019; Lim, Tuli and Grewal, 2020). Further research has also indicated that the expectations of ever demanding consumers today are pushing retailers to seek new means to meet and respond to their desire for personalised experiences, not just to differentiate themselves, but also to survive by using smart technology and proprietary data (Lindecrantz et al., 2020). These demands and expectations of personalisation have left retailers facing tactical challenges (such as consumer ethical concerns and data management, including tools and technology enablement) in meeting consumer demands (Davenport, 2018; Davenport *et al.*, 2020; Lindecrantz, Tjon Pian Gi and Zerbi, 2020; Gauri *et al.*, 2021). Successful personalisation initiatives result in more engaged consumers. This has highlighted a high degree of awareness of consumers' real-time demands and has led retailers to establish truly customer-centric strategies. However, recent research on the use of artificial intelligence in retail highlights potential negative aspects and consumer harm concerns (Culnan and Armstrong, 1999; Kaltcheva and Weitz, 2006; Pizzi and Scarpi, 2020). These concerns include privacy and security dilemmas, trust, job loss, artificial intelligence-based bias and superintelligence's harmful developments (Kaltcheva and Weitz, 2006; Poncin *et al.*, 2017; Bleier, Goldfarb and Tucker, 2020; Martin and Palmatier, 2020; Pizzi and Scarpi, 2020).

Retailers may expose consumers to a mix of physical and online touchpoints and advance towards the digitisation of commerce by embracing digital technology; however, in the midst of this are consumer harm concerns. In a broader sense, this conversation is not new. For a long time, ethical implications regarding the use of smart technology, including IoT, AI, VR, AR, MR, and ML, have been a source of debate and concern in the technology world (Kumar, Ramachandran and Kumar, 2021). Although recent research has investigated the ethical, moral and trust difficulties surrounding the usage of innovative technology, such as artificial intelligence, there is also a dying need to investigate changes in behaviour, after consumers have expressed ethical concerns, to further understand the harm faced by consumers when interacting with these innovative technologies (Ameen *et al.*, 2021).

1.1.7 Consumer Well-being and Mindfulness

Overtime, smart technology has somewhat become a norm in a consumer's user experience journey, and without the use of it, consumers could struggle with simple day to day retailing/shopping activities as discussed above (Banker and Khetani, 2019; Gauri et al., 2021). The reliance on smart technology has advanced immensely, so that consumers are relying on these technologies for algorithmic decision making rather than personal intuition (Banker and Khetani, 2019). The change in dynamism over the century has meant consumers' trends and patterns are parallel to the advancement of these technologies. Previous studies had predicted that consumers' influence with technology was imminent and would somewhat change the shape of the future of retail (Kozinets, 2008). However, research has shown that despite the efforts of retailers to increase the accuracy of smart technlogoy-based decision-making systems, consumers regularly encounter vulnerable scenarios in today's smart retail ecosystem, where smart technology-based bias and poorer decision-making preferences are common. Consumers sometimes struggle to articulate their own preferences, whereas retailers also have challenges measuring their consumers' preferences (Bettman and Park, 1980; Bettman, Luce and Payne, 1998a; Kozinets, 2008; van Harreveld, van der Pligt and Nordgren, 2008; Mora Cortez, Højbjerg Clarke and Freytag, 2021). These kinds of scenarios can result in stress, mistrust, and unsatisfactory smart technology-based decisions to the consumer, borne out of incorrect inputs from the retailers (Martin, Borah and Palmatier, 2017; Banker and Khetani, 2019a; Martin and Palmatier, 2020; Grewal, Gauri, Roggeveen, *et al.*, 2021). Research states that the developments of smart technologies are gradually contributing to the automation of demand. This is achieved by utilising preference data and using systems to identify the consumer's choices, trends and purchasing activities (Banker and Khetani, 2019).

Given the increasingly complex decision-making settings in which consumers find themselves, retailers have identified that they are able to manipulate the behaviour of the consumer and obtain their engagement. Studies have indicated that vulnerable consumers are more likely to be targeted as they are not able to make a wise decision (Fletcher-Brown *et al.*, 2020). According to recent studies, whilst there are significant beneficial effects of technologies on capabilitarian well-being, arguably there are also unintended negative effects. Although technology can be used to ethically monitor and assess the well-being of consumers, consequently, it can also be used to take advantage of consumers (Robeyns, 2020). Extant literature supported the claim and indicated that smart technology, including artificial intelligence, has played a pivotal role in the last decade and it has only grown due to several enablers, contributed through consumers, such as the availability of data to train learning machines and the widespread availability of compatible technologies, such as ubiquitous computing and the internet of things. This has led to consumers relying on machines to support them with their everyday life, thus impacting their well-being (Feijóo *et al.*, 2020).

The increasing significance of the integration of smart technologies in retail and their benefits is becoming more evident both in practice and in the literature, attracting the attention of retailing and operations scholars, as highlighted earlier. However, several previous studies have argued that smart technology-enabled features in retail settings can have negative effects on consumers. For instance, Wiederhold (2018) discovered a link between frequent use of smart technology, like touchscreen devices, and compulsive engagement behaviours like endless scrolling, which bear similarities to addiction. In agreement, Coyne, Stockdale and Summers (2019) and Deng, Li and Xiang (2024) argued that this usage is closely tied to problematic behaviours, including aggression, disruption in self-regulation, and increased levels of anxiety and depressive symptoms (Barrios-O'Neil and Pakalkaitė, 2022). Likewise, previous study (Turkle, 2011; Ward *et al.*, 2017; Barrios-O'Neil and Pakalkaitė, 2022) exploring digital well-being has stated that spending more time in noisy, tech-enabled environments can have a negative impact on consumers' minds, leading to changes in how they think and remember things, significantly shorter attention spans, slower social skill development, and weaker basic reading and writing abilities. Existing literature (e.g., Lee and Shin, 2020) has also revealed that the high visual-verbal informational load of these technologies has a demonstrably huge impact on the consumer experience, raising questions about consumers' relationships with smart technology and emerging digital platforms and their consequential effect on our well-being. Ryff, (1989) identified six key factors contributing to well-being, which include self-acceptance, personal growth, life purpose, environmental mastery, autonomy, and positive relations with others. Despite consumers' growing smart retail technology adoption, understanding their effect on their digital well-being remains nebulous (Hollebeek and Belk, 2021). Against this backdrop, it is vital to explore the factors that facilitate consumers' digital well-being in smart technology-enabled retail environments, as they may play a significant role in making online purchase decisions. Thus, this study contributes to the literature on perceived risk, digital ethics in smart retailing environments, and consumer digital well-being in such environments.

1.2 Reasearch Objectives and Questions

Given the current wave of technological advancements and persistent digital disruptions, serving as a clear warning for businesses, societies, and global economies (Gupta, Gaurav and Panigrahi, 2023), this study adopts a comprehensive stance to probe the repercussions of digital transformations and smart technology-embedded shopping experiences. This study scrutinises the perceptions of privacy concerns, fairness, risk, trust, shopping experience, purchasing behaviour and overall digital well-being and loyalty within the UK retail sector. In exploring this dynamic retail landscape, smart retailers and stakeholders are fervently encouraged to adapt and implement tailor-made measures, policies, and practises (Hall *et al.*, 2021; Gupta, Gaurav and Panigrahi, 2023). In the ever-evolving digital retail environment, retailers must decipher current digital trends as cautionary signals. Smart retailers must demonstrate preparedness and proactivity in addressing the potential impacts and consequences stemming from the use of smart technologies in retailing (Lopes and Reis, 2021; Shankar *et al.*, 2021; Del Vecchio, Secundo and Garzoni, 2023; Gupta, Gaurav and Panigrahi, 2023). The smart retail sector has already undergone significant shifts due to the increased demand for online shopping, consequently altering consumer behaviour and placing considerable strain on the supply chain (Grewal, Kroschke, *et al.*, 2020; McKinsey & Company, 2020; Barney *et al.*, 2022; Gupta, Gaurav and Panigrahi, 2023).

Rooted in these theoretical assertions and considering the persistent challenges posed by smart technologies, digital trends, and potential disruptions, the research objectives are as follows:

a) Conduct a meticulous systematic literature review to discern seminal works, identify leading publication venues, and explore research topics related to smart technology, such as AI in retailing and consumer ethics and behaviour. This process will specifically focus on unravelling the nuances of consumers' perceptions of privacy, fairness, risk, and trust in the context of smart technology integration.

b) Craft a robust and comprehensive framework that not only encapsulates an understanding of the role of digital ethics, consumer perceived risk, and smart technology-embedded online experiences but is also precisely tailored to address the intricacies of how these factors shape trust formation, the smart shopping experience, and satisfaction among consumers.

c) Systematically delve into and analyse various constituents of the digital consumer experience within smart retail settings. This exploration will distinctly emphasise unveiling the intricate connections between the smart shopping experience and smart satisfaction among consumers. Importantly, this contribution directly addresses the extant gap in the literature concerning the impact on purchasing behaviour, loyalty, and digital well-being.

Drawing upon extant literature and the discussion above, it is evident that further research is needed to measure and manage consumer experience in smart technology environments and to address research gaps in the current understanding of smart technology's impact on consumer experience scholarship.

This journey through the empirical wilds is guided by four interrelated research questions, focusing on the perceived risk and digital ethics affecting consumer experiences and decision-making in smart retailing:

RQ1. How does the integration of smart technology in retail influence consumers' perceptions of privacy, fairness, risk, and trust?

RQ2. How does trust shape the smart shopping experience and satisfaction for consumers using smart retail technologies and platforms?

RQ3. In what ways does the smart shopping experience contribute to smart satisfaction among consumers?

RQ4. To what extent does satisfaction impact consumer purchasing behaviour and contribute to e-loyalty and digital well-being in smart retailing?

1.2.1 Problem Statement and Research Justification

As explained in the introduction, smart retailers rely heavily on the integration of emerging retail technologies and digital platforms to establish effective consumer relationships (Capatina et al., 2020; Prentice et al., 2020). These technologies significantly influence consumer purchasing behaviour by providing valuable information about products and services (Pantano and Priporas, 2016; Martins *et al.*, 2019; VO, Chovancová and Tri, 2020). By implementing these technologies, smart retailers can maintain a prominent position for their products and services in the minds of consumers (Choi and Kandampully, 2019). For example, technologies like personalised product recommendations, optimised pricing, and enhanced consumer services have yielded higher sales, fostered greater consumer engagement, and improved perceived usefulness and satisfaction (Shankar, 2018; Guha *et al.*, 2021; Shankar *et al.*, 2021). The COVID-19 pandemic further accelerated these trends, compelling retailers to adopt digital solutions, such as Amazon Go's autonomous stores, to meet rapidly evolving consumer demands and ensure operational resilience (Chen et al., 2022). While these advancements underscore the opportunities afforded by smart technologies, they also reveal significant challenges, including ethical dilemmas, data privacy risks, and consumer trust issues (Bleier, Goldfarb and Tucker, 2020; Martin and Palmatier, 2020). The widespread use of consumer data for personalisation has heightened anxieties about transparency, fairness, and security, factors critical to the sustained adoption of smart technologies (Xu, Jia and Tayyab, 2023). For instance, incidents like the Target data breach in 2013 revealed vulnerabilities in data security systems, and algorithmic bias in Amazon's hiring tool highlighted ethical concerns about fairness in automated decision-making (Mittelstadt *et al.*, 2016; Raji *et al.*, 2020). These challenges have eroded consumer confidence and trust in smart retail platforms, emphasising the urgency of addressing ethical concerns to foster sustainable adoption and "digital well-being" remain underexplored, particularly regarding their predominantly focused, perceived risk, and consumer loyalty (Martin and Palmatier, 2020; Guha *et al.*, 2023). This gap underscores the need to understand how consumers perceive and engage with smart technologies and how these perceptions influence their behaviours.

Existing theoretical frameworks, such as affordance theory (Gibson, 1977; 1979) and the unified theory of acceptance and use of technology (UTAUT) (Venkatesh *et al.*, 2003a; Venkatesh, James Y. L. Thong and Xu, 2012; Schmitz, Díaz-Martín and Yagüe Guillén, 2022), provide valuable insights into technology adoption but fail to address the ethical and psychological complexities of smart retailing. For example, affordance theory emphasises the relationship between users and technology capabilities but does not account for the role of ethical concerns like privacy or fairness in shaping consumer behaviour. Similarly, UTAUT focuses on constructs like performance expectancy and effort expectancy but overlooks critical factors like digital well-being and the nuanced impacts of perceived risks (Ben Arfi *et al.*, 2021). Furthermore, these constructs provide a novel framework for understanding consumer interactions with smart technologies. For instance, "smart consumer experience" captures cognitive, emotional, and social dimensions of consumer interactions across pre-purchase, purchase, and post-purchase stages, while "smart satisfaction" examines the fulfilment derived from seamless, personalised retail interactions. "Digital well-being" focuses on the psychological outcomes of engaging with social media platforms, including trust, fairness, and security (Keyser et al., 2015; Chaney, Lunardo & Mencarelli, 2018). By operationalising these constructs, this research extends theoretical models to address these critical dimensions. Practically, this study offers actionable insights for retailers, policymakers, and technologists. Retailers, for example, can enhance transparency in data governance by implementing dashboards that allow consumers to monitor how their data is collected and used, fostering trust and loyalty (Bleier et al., 2020). Policymakers can develop algorithmic audit frameworks to mitigate bias and ensure fairness in smart technology deployment (Raji et al., 2020). Similarly, technologists can design ethical AI systems that prioritise user experiences while addressing perceived risks and ethical concerns (Brey and Dainow, 2023).

The findings of this research are not limited to retail but also have implications for other sectors, such as healthcare, education, and finance, where smart technologies are increasingly being adopted. For instance, healthcare providers can design smart systems that enhance patient autonomy and build trust through transparent data practises (Guerrero

Quiñones, 2024). Financial institutions can apply these findings to ensure fairness in AI-driven credit scoring and decision-making systems. Addressing these issues provides a framework for fostering ethical and sustainable innovation across industries. In addition to its theoretical and practical contributions, this research responds to the growing societal need for responsible technology adoption. As smart technologies become integral to consumers' lives, addressing their ethical and psychological concerns is essential for fostering trust and long-term sustainability. By bridging these gaps, the study advances academic understanding and equips stakeholders with tools to navigate the complexities of smart technology adoption.

1.3 Data and Methods

The primary data collection method selected for this empirical inquiry was an online survey because of its capacity to reach a broader population in a shorter duration and at reduced expenses compared with conventional surveys. The survey sought to collect data on multiple factors that impact consumers' experiences, their perception of digital ethics, perceived risk, their behaviour when making online purchases and repurchases, and their intentions to continue shopping online, as described in the conceptual model. To guarantee the dependability and accuracy of the questionnaires, a comprehensive approach was employed, which involved conducting surveys using questionnaires and incorporating measurement scales from previous research. This study sought to enhance the reliability of the data gathered and the accuracy of the obtained results by employing various approaches. The study's target population comprised individuals who engaged in online shopping using smart technology. A total of 564 individuals (consumers) were contacted to complete the online questionnaires, and data analysis was performed on the responses of 510 participants who successfully completed the survey. This population was deemed suitable for the study because its purpose was to investigate the factors that impact shopping behaviour in smart technology-enabled retail settings. The methodology section of this study presents a comprehensive description of the research procedure, which encompasses the actions undertaken to create the questionnaire, the method of selecting participants, and the process of gathering data. In addition, this chapter describes the analytical methods employed to verify the conceptual model and research hypotheses, such as factor analysis, assessments of discriminant validity, and structural equation modelling. Factor analysis was used to identify the latent constructs that influenced the intention to persist in online shopping, while discriminant validity assessments were conducted to ensure that the constructs were separate and not measuring the same concept. Structural equation modelling was employed to examine the research hypotheses and establish the relationships between the constructs identified through factor analysis.

This study used several established criteria to assess the reliability and validity of the measures. The computed Cronbach's alphas for each construct adhere to the recommendations of Bagozzi and Yi (1988), setting a minimum threshold of 0.7. The study used a squared multiple correlation minimum threshold of 0.7 and an average variance extracted (AVE) minimum threshold of 0.5, following Bagozzi and Yi (1988) and (Byrne, 2010a) recommendations. In addition, the measures used in the study underwent a rigorous assessment of convergent reliability and discriminant validity to ensure the accuracy and consistency of the results. The evaluation of the proposed conceptual model and hypotheses regarding the factors that influence consumers' digital ethical perception, impact their online purchasing and repurchasing behaviour, and intention to continue shopping online involves the assessment of goodness-of-fit indices. One of such indexes is the chi-square/degrees-of-freedom (CMIN/DF) ratio developed by (Bentler and Bonett, 1980), which should not exceed five (Bentler, 1990).

To evaluate the appropriateness of the proposed model for this study, a structural equation model (SEM) was employed using SPSS and SmartPls4 software. The critical ratio (CR), chi-square (CMIN), degrees of freedom (df), root mean square residual (RMR), root mean square error of approximation (RMSEA), goodness-of-fit index (GFI), comparative fit index (CFI), normed fit index (NFI), incremental fit index (IFI), and relative fit index (RFI) were rigorously assessed to determine the best fit. Once the best fit was found, the regression weights (path significance) and R2 values of each relationship in the proposed research model were investigated as recommended by (Bagozzi, 1994; Byrne, 2001; Hair JR *et al.*, 2010). The software generates standardised regression weights, standard errors, and critical ratios (CRs) for each path. Detailed descriptions of the measures, including convergent reliability and discriminant validity, are provided in Chapters 5 and 6. It is crucial to make sure that all participants understand and interpret survey items in the same way in order to prevent potential research biases that may develop when comparing cultures or groups. Scholars have emphasised the need to minimise these biases in cross-national and cross-cultural research. To address this issue, a pilot study was conducted to test the questionnaire, and careful back-translation methods were employed (Brislin, 1986). Furthermore, the study examined measurement invariance (equivalence) across groups to determine the constructs' factorial invariance (Cheung and Rensvold, 1999). This approach helps minimise potential biases and ensures that the data collected are comparable across different cultural or group contexts.

1.3.1 Research Ethics

The level of attention paid to ethical conduct, encompassing personal, professional, and research activities, has significantly increased in response to society’s demand for greater accountability (Zegwaard, Campbell and Pretti, 2017). The importance of research ethics lies in its crucial role in safeguarding study participants and in upholding the integrity and accuracy of research analysis results. To address any concerns and maintain ethical standards and guidelines, the following actions were implemented:

Informed Consent: Considered the cornerstone of ethical research, informed consent comprises two essential components: “informed” and “consent.” All participants were provided with thorough information regarding the objectives, methodologies, potential hazards, and advantages of the study before they started their involvement. We have furnished this information in both written and verbal forms. The participants were granted sufficient time to pose inquiries and were reassured that their withdrawal from the study would not incur any adverse repercussions.

Anonymity and Confidentiality: Participants were assured in writing that their identities would not be revealed in any publication or presentation of research findings, and participant personal information would be kept private. Every piece of information given or gathered will be encrypted and kept safely in compliance with Brunel University London ethical policies to protect personal information.

Data Usage: In writing and, in some cases, verbally, the participants were provided with the assurance that the data gathered would be used exclusively for research objectives. The participants' identities shall remain confidential in all research publications and presentations, in line with Brunel University London research ethics policies, unless they provide explicit consent for such disclosure.

Withdrawal: Every participant in the research study had been informed they might choose to voluntarily leave at any time without any consequences or penalties. It was also urged on them to let researchers know if they were unhappy with any part of their participation. The study was carried out in compliance with Brunel University London's principles and ethical standards. The integrity of the scientific method was preserved, while participants' rights and well-being were protected by these steps.

1.4 Theoritical Contribution of the Study

This thesis makes four significant contributions to understanding how smart technology enhances consumers' virtual and online shopping experiences. In an era marked by rapid advancements in artificial intelligence (AI), the Internet of Things (IoT), augmented reality (AR), and other smart technologies, retailers are increasingly leveraging these tools to enrich their online platforms and improve consumer engagement (Grewal et al., 2021; Shankar et al., 2021).

First, this thesis provides a robust theoretical foundation for understanding consumer-facing smart retail technologies, focusing on digital ethical concerns and perceived risks. Specifically, it identifies critical barriers to adoption, such as privacy concerns, trust deficits, and perceived fairness, which play pivotal roles in shaping consumer behaviour. For example, the study reveals that consumers' trust in autonomous retail tools—such as chatbot-assisted shopping, AR-powered virtual try-ons, and location-based recommendations—significantly influences their purchasing behaviours and perceptions of digital well-being. This nuanced perspective extends traditional technology acceptance models (Venkatesh *et al.*, 2003a) by integrating psychological and ethical dimensions into the discourse on smart retail adoption (Davenport et al., 2020).

Second, this thesis introduces and empirically validates a novel subdimension of consumer-perceived digital ethics and risk, tailored specifically to the context of smart retail technologies. Constructs such as perceived privacy concerns, fairness and risk are analysed across the pre-purchase, purchase and post-purchase stages, offering a granular understanding of the consumer journey. By applying affordance theory (Gibson, 1977), this study explores how smart technologies can create actionable possibilities while simultaneously raising ethical dilemmas. For instance, AR-powered virtual try-ons afford consumers the ability to visualise product utility in personalised contexts, alleviating some privacy-related anxieties while exposing concerns about data misuse and algorithmic bias. This dual focus on opportunities and risks provides a deeper understanding of consumer interactions with smart retail platforms.

Third, this thesis significantly contributes to the literature by shifting the focus from operational benefits, such as efficiency and personalisation—to psychological and ethical hurdles, including perceived risks, trust and fairness. Unlike prior studies that predominantly examined technology's role in streamlining retail operations, this research demonstrates how features like automated recommendations and predictive analytics systems inadvertently raise ethical questions that affect consumer loyalty and satisfaction (Bleier et al., 2020; Guha et al., 2021). The survey findings reveal that trust mediates privacy concerns and purchasing intentions, while fairness concerns persist across consumer demographics, emphasising the need for retailers to address these barriers holistically.

Finally, this thesis enhances academic discourse by proposing and validating a conceptual framework that integrates constructs such as "smart consumer experience," "smart satisfaction," and "digital well-being." These constructs offer stakeholders actionable insights. The findings demonstrate that increasing transparency in AI-based recommendations can bolster consumer trust while mitigating perceived risks. Retailers can implement these insights to design ethically responsible strategies, while policymakers can develop guidelines to ensure fairness and privacy in smart retail environments. Beyond retail, the research has interdisciplinary relevance, particularly in sectors such as healthcare and education, where trust and ethical concerns shape the adoption of smart technologies. For example, AI-driven diagnostic tools in healthcare face similar challenges of balancing transparency with privacy, as do personalised learning platforms in education, which must address fairness concerns in algorithmic decision-making. In addition to advancing theoretical understanding, the findings underscore practical applications. Technologies such as voice-enabled virtual assistants and augmented reality shopping tools illustrate how personalised interactions can enhance consumer satisfaction while addressing privacy concerns. For instance, data from the study reveal that consumers are more likely to engage with technologies offering reciprocal benefits, such as convenience and transparency, without compromising data security.

By addressing the interplay of trust, fairness, and digital well-being, this research deepens scholarly understanding and equips stakeholders with strategies to navigate the complexities of smart retail adoption. This approach ensures that the transformative potential of smart technologies serves both consumer well-being and organisational goals in an ethically sustainable manner. Furthermore, by integrating ethical considerations into the discourse, this thesis helps shape the future of digital innovation and fosters trust and accountability across technology-driven sectors.

1.5 Thesis Outline

The organisation of the thesis is outlined in Table 1. The subsequent section presents a more comprehensive framework for structuring a thesis.

Table 1 Structure of thesis

	Chapters	Overview
Chapter One	Introduction	This chapter provides an overview of the context and rationale underlying the doctoral dissertation, outlining the research goals and objectives, and highlighting the research's potential contributions. Additionally, the chapter presents the study's structure and organisation.
Chapter Two	Literature review	This chapter provides a scholarly evaluation of the concept of smart retailing and the integration of emerging technologies into retail and its impact on consumer behaviour. The concluding section of the chapter emphasises the existing gap in knowledge regarding the use of AI in retail, consumers expectations and digital ethical concerns. This gap is further addressed in the subsequent chapter, which introduces a conceptual framework.
Chapter Three	Systematic Literature Review	This chapter provides a scholarly evaluation of the concept of smart retailing in the form of a systematic literature review.
Chapter Four	Conceptual framework and hypotheses development	This chapter provides a discourse that establishes a linkage between all the concepts, culminating in a conceptual framework.
Chapter Five	Methodology	This chapter expounds upon the research methodology and design that were employed for the current study. Additionally, the sample population is elucidated upon, and the process of survey data collection is discussed. Furthermore, the reliability and validity of the instruments utilised in the study are scrutinised. Novel techniques for data analysis are currently under development to demonstrate the way data is scrutinised. Additionally, ethical considerations are being considered for the study.
Chapter Six	Analysis and Findings	This chapter is devoted to the examination and interpretation of the data, as well as the presentation of the findings, in relation to the study.
Chapter Seven	Discussion of Findings	This chapter provides an analysis of the research outcomes, which were obtained in accordance with the predetermined objectives aimed at addressing the primary research goal.
Chapter Seven	Summary and Conclusions	This chapter provides a comprehensive overview of the research findings, conclusions, implications and recommendations for both theoretical and practical applications.

Chapter 2: Literature Review

This chapter critically reviews the existing literature on smart retailing, focusing on how advanced technologies, such as artificial intelligence (AI), the Internet of Things (IoT), augmented reality (AR), and virtual reality (VR), influence consumer experiences, engagement, satisfaction, and decision-making processes. First, it examines the integration of these technologies; this chapter explores how retailers are reshaping the consumer journey across pre-purchase, purchase, and post-purchase stages, fostering hyper-personalised and immersive shopping experiences. The chapter then discusses the key barriers to smart retail adoption, including data privacy concerns, perceived risks, and ethical challenges that affect consumer trust and technology acceptance. For example, while AI-powered recommendation systems enhance personalisation, their reliance on consumer data raises critical questions about transparency and trustworthiness. This section also considers the evolving role of smart retail platforms, such as interactive service bots and AR-enabled virtual try-ons, in enhancing convenience and decision accuracy. This discussion is anchored in established theoretical frameworks, such as the Technology Acceptance Model (TAM) and affordance theory, to provide a deeper understanding of the factors influencing consumer adoption and engagement. By synthesising historical and contemporary perspectives on consumer experience, this chapter identified critical gaps in the literature, particularly the need for empirical evidence on how smart technologies impact consumer well-being, trust, and loyalty.

This chapter contributes to a broader understanding of smart retailing by establishing a structured analysis of emerging technologies, behavioural influences, and barriers, providing actionable insights for researchers and practitioners seeking to advance digital transformation and sustainable consumer engagement.

2.1 Smart Retailing Overview

Reflecting on the existing literature and earlier discussions, recent technological advances in retail, such as AI-based chatbots, smart mirrors, and voice assistance, have revolutionised consumer-facing retail technologies (Pantano and Timmermans, 2014; Roy *et al.*, 2017; Pantano and Dennis, 2019). These advancements have empowered retail technologies to operate increasingly autonomously, marking autonomy as a key characteristic of smart retail technologies, often overlooked in the discourse. However, while autonomy is an important factor, its implications for both consumers and retailers should be critically examined. For example, how does increased autonomy affect consumer trust, and what operational challenges might arise for retailers?

This evolution represents a significant advancement in the integration of smart technology within the retail sector, effectively bridging the gap between physical and digital shopping experiences. Nevertheless, the potential risks, such as privacy concerns or the over-reliance on technology, are areas that require further exploration to provide a balanced perspective.

Multiple definitions exist for smart retailing, which are detailed in Table 2. From a consumer perspective, smart retailing involves the incorporation of connected technologies in retail spaces to enhance the consumer experience by seamlessly blending physical and digital elements, resulting in an interactive and personalised context-specific experience (Riegger *et al.*, 2021). While the concept of smart retailing is not entirely novel, its evolution revolves around a platform where retailers and consumers harness smart technology to transform and strengthen their respective roles within the smart retail ecosystem, ultimately leading to improved quality of consumer experiences (Belk, 2010; Pantano and Priporas, 2016; Roy *et al.*, 2017; Hoffman and Novak, 2018b; Gauri *et al.*, 2021).

Table 2: List of definitions for smart retailing

Authors	Definition of smart retailing
(Pantano and Timmermans, 2014)	"Smart retailing emerges as a part of a broader concept of smart cities by focusing on a new approach to retail management, which considers technologies as enablers of innovation and improvements in consumers' quality of life. In particular, it starts from the same idea of considering smart use of technology applied to the new vision of retailing enabled by modern technology."
(Roy *et al.*, 2017)	"An interactive and connected retail system which supports the seamless management of different customer touchpoints to personalize the customer experience across different touchpoints and optimize performance over these touchpoints".
(Vrontis, Thrassou and Amirkhanpour, 2017)	"Smart, technology-based interactions and synergies between businesses and consumers"
(Priporas, Stylos and Fotiadis, 2017)	The employment of various innovative (smart) technologies in retail to improve consumer shopping experience.
(Pantano and Dennis, 2019)	"Smart retailing emerges as a consequence of the vision of a smart city, considering the use of modern technologies to improve human life with respect to the shopping experience and retail settings."

As discussed above, smart retailing is gaining popularity among consumers due to the widespread adoption of smart technology, including artificial intelligence. For retailers, the increased use of smart technology brings greater efficiency by automating repetitive retail operations intelligently. It also enhances retailers' predictive capabilities and revenue generation (Bourg *et al.*, 2021). From the consumers' perspective, smart technology in retail provides a digital platform for quick, seamless, and enjoyable shopping experiences. There has been a rapid emergence of artificial intelligence-based technologies, such as chatbots and voice search, that offer on-the-go answers to consumers, anticipate their needs, and facilitate interactions with retailers (Adam, Wessel and Benlian, 2021a). As the growing shift from brick-and-mortar (offline) to smart or online shopping continues to unfold, significant attention has been directed toward understanding the impact of the use of emerging technology on both retailers and consumers in retail and shopping environments (Kim, Ferrin and Rao, 2009; Hong and Pavlou, 2014; Xu *et al.*, 2017a; Shankar, 2018; Davenport *et al.*, 2020; Guha *et al.*, 2021; Guo and Wang, 2023; Yang *et al.*, 2023). However, despite extensive research, it remains inconclusive whether the use of emerging technologies in retail and online shopping platforms leads to greater or lesser consumer engagement with this new paradigm and how it affects consumer behaviour. The existing literature presents conflicting findings, including a notable paradox: while previous studies acknowledge operational and environmental differences between online (Aguirre et al., 2015; Ratchford et al., 2022) and offline or physical shopping (Hess *et al.*, 2020) that can affect consumer-retailer relationship and decision-making, it remains unclear how consumers respond differently towards these differences. For example, previous studies have found that smart retailing platforms or online shopping offer more choices for consumers compared to brick-and-mortar stores. However, there are varying perspectives on how consumers would respond to this retail environmental difference. Some studies conclude that consumers will become more price-conscious, thereby making them less loyal to a brand (Lynch and Ariely, 2000; Guo and Wang, 2023). Contradictory evidence suggests that consumers tend to narrow their consideration set when shopping online, a behaviour that can reduce their price awareness and increase their commitment to a brand (Degeratu, Rangaswamy and Wu, 2000; Melis *et al.*, 2015; Gielens *et al.*, 2021). Furthermore, past studies have highlighted that smart retailing platforms, as opposed to offline shopping, offer a more technology-focused setting. However, it remains unclear how consumers perceive this distinction in retail environments. For example, evidence suggests that the technological disparities between smart retailing platforms and brick-and-mortar stores have the potential to either diminish consumer retention by eliciting apprehension over privacy concerns and the absence of interpersonal interaction (Meuter *et al.*, 2000; Martin, Borah and Palmatier, 2017; Martin and Palmatier, 2020; Martin *et al.*, 2020) or enhance consumer commitment by offering ease of use and access to information (Shankar, Smith and Rangaswamy, 2003a; Guo and Wang, 2023).

To elaborate, the impact of smart retailing on consumer behaviour is unambiguous. Consumers have become more empowered due to the use of smart technology in retail. Smart retailing has provided consumers with unlimited access to product information and a platform to compare products in real-time, mix and match items and services at their convenience, and while on-the-go (Roy *et al.*, 2017; Roy, Balaji and Nguyen, 2020). The integration of smart technology, including IoT, AI, VR, AR, MR, and ML, has improved the retail experience, leading to the emergence of numerous applications and channels throughout the retail landscape. However, the rapid and extensive technological transition in retail has surpassed expectations, and it is beginning to test consumers' ability to adapt. Consequently, a range of ethical concerns has arisen among consumers, including digital well-being, trust, privacy, reliability, and safety (Pizzi and Scarpi, 2020; Du and Xie, 2021; Vimalkumar *et al.*, 2021). Thus, the environmental differences between smart retailing platforms and shopping at brick-and-mortar stores are inevitable. However, the essential environmental differentiation and its varying appeal to individuals remain ambiguous. To reconcile the discussed ambiguities and inconsistencies, the upcoming sections will discuss smart consumer engagement, including experiences and their consequences, in the context of smart retailing. Additionally, individual-level variables that can account for consumers' divergent views regarding the use of technology in retail will be identified.

2.1.1 Why Smart retailing matters

Smart retailing is an innovative strategy that emphasises product availability, extensive knowledge sharing, and intelligent collaborations between consumers and retailers. It offers numerous benefits, including easy access to a wide variety of products through advanced technologies, customisation options, and enhanced inventory management. Additionally, it promotes knowledge sharing between retailers and consumers by facilitating the exchange of product experiences, ratings, requests, and complaints (Pantano and Timmermans, 2014; Pantano and Dennis, 2019). Evidence from prior literature indicates that smart retailing prioritizes and encourages intelligent collaborations between smart retailers, front-line retail staff, and consumers (Ostrom, Fotheringham and Bitner, 2019; Pillai, Sivathanu and Dwivedi, 2020; Cukier, 2021; Baabdullah *et al.*, 2022). This cooperative approach helps mitigate the challenges inherent in traditional retailer-consumer relationships, allowing consumers to select products and services that align with their preferences and facilitating their provision. The implementation of smart technologies enables the delivery of flexible and personalized services, requiring active consumer involvement in the purchasing process through the submission of preferences, needs, and requests (Pantano and Dennis, 2019; Davenport *et al.*, 2020; Shankar *et al.*, 2021). Efficient retail management relies on the collection and analysis of data pertaining to products, consumers, retailers, and other relevant aspects. The utilisation of emerging technologies, including IoT, AI, VR, AR, MR, and ML, enables the gathering of vast amounts of data, which can be leveraged through novel analytical methodologies and big data analytics to gain a competitive edge (Competition and Markets Authority, 2021).

Smart retailers offer various advantages, including more engaging atmospheres, increased consumer engagement, and favourable behavioural responses. Smart technologies provide novel and enjoyable features that foster enhanced consumer engagement and improve product and service excellence, leading to higher consumer satisfaction. (Pantano and Dennis, 2019). Studies have shown that smart retailers provide consumers with autonomous access to technologies, enhancing their sense of control and the overall quality of their shopping experience (Bahmani et al., 2022; Gulfraz et al., 2022). This approach facilitates increased interactivity between consumers and brands/retailers, while also improving integration across various smart retailing platforms. Previous research has demonstrated that when consumers have a positive shopping environment, they are more likely to interact with the retailer and the brand, resulting in increased purchasing behaviour (Kim and Kim, 2008). Furthermore, consumers are more likely to recommend and revisit a smart retail platform when they hold a favourable attitude towards it. Conversely, a negative consumer perception of a smart retail platform will hinder their engagement with it (Roman, 2007; Yang *et al.*, 2019; Mainardes, Coutinho and Alves, 2023). In sum, smart retailers and retailing platforms prioritise emerging and smart technologies, collaborative knowledge dissemination, and strategic partnerships to create a novel and engaging retail experience for consumers. These factors can influence consumer experience and behaviour based on their perceived risk or usefulness, including enjoyment. The next section will discuss consumer behaviour in further detail.

2.1.2 Forces Driving Consumer behaviour within Smart Retailing.

As discussed earlier, the concept of smart retailing has revolutionised the retail industry and reshaped consumer shopping behaviour. The integration of emerging technology and data empowers retailers to offer customised, efficient, and convenient shopping experiences. Today's consumers are inclined to engage with smart stores where physical products are connected to the internet, despite prior research indicating that smart technology might have adverse effects on the consumer experience (Cecere, Le Guel and Soulié, 2015; Inman and Nikolova, 2017; Martin and Palmatier, 2020; Alkis and Kose, 2022). Consumers leading busy lives seek ways to optimise, streamline, and simplify their shopping journeys. Consequently, they tend to respond positively to retailers' initiatives aimed at enhancing convenience, speed, affordability, and overall shopping enjoyment. The impetus behind the rise of smart retailing is the imperative to redefine offerings and create value from the consumer's perspective (Seiders et al., 2000).An essential growing trend of personalisation is identified as another significant driver of consumer behaviour in the context of smart retailing. Retailers with advanced technological capabilities can leverage extensive consumer data to tailor their products, services, and promotional communications to cater to unique requirements and Inclinations of individual consumers (Riegger *et al.*, 2022). The implementation of personalisation strategies in retailing fosters a perception of distinctiveness and selectiveness among consumers, resulting in heightened levels of brand allegiance and sustained patronage. According to research by Kim, Barasz and John (2019), personalisation significantly enhances consumer satisfaction, trust, and loyalty. The research also revealed that customisation amplifies the effectiveness of promotional communications and increases consumers' propensity to allocate more financial resources toward products and services. However, it is worth noting that personalisation may also raise concerns about privacy, as evidenced in the literature.

Recent research on the impact of smart technology in retailing contends that smart retailing is leading a technological revolution driven by two primary factors (McKinsey and Company, 2020). One factor is evolving consumer behaviour, which is marked by the adoption of smart retail, a shift towards smaller store formats, and new forms of engagement with retailers across various platforms. The other factor is the intense pressure on traditional retailers' profitability, stemming from the costs associated with meeting evolving consumer expectations while competing with smart retailers and discounters (McKinsey and Company, 2020). However, further research argues that there is limited knowledge regarding the effects of emerging technologies, such as MicroCloud computing, new robotics, fifth generation (5G) telecommunications, the Internet of Things (IoT), virtual reality (VR), augmented reality (AR), and mixed reality (MR), on consumers and retailing (Shankar *et al.*, 2021).

The increased adoption of smart retail technology by consumers has prompted academics and practitioners to recognise its profound impact on consumers' shopping experience (Foroudi *et al.*, 2018). For example, a 2020 report revealed that nearly one-fifth of consumers in the United Kingdom conduct "most or all" of their shopping online. Similar trends are observed in other major economies such as the United States, France, and Germany, as illustrated in *Figure 1*. Despite the widespread use of smart technology in retail, research indicates that there is a dearth of academic literature addressing the impact of smart technology usage on consumer dynamics and experiences, as well as its underlying behavioural motivations (Foroudi *et al.*, 2018).

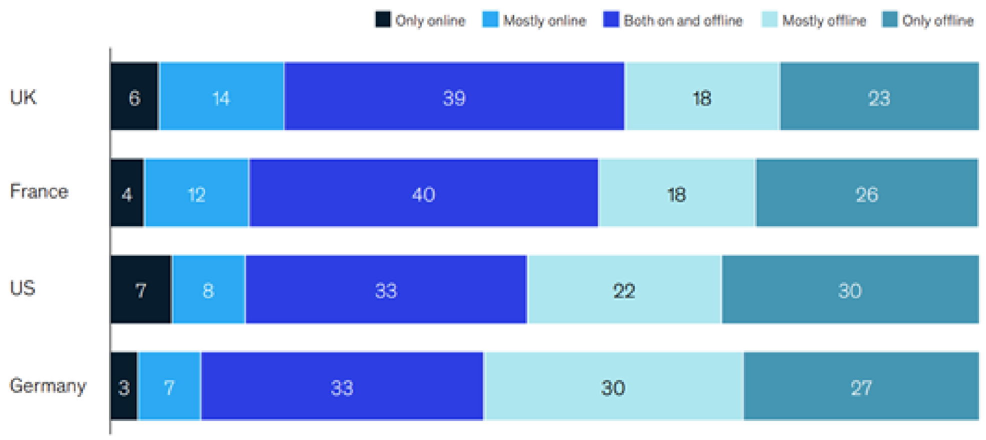


Figure 1:Consumers increased usage of technology (online vs offline). Source: McKinsey & Company, 2020.

A previous study observed that consumers have become increasingly tech-savvy and internet-oriented (Foroudi *et al.*, 2018). Simultaneously, the capabilities of smart retail technology have reached unprecedented heights. Smart retailers are now confronted with a growing array of sophisticated and often expensive retail solutions (Inman and Nikolova, 2017; Hoyer *et al.*, 2020; McKinsey & Company, 2020; Shankar *et al.*, 2021). A recent study on the use of smart technology such as artificial intelligence (Atos, 2021) projected that global spending on artificial intelligence will surpass €40 billion by 2020, as depicted in *Figure 2*. Sectors emphasising human-centric services, including finance, retail, and healthcare, are expected to lead in expenditure, followed closely by asset-intensive industries such as manufacturing, energy and utilities, and transportation. These investments improve business efficiency, enhance consumer services and experiences, and strengthen cybersecurity and advanced analytics. The rapid expansion of smart technology adoption is poised to have profound and far-reaching implications (Shankar, 2018; Davenport *et al.*, 2020; Atos, 2021).

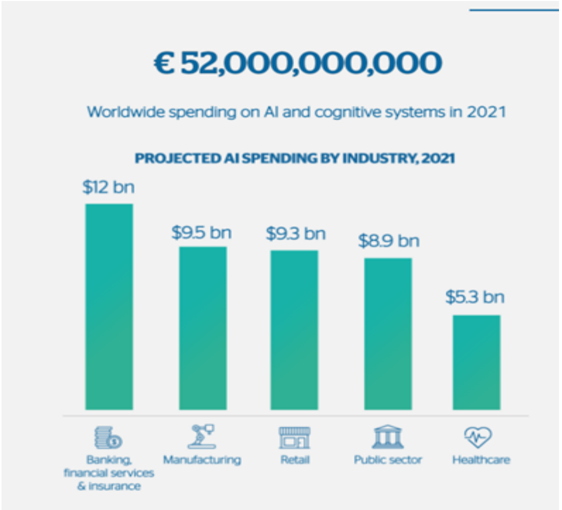


Figure 2:Projected smart technology spending by industry in 2021 cited in (Atos, 2021).

In the contemporary landscape, smart retailers face the imperative of crafting distinctive consumer experiences across prevalent channels while also striving for cost-effectiveness. However, this pursuit raises significant policy concerns concerning privacy, bias, and ethics (Davenport, 2018; Davenport *et al.*, 2020). The relentless pace of technological disruption in retail compels retailers to precisely strategize and discover novel avenues that grant consumers unprecedented access to their products, product information, and services, including various consumption channels (Shankar, 2018; Narang and Shankar, 2019; Shankar *et al.*, 2021). The role of smart technology in retailing is of paramount importance, especially in the context of the COVID-19 pandemic. Social distancing measures and nationwide lockdowns, implemented to curb the spread of the virus, compelled brick-and-mortar retailers to shutter some, if not all, physical stores and expedite their transition towards technology-driven solutions such as online ordering and fulfilment, click-and-collect, and robot-assisted operations (Hoyer et al., 2020; Grewal et al., 2021b; Shankar et al., 2021). Smart technology and platforms, including artificial intelligence and metaverse, is poised to remain a potent force shaping retailing strategies, encompassing business models, sales processes, consumer service choices, and consumer behaviours in the foreseeable future (Davenport *et al.*, 2020; Guha *et al.*, 2021; Yoo *et al.*, 2023). Despite the increasing demand among consumers for smart technology-driven enhancements and the concurrent reliance of retailers on these technologies to make their offerings more appealing, the full impact of these innovative and futuristic retail technologies remains largely unknown (Pantano and Priporas, 2016; Roy *et al.*, 2017; Riegger *et al.*, 2022). Retailers and service providers have at their disposal an array of innovative and futuristic technologies that can be integrated into their operations. The critical question confronting these stakeholders pertains to how these smart technologies influence consumer experiences and behaviours as well as the backend operations of retailing (Grewal, Roggeveen and Nordfält, 2017; Davenport *et al.*, 2020; Guha *et al.*, 2021). To date, there is a paucity of academic literature comprehensively addressing the obstacles to delivering a positive consumer experience within the smart retail ecosystem. The components and repercussions of the smart consumer experience and behaviours in retailing will be explored in the subsequent sections to further elucidate barriers to consumer satisfaction, perceived risks, and consumer well-being, with the aim of establishing a relationship between smart consumer experiences and resultant behaviours, as depicted in the conceptual framework referenced in (Roy *et al.*, 2017) below in *Figure 3*.

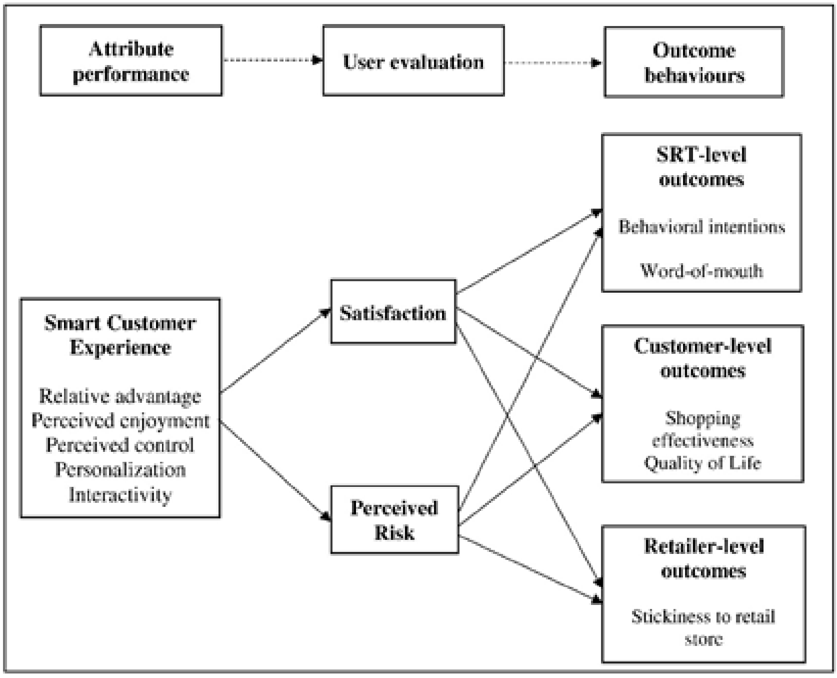


Figure 3:Smart consumer experience conceptual framework adopted from (Roy et al., 2017).

2.2 Consumer Smart Experience and Journey Overview

Understanding the smart consumer experience and their journey within a smart retail environment is of paramount importance for modern retailers. In this study, a smart consumer is defined as an individual who actively engages with smart retail technologies and platforms, leveraging tools such as artificial intelligence (AI), augmented reality (AR), the Internet of Things (IoT), and social media to facilitate informed decision-making, personalised interactions, and efficient shopping experiences (Grewal, Roggeveen and Nordfält, 2017; Shankar et al., 2021). These consumers are characterised not only by their reliance on advanced technologies but also by their heightened expectations for seamless, adaptive retail encounters and their increased sensitivity to ethical concerns such as privacy, transparency, and fairness (Verhoef, Kannan and Inman, 2015; Lemon and Verhoef, 2016).

Smart consumers engage with retailers through numerous touchpoints across diverse smart retailing platforms, including mobile apps, AR-powered try-ons, and chatbot-assisted interactions. These touchpoints collectively shape the smart consumer experience, a multidimensional concept that incorporates cognitive, emotional, behavioural, sensorial, and social elements (Puccinelli et al., 2009; Homburg, Jozić and Kuehnl, 2017). The literature presents various perspectives on consumer experience, encompassing diverse dimensions such as sensory, affective, cognitive, physical, social identity, and brand-related experiences, as shown in *Table 3*. In this context, the growing complexity of consumer journeys requires retailers, whether online or brick-and-mortar, to integrate diverse business operations, adopt omnichannel strategies, and collaborate with external partners to deliver cohesive and positive consumer encounters (Verhoef, Kannan and Inman, 2015; Lemon and Verhoef, 2016; Thaichon, Phau and Weaven, 2022). The proliferation of social media platforms further complicates this landscape because peer-to-peer interactions among consumers significantly influence their perceptions and behaviours within smart retail environments (Rapp *et al.*, 2015; Park and Hur, 2023). These developments present both opportunities and challenges for retailers. On the one hand, social interactions can amplify positive experiences and foster brand loyalty. However, negative reviews or perceived ethical breaches can rapidly erode consumer trust. Edelman and Singer (2015), Lundin and Kindström (2023) and Sheth, Jain and Ambika (2023), noted that creating, managing, and regulating the experiences and journeys of individual consumers has become increasingly intricate in this dynamic, technology-driven environment. Despite these complexities, research on the smart consumer experience remains fragmented, with scholars primarily focusing on traditional conceptualisations of consumer behaviour. Recognising the growing number and complexity of consumer touchpoints, the Marketing Science Institute (2021) identified consumer experience as a critical area of research inquiry. This study synthesises existing literature on the smart consumer experience, elucidates its historical and conceptual foundations, and identifies significant gaps in understanding. These gaps are bridged by integrating insights from technology adoption models, psychological dimensions, and ethical considerations to establish a comprehensive framework for analysing consumer journeys in smart retailing contexts.

The origins of consumer experience research can be traced to the mid-20th century, when scholars such as Abbott (1955) and Alderson (1957) emphasised the centrality of fulfilling experiences over mere commodities in achieving consumer satisfaction. Subsequent work by (Hirschman and Holbrook, 1982; Holbrook and Hirschman, 1982; Thompson, Locander and Pollio, 1989) expanded this perspective, highlighting the role of affective and experiential dimensions in consumer decision-making. Over time, the fields of retailing and marketing have increasingly integrated these insights, with contemporary scholars advocating for a multidimensional approach to understanding consumer experience, encompassing sensory, affective, cognitive, social, and brand-related dimensions (Homburg, Jozić, and Kuehnl, 2017; Grewal, Roggeveen, and Nordfält, 2017). In the context of smart retailing, these dimensions are further augmented by technological factors such as interactivity, personalisation, and automation, which reshape traditional retail experiences (Davenport *et al.*, 2020; Shankar *et al.*, 2021). For example, AR-powered virtual try-ons afford consumers the ability to visualise products in personalised contexts, enhancing convenience while raising new ethical challenges around data security and algorithmic bias (Bleier, Goldfarb and Tucker, 2020; Guha *et al.*, 2021). Similarly, chatbot-assisted interactions streamline purchasing processes but require careful management of consumer trust to mitigate privacy concerns (Martin and Palmatier, 2020). This study also underscores the interdisciplinary implications of smart consumer experiences, extending beyond retail to sectors such as healthcare, education, and finance. For instance, insights from this research can inform the design of personalised healthcare platforms that balance data-driven recommendations with patient autonomy. In education, smart learning environments can leverage findings on interactivity and trust to enhance student engagement while addressing concerns about data privacy and fairness (Grewal *et al.*, 2023). These broader applications highlight the relevance of consumer experience research in navigating ethical dilemmas in diverse technology-driven domains.

Finally, this study emphasises the importance of future research in addressing emerging challenges in smart retailing. While the integration of technologies such as AI and IoT has enhanced operational efficiency, it has also introduced new complexities in managing consumer expectations and ethical concerns. By providing a nuanced understanding of how smart technologies shape cognitive, emotional, and behavioural responses, this research offers actionable insights for retailers and policymakers seeking to foster trust, satisfaction, and loyalty in an ethically sustainable manner (Raji *et al.*, 2020; Thaichon, Phau and Weaven, 2022).

Table 3: Some Historical Perspective and Contributions to Consumer Experience

Author	**Contribution to Consumer Experience**
(Lavidge and Steiner, 1961)	Scholars have reframed advertising research by examining its goals and functions. The scholars propose a model that views advertising as a force that must guide consumers to purchase, with seven steps and three main functions: awareness and knowledge, liking and preference, and conviction and purchase. This study improves consumer experience by providing a framework for measuring advertising campaigns based on the consumer journey rather than sales results. This can help retailers understand how advertising affects consumer behaviour over time and optimise their strategies.

(Oliver, 1980)	This study was conducted to evaluate a theoretical model for consumer decision-making and post-purchase behaviour. To validate the theoretical model, the scholars used a completely recursive route analysis and analysed a variety of factors, including levels of pleasure, attitude, disconfirmation, and intention. Testing the theoretical model that provides insights into how consumers make decisions, experience pleasure or disconfirmation, and establish attitudes and intents towards products or services is the contribution that this work makes to the field of consumer experience. The findings of this study can be used to inform marketing tactics to increase consumer experience and satisfaction. This can be accomplished by identifying the elements that influence post-purchase assessments and decisions made by consumers.
(Zeithaml, 1988)	This study made significant advancements to the understanding of consumer experience by scrutinising the way consumers perceive and assess the value of the products or services they procure. The study established a means-end framework that elucidates the cognitive process through which consumers associate product characteristics, such as price and quality, with their objectives or principles, such as self-worth and social recognition. The study indicates that consumers' product evaluations are not limited to price and quality but encompass additional factors such as the product's social status implications, emotional benefits, and purchase risk level. The means-end model offers a comprehensive perspective on how consumers assess products and the compromises they make while contemplating various alternatives. This study underscores the significance of understanding consumers' viewpoints regarding price, quality, and value and the interconnection between these viewpoints and consumers' objectives and principles. By understanding these factors, retailers can enhance the design of their products and services to cater to the requirements of consumers and ensure a positive consumer experience.
(Bolton and Drew, 1991)	This study proposes a multistage model that elucidates how consumers evaluate service quality and value. This study emphasises the significance of incorporating both cognitive and affective dimensions of consumers' encounters when evaluating service quality and value. The study presented a theoretical framework comprising five distinct phases of consumer evaluation: (1) initial expectations, (2) perceived quality of service, (3) perceived value, (4) consumer contentment, and (5) post-purchase behaviour. According to the model, perceptions of service quality and value are significantly affected by consumer expectations. Perceived service quality and perceived value are

	distinct yet interconnected constructs that impact consumer satisfaction and subsequent consumer actions. A significant aspect of this study is its emphasis on the affective dimension of consumer experience. The study posits that consumers' emotions are of paramount importance in influencing their evaluations of service quality and value. Empirical evidence indicates that positive affective states, such as joy and surprise, positively influence consumers' perceptions of service quality and value. Conversely, negative affective states, such as frustration and disappointment, may result in lower evaluations of service quality and value. In general, this study presents a thorough framework for assessing the assessment of service quality and value by consumers. This study emphasises the significance of cognitive and affective factors in shaping consumer experience. The use of a model can aid commercial entities in comprehending and enhancing the consumer experience by identifying pivotal factors that influence consumer satisfaction and subsequent post-purchase behaviour.
(Rust and Chung, 2006)	This study made a notable scholarly contribution to the understanding of consumer experience. This study proposes a comprehensive framework that combines diverse marketing models to enhance the understanding of consumer relationships with service providers. This study highlights the significance of adopting a comprehensive and unified methodology for understanding consumer experience. The framework proposed by the scholars incorporates three distinct marketing models: the conventional marketing mix model, the service quality model, and the relationship marketing model. The conventional marketing mix framework centres on four key elements: product, price, promotion and place (distribution), whereas the service quality model prioritises fulfilling or surpassing consumer expectations regarding service quality. The model of relationship marketing prioritises the establishment of enduring connections with consumers through personalised interactions and the generation of reciprocal benefits. This study emphasises the significance of incorporating all three frameworks in comprehending consumer encounters. Through this process, retailers can enhance their understanding of how to generate and provide value to their clientele, establish robust and enduring connections with them, and enhance their comprehensive contentment. In general, this study offers a thorough framework that underscores the significance of adopting a comprehensive and integrated methodology to comprehend consumer experience. Through the incorporation of all three

	marketing models, enterprises can develop a marketing strategy that is more focused on the consumer, resulting in enhanced consumer experiences and more robust relationships.
(Kumar *et al.*, 2013)	This study made a noteworthy scholarly contribution by showcasing the efficacy of a social media marketing strategy in augmenting consumer engagement, loyalty, and purchase behaviour, thereby enhancing the understanding of consumer experience. This study examined Hokey Pokey, a high-end ice cream brand in India, and its approach to social media marketing. The proposed framework delineates four fundamental constituents, namely, awareness, engagement, influence, and value, for evaluating the efficacy of social media marketing tactics. This study showcases the efficacy of Hokey Pokey's social media marketing approach in augmenting consumer involvement and allegiance, along with stimulating purchasing behaviour. Through the utilisation of social media platforms, Hokey Pokey was able to establish customised and interactive encounters for their consumers, ultimately enhancing their affinity towards the brand and augmenting the probability of recurring transactions. In summary, this study offers a pragmatic illustration of how social media marketing tactics can augment consumer experience through the provision of personalised and engaging experiences. Hokey Pokey assessed their social media marketing approach to determine its efficacy. This enabled them to pinpoint areas that required enhancement and refine their strategy to enhance consumer engagement and stimulate purchase behaviour. This research showcases the significance of incorporating social media into a brand's marketing plan to amplify the customer experience and stimulate business results.
(Hollebeek et al., 2014)	This study made a notable contribution to the understanding of consumer experience. This study presents a comprehensive framework for consumer brand engagement in social media that encompasses three dimensions: cognitive, affective, and behavioural. The cognitive aspect pertains to the brand knowledge and perceptions held by consumers, while the affective aspect concerns the emotional attachment that consumers have towards the brand. The behavioural aspect, on the other hand, pertains to the actual interactions that consumers have with the brand on social media platforms. Scholars have devised a metric to assess the level of consumer involvement with a brand on

	social media platforms, which has been verified through empirical investigation. The measurement tool comprises individual items that assess three distinct dimensions of consumer brand engagement on social media platforms. This study offers a comprehensive framework and validated scale for assessing consumer brand engagement in social media. The utilisation of social media can aid businesses in comprehending the ways in which consumers interact with their brand, thereby enabling them to enhance their social media marketing strategies and augment the overall consumer experience. By comprehending the diverse facets of consumer brand engagement in social media, enterprises can develop specific social media content that effectively connects consumers and reinforces their affiliation with the brand.
(Barwitz and Maas, 2018)	This study made a noteworthy contribution to the understanding of consumer behaviour. This study identified crucial determinants that influence consumers' selection of interaction channels during the omnichannel consumer journey. This study presents a theoretical framework that consolidates multiple determinants that impact consumer selection of interaction channels. These determinants comprise situational factors such as time constraints and task intricacy, channel attributes such as ease of use and customisation, and customer traits such as age and technological proficiency. The scholars conducted an empirical investigation to assess the soundness of the conceptual framework and determined that situational factors exert the most significant impact on consumers' selection of interaction channels. Nonetheless, the study discovered that the impact of situational factors on consumers' interaction preferences can be moderated by channel and consumer characteristics. In general, this study presents a thorough structure for comprehending the factors that influence the selection of interactions in the omnichannel consumer experience. Through the identification of pivotal determinants that impact consumers' selection of interaction channels, enterprises can attain a more comprehensive comprehension of how to optimise their omnichannel approach to augment the consumer experience. Through the provision of a cohesive and tailored omnichannel encounter, enterprises can establish more captivating and gratifying interactions with their consumers, resulting in more robust consumer connections and heightened allegiance.

The selected studies mentioned in *Table 3* further advance our understanding of the consumer experience by presenting frameworks, models, and scales that measure diverse facets of the consumer experience in different retail settings.

Zeithaml (1988) introduced a means-end model that facilitates the comprehension of consumer perceptions regarding price, quality, and value. This framework has gained widespread adoption as a tool for comprehending consumer decision-making. Bolton and Drew (1991) created a multistage model that evaluates service quality and value. This model has had a significant impact on service marketing research. The study by Rust and Chung (2006) aimed to establish marketing models that could facilitate comprehension of service and relationships, thereby making a significant contribution to the advancement of relationship marketing theory. Hollebeek, Glynn and Brodie (2014) has significantly contributed to the field of social media marketing research by devising a multi-dimensional framework and a validated scale for gauging consumer brand engagement on social media. Kumar et al. (2013) demonstrated the practical application of social media marketing in improving consumer experiences and achieving business objectives.

Despite prior studies yielding significant findings regarding consumer experience, none of them have specifically centred on the smart retail context, which has gained considerable significance in contemporary times. Consequently, additional investigation is required to scrutinise the consumer experience within the smart retail framework, specifically regarding the influence of technology and automation on the consumer journey and their effect on consumer perceptions of value, quality, and engagement. Subsequent research endeavours may leverage the outcomes of these investigations to construct novel conceptual structures, paradigms, and metrics that are custom-tailored to the smart retail milieu, thereby enriching our understanding of patron encounter within this nascent scope.

2.2.1 The purchase phases in consumer journey

The concept of total consumer experience (TCE) underscores the importance of perceiving consumer experience as a dynamic process that surpasses the act of making a purchase. TCE acknowledges that consumers' experiences are shaped by various touchpoints and interactions that arise over a period. The process can be divided into three primary phases, namely the pre-purchase, purchase, and post-purchase stages, as demonstrated by Lemon and Verhoef (2016) and illustrated in *Figure 4* and consistent with prior studies (John A Howard and Sheth, 1969; Neslin et al., 2006; Puccinelli et al., 2009). Every stage signifies a crucial touchpoint where consumers encounter diverse interactions with the brand, some of which are within the retailer's purview, while others are influenced by external factors (Schmitt, 2010; Lemon and Verhoef, 2016).

During the pre-purchase phase, consumers interact with the brand by engaging in activities such as recognising their needs, conducting searches, and evaluating their options. Understanding the consumer's encounter during this phase is pivotal in moulding their comprehensive impression of the brand (Pieters, Baumgartner and Alien, 1995; Frank, Herbas-Torrico and Schvaneveldt, 2021). Likewise, in the purchasing phase, consumers engage with the brand throughout the actual transaction. This phase encompasses the selection, procurement, and transactional conduct of the consumer. It is imperative for retailers to direct their attention towards the impact of the marketing mix and environmental factors on consumers' decision-making processes (Ofir and Simonson, 2007; Elberse, 2010; Lemon and Verhoef, 2016).

The post-purchase stage pertains to the customer's interactions with the brand and its surroundings after the tangible purchase. During this phase, consumers engage in various actions, including product usage and consumption, post-purchase engagement, and service inquiries. During this stage, the product assumes a crucial touchpoint, and scholarly investigations have focussed on the consumption experience, service recovery, and consumer loyalty. Retailers should identify distinct trigger points that prompt consumers to either persist or terminate their progression in the purchasing process (Court *et al.*, 2009; van Doorn *et al.*, 2010; Lemon and Verhoef, 2016). Even if various recent research in the field of consumer experience looks at the complete, holistic consumer journey, the three stages help to manage the process (Lemon and Verhoef, 2016). However, because the retail sector is changing quickly and technology is having a significant impact on how consumers engage with retailers (Shankar *et al.*, 2021), further research is necessary in the context of smart retail. Virtual shopping assistants, mobile payments, and customised recommendations are just a few of the new touchpoints that smart technology in retail has introduced (Davenport *et al.*, 2020; Shankar *et al.*, 2021). Therefore, the influence of these touchpoints on the entire consumer experience at each of the three stages of the consumer journey must be considered. In the context of smart retail, understanding the TCE is imperative for enhancing the retention of consumers and loyalty. Merely concentrating on purchase occurrence is insufficient; instead, retailers must consider the consumer's journey and encounter the entire process. By comprehending every phase of the TCE, retailers can pinpoint opportunities for enhancement and furnish a more individualised and uninterrupted consumer encounter. The outcome can result in elevated levels of consumer contentment, allegiance, and recurrent purchasing behaviour, all of which are imperative for the enduring prosperity of any retail undertaking.

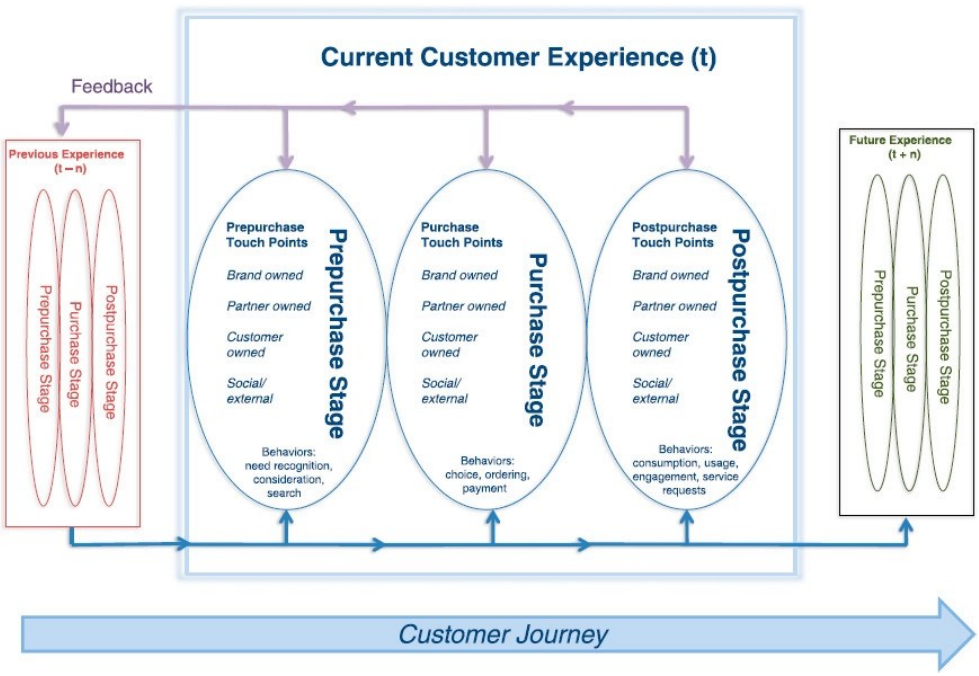


Figure 4:Process Model for Consumer Journey and Experience. Source:(Lemon and Verhoef, 2016).

2.2.2 The rising importance of smart shopping convenience.

In response to consumers' increasing demand for convenience, smart retailers are proactively expanding their offerings to include one-stop shopping while simultaneously reimagining and optimising their store operations. They also emphasise the range of products and services they provide. To achieve greater accessibility, many retail businesses have introduced self-scanning options that allow consumers to scan their own purchases at checkout, with the overarching goal of enhancing the efficiency of the shopping experience. For consumers, retail convenience is synonymous with both speed and ease of shopping (Seiders et al., 2000) as shown in Table 4.

Table 4: Type of convenience. source:(Seiders et al., 2000)

Four Ways to Offer Type of Convenience	
Convenient Shopping	Speed and Ease with Which…
Access	...consumers can reach a retailer.
Search	...consumers can identify and select products they wish to buy.
Possession	...consumers can obtain desired products.
Transaction	...consumers can effect or amend transactions.

Convenience plays a pivotal role in shaping consumer behaviour within smart retail settings. The surge in revenues from online retailers can be attributed to the ease with which consumers can compare prices, peruse reviews, and make purchases with just a few clicks. As the shift from brick-and-mortar to smart shopping gains prominence, findings from both existing and recent literature (Jiang, Yang and Jun, 2013; Duarte, Costa e Silva and Ferreira, 2018; Bin Kim and Jung Choo, 2023) consistently underscore convenience as a fundamental driver of online purchasing behaviour. These insights indicate that convenience significantly influences consumer satisfaction, thereby enhancing their intention to repurchase. The impact of convenience is vividly reflected in e-commerce sales, with global retail e-commerce sales estimated at 5.2 trillion U.S. dollars in 2021. Projections indicate a 56 % growth rate in this figure within the coming years, reaching an estimated value of approximately 8.1 trillion dollars by 2026 (Chevalier, 2022). This shift towards convenience stems from consumers allocating less time to shopping and diverting more of their time towards alternative activities, consequently fuelling the demand for convenience (Duarte, Costa e Silva and Ferreira, 2018; Kumar and Kashyap, 2018; Shankar *et al.*, 2021). As Berry and Cooper (1990) noted, the limited availability of time prompts consumers to prioritise time and effort-saving measures in their purchasing processes. Copeland coined the term "convenience" in 1923 to describe the amount of time and effort required to acquire a consumer good. Retail convenience, therefore, represents the temporal and effort-related costs associated with retail shopping (Copeland, 1923; Jiang, Yang and Jun, 2013; Duarte, Costa e Silva and Ferreira, 2018). The field of retail and marketing scholarship categorises the utilisation of time and effort by consumers as non-monetary costs that influence their purchase decisions (Bender, 1964; Herrmann and Beik, 1968; Duarte, Costa e Silva and Ferreira, 2018). Retailers have recognised the critical importance of improving the efficiency and convenience of the consumer's shopping experience, leading them to offer services geared towards optimising this facet of the consumer journey (Shaheed, 2004; Jiang, Yang and Jun, 2013; Shankar *et al.*, 2021; Maroufkhani *et al.*, 2022).

Extensive literature on convenience has explored the impact of extended waiting times on consumer experiences, especially in the context of time-saving benefits (Gehrt and Yale, 1993). According to (Berry et al., 2002), the length of waiting time is frequently considered an opportunity cost, underscoring its significance as an asset in a person's daily routine. The concept of effort-saving pertains to reducing the cognitive, physical, and emotional efforts that individuals must exert to procure goods and services. This includes activities such as seeking out product details, selecting the desired product for purchase (Emrich, Paul and Rudolph, 2015; Burns *et al.*, 2018), or finalising the transaction process (Berry et al., 2002). Scholars have demonstrated an inverse relationship between the perceived convenience of a service and associated time costs; as time costs increase, perceived convenience decreases. Hui, Thakor and Gill (1998) highlight a correlation between a consumer’s level of effort and the resources they devote, which increases the likelihood that they will feel frustrated.

The prior literature on convenience also supports the view that retailers can enhance the value of their market offer by enhancing convenience and saving consumers' time and energy (Seiders et al., 2000). At present, the Internet and emerging smart technologies represents a suitable alternative for individuals seeking to economise on time and energy. The preference for online stores can be attributed to the time constraints of individuals, who are increasingly burdened with professional demands. This limits the time available for daily tasks, leading them to opt for retail formats that require minimal time investment (Bhatnagar et al., 2000; Duarte et al., 2018). Kaltcheva and Weitz (2006) assert that the primary objective of consumers is to accomplish their shopping tasks efficiently and with minimal exertion, thereby obtaining the desired product or service.

Existing empirical findings concerning convenience emphasise its pivotal role in the relationship between consumers and service providers. The lack of convenience has been identified as a significant factor contributing to consumer churn (Keaveney, 1995; Pan and Zinkhan, 2006; Duarte, Costa e Silva and Ferreira, 2018), while convenience has been identified as a key driver in strengthening consumer relationships (Seiders *et al.*, 2007). However, despite its significance, there is a lack of consensus among scholars regarding the constituents of online convenience. For some (Farquhar and Rowley, 2009), online convenience is viewed not as an intrinsic attribute of a service but as a reflection of the resources utilised by consumers. Others (Yale and Venkatesh, 1986; Berry, 2000; Berry, Seiders and Grewal, 2002), consider convenience to be a multidimensional concept encompassing various types of time and effort costs. While there is acknowledgement of multiple dimensions within the concept of convenience, there remains a lack of consensus on the specific dimensions involved (Seiders *et al.*, 2007; Reimers and Chao, 2014). Berry, Seiders and Grewal (2002), introduced the SERVCON scale, a five-dimensional tool (as shown in *Figure 5*) originally designed for conventional brick-and-mortar retail settings.

However, this scale falls short of fully capturing the distinct dimensions of convenience in smart retail settings.

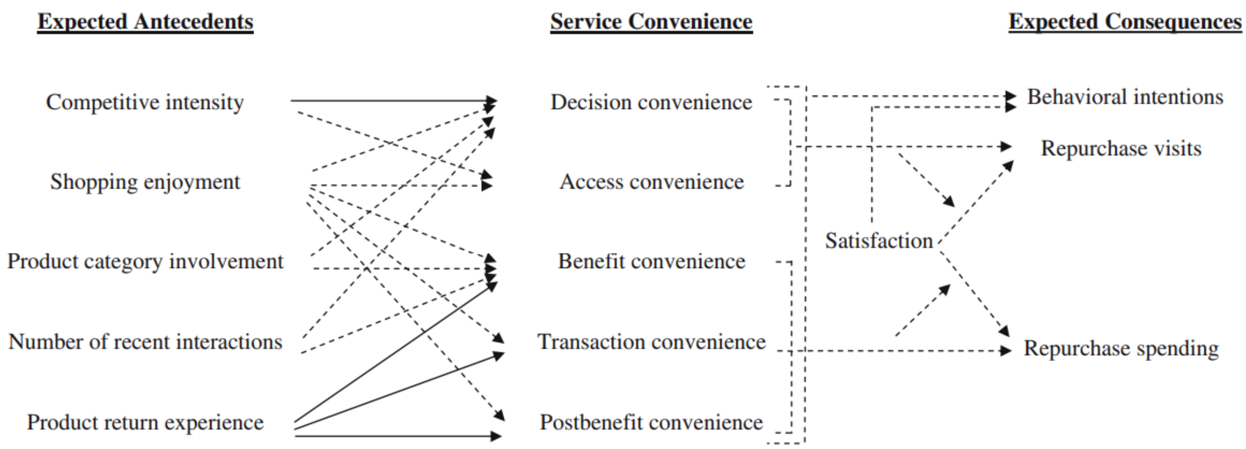


Figure 5*:Nomological network for the five service convenience dimensions. Notes: Between antecedents and service convenience dimensions, dotted lines indicate relationships expected to be positive; solid lines indicate relationships expected to be negative. Source:* (Seiders *et al.*, 2007)*.*

Today, retailers are encountering a new breed of consumers, who highly prioritise the resource of time, often viewing it as equally, if not more, valuable than money. Given the modern consumer’s increasingly hectic lifestyle, it is imperative to thoroughly assess the importance of convenience as a fundamental concept in consumer behaviour. This study aims to bridge the existing gap by delving into a range of convenience dimensions that are relevant to both online and offline shopping contexts. These dimensions encompass the expectations of consumers when they engage with smart retailing platforms.

2.3 Consumer Engagement Overview

Understanding consumers and their needs has evolved significantly, as evident from the indicators used in various phases of retailing emphasis (see *Figure 6*). Before the 1990s, the fields of retailing and marketing primarily revolved around consumer transactions. Key metrics to evaluate the impact of these transactions on retailer profitability include past consumer value, share of consumer spending, and recency, frequency, and monetary value of purchases (Pansari and Kumar, 2017).

This transaction-centric perspective gradually transformed into retailing relationships in the late 1990s and early 2000s. During this period, the primary focus of retailers was to build strong relationships with consumers, enhance consumer satisfaction, and foster loyalty through the delivery of superior products and service (Morgan and Hunt, 1994; Berry, 1995; Liang and Wang, 2007; Pansari and Kumar, 2017).

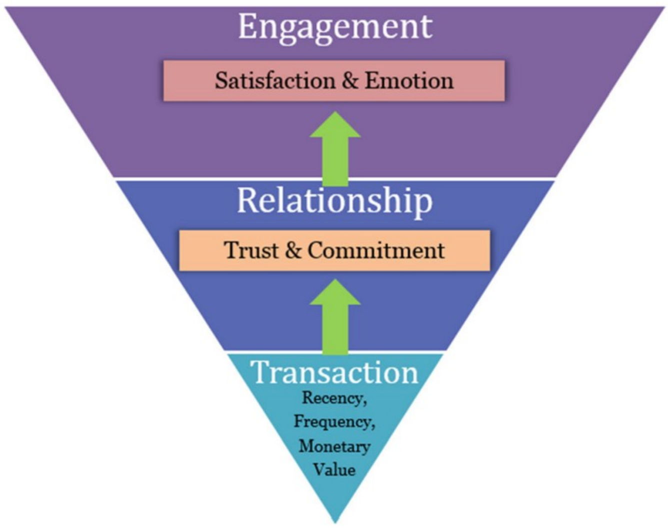


Figure 6: The evolution of customer management (Source: Pansari and Kumar, 2017)

A review of the literature from that era (Homburg and Giering, 2001; Shankar, Smith and Rangaswamy, 2003a; Wirtz and Lihotzky, 2003) extensively discusses the relationship between consumer satisfaction, loyalty, and profitability. Scholars have engaged in discussions regarding the profitable management of a consumer's tenure with a retailer, emphasizing the assessment of a consumer's lifetime value (Kumar, 2008). However, it has become widely accepted in both managerial and academic circles that mere consumer satisfaction is inadequate for fostering long-term consumer loyalty and profitability. The focus of retailers consequently shifted from relationship marketing to engaging consumers in every conceivable manner. As shown in Figure 6, this shift gave rise to the term "engagement" within the domains of retailing academics and practitioners (Pansari and Kumar, 2017).

The concept of engagement has been discussed across various contexts with differing interpretations. In the business context, engagement is defined as a formal agreement or contract (Pansari and Kumar, 2017; Jiang and Stylos, 2021). In management literature, it is considered an organisational activity involving internal stakeholders. In marketing and retail literature, consumer engagement has been extensively explored and defined as a consumer's active involvement with a business (Kumar *et al.*, 2010; Vivek, Beatty and Morgan, 2012; Pansari and Kumar, 2017).

Retailers have shifted their focus from the mere goal of selling products or providing services to emotionally connecting with consumers to drive sales and establish long-term, profitable consumer relationships. In other words, retailers are now emphasising personalised interactions, delivering exceptional consumer experiences, understanding consumers' unique challenges to enhance their quality of life, and engaging them as advocates for their business. These examples illustrate the ways in which retailers actively involve consumers on a global scale. In both extant and recent literature (Kumar *et al.*, 2010; Brodie *et al.*, 2011; Vivek, Beatty and Morgan, 2012; Roggeveen and Sethuraman, 2020; Grewal, Gauri, Roggeveen, *et al.*, 2021; Shankar *et al.*, 2021), the concept of consumer engagement has recently been a focal point of discussion in the fields of marketing and retailing. It is considered a metric for evaluating the effectiveness of a retailer's operations. Scholars and industry experts have engaged in discourse concerning various customer-centric metrics, including but not limited to consumer satisfaction, consumer involvement, consumer commitment, and consumer brand value. Table 5 differentiates and defines some of these variables under the umbrella of consumer engagement, elucidating their correlation with consumer engagement.

Table 5: Some constructs related to consumer engagement.

Related Constructs	Definition	Relationship to consumer engagement
consumer satisfaction	The concept of consumer satisfaction pertains to the degree of contentment and fulfilment that consumers feel after making a purchase from a retailer (Byun et al., 2023)	A satisfied consumer may buy product or services again. However, if the consumer feels connected with the business, they will go beyond purchases and make referrals, talk about the brand on digital platforms, and provide feedback, all of which are consumer engagement components.
consumer commitment	A persistent desire to preserve a valued relationship (Alvarez et al., 2023)	Commitment is the intensity of consumers attitude towards a brand, which is embodied in the consumer engagement foundation through the purchase of more goods or services (time and money).
Consumer brand value	The variations in how a consumer responds to brand marketing depending on their brand knowledge, brand attitude, brand purchase intention, and brand behaviour. (Kumar and Pansari, 2016)	The consumer brand value provides a quantitative assessment of how consumers perceive the brand. It interacts with consumer engagement components to foster positive consumer-retailer relationships.

The literature on consumer engagement presents various definitions and conceptualisations. Kumar et al. (2010) proposed a distinct definition and conceptualisation of consumer engagement, differing from Vivek, Beatty and Morgan (2012), who focussed on the degree of consumer involvement with the business, and Brodie et al. (2011), who emphasised that consumer engagement is a psychological state that arises within a specific context. Nevertheless, these studies collectively demonstrate that consumer engagement is a multifaceted concept. Several scholarly studies argue that diverse marketing and retail initiatives can influence consumer engagement, including the overall consumer experience, and, in turn, can impact the overall performance of a given retail business. The array of definitions helps clarify the distinction between defining and conceptualising consumer engagement. Therefore, this study provides a comprehensive characterization that encompasses all aspects of consumer activities.

2.3.1 Consumer engagement within a smart retail environment.

Owing to the pervasive influence of smart technologies in contemporary lifestyles, the advancement of interactive consumer engagement across smart retail platforms has recently become an operational imperative (Li, Juric and Brodie, 2017; Brodie *et al.*, 2019; Ferreira, Zambaldi and Guerra, 2020; Morgan-Thomas, Dessart and Veloutsou, 2020). Innovative technological solutions, particularly smart technologies, have brought about rapid changes in retail dynamics, including consumer engagement. This shift has elevated consumers beyond passive recipients of retailer messages; they now actively participate in interactive relationships with retailers (Morgan-Thomas, Dessart and Veloutsou, 2020). Previous studies on consumer management have highlighted the enduring, exploratory, and mutually beneficial connections between consumers and brands. Engagement now encompasses a continuum of stages, including pre-purchase, during purchase, and post-purchase (Vivek, Beatty and Morgan, 2012; Verleye, Gemmel and Rangarajan, 2014; Harmeling *et al.*, 2017). While consumer engagement exists in both physical (brick-and-mortar) and digital (online) settings (Schau, Muñiz and Arnould, 2009; Wirtz *et al.*, 2013; Breidbach, Brodie and Hollebeek, 2014; Morgan-Thomas, Dessart and Veloutsou, 2020), social interaction, communication, and sharing supporting brand clustering are increasingly connected to the online environment (Brodie *et al.*, 2013; Baldus, Voorhees and Calantone, 2015; Hollebeek, Juric and Tang, 2017).

The emergence of smart technology has transformed the consumer environment in which retailers provide services (Dacko, 2017). Smart and digital platforms, apps, and games encompass various technologies of engagement (Petit, Velasco and Spence, 2019; Chahal, Wirtz and Verma, 2020). Recent academic scholarship has concentrated on the normative, continuous, and persistent features of consumer engagement, reflecting contemporary realities (Wirtz and Lihotzky, 2003; Morgan-Thomas, Dessart and Veloutsou, 2020); The evolving mesh of digital technologies has created numerous opportunities for engagement (Venkatesan, 2017; Hollebeek and Macky, 2019; Veloutsou and Ruiz Mafe, 2020). This situation empowers retailers to gain additional capabilities for generating insights that benefit stakeholders, consumers, and partners in optimising product performance, including monitoring, control, and autonomy. Despite substantial progress in understanding consumer engagement, the role of digital technologies in smart retail ecosystems remains only partially understood. While prior studies acknowledge the role of digital technology in consumer engagement, empirical explanations that emphasise the importance of technology in engagement are scarce (Hollebeek et al., 2014; Morgan-Thomas et al., 2020).

According to Dessart, Veloutsou and Morgan-Thomas (2016), Breidbach and Brodie (2017) on engagement platforms, and Hollebeek et al. (2019) on consumer engagement in developing technological environments, the effective use of smart technologies is a significant aspect of consumer engagement research. The proliferation and sustained evolution of engagement platforms, including smart retailing platforms and applications, are perpetuating novel opportunities for consumer engagement and interaction (Harmeling *et al.*, 2017; Li, Juric and Brodie, 2017; Morgan-Thomas, Dessart and Veloutsou, 2020; Viglia *et al.*, 2023). Smart technologies, such as artificial intelligence and voice assistants, such as Amazon's Echo (Alexa), Apple's Siri, Microsoft's Cortana, and Google's Google Assistant, are altering the way consumers engage with retailers to seek service help, receive information, and make purchases. These technologies have become indispensable in consumers' daily lives. In 2018, over 70% of consumers' total digital minutes were spent on smart devices, a 28% increase from 2011. Global app downloads from 2016 to 2020 also surged, with consumers downloading 218 billion mobile applications to their smart devices in the most recent year, up from 140.7 billion app downloads in 2016, as shown in *Figure 7* below (Statista, 2021). These data underscore the essential role of smart technologies in modern lifestyles and consumer habits, ushering in a global revolution in the smart retail ecosystem.

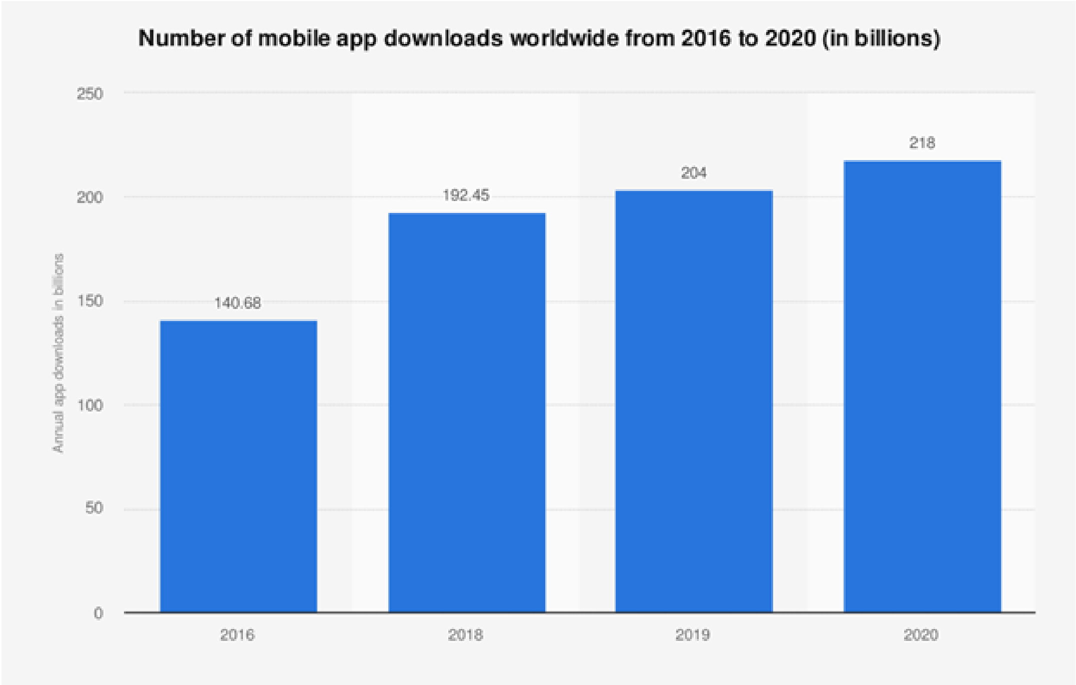


Figure 7: The data illustrates how smart technologies have become indispensable in modern lifestyles and consumer consumption habits, catalysing a global transformation of the smart retail landscape.

The emergence of these digital innovations has also triggered significant changes in managerial agendas, compelling retailers to adopt these advancements and proficiently manage consumer engagement in the evolving digital landscape (Morgan-Thomas et al., 2020). It is argued that the proliferation of smart technology significantly drives scholarly focus on engagement. This assertion finds support in previous studies (Vivek, Beatty and Morgan, 2012; Venkatesan, 2017; Hollebeek and Macky, 2019; Morgan-Thomas, Dessart and Veloutsou, 2020) which have contended that technological advancements underpin the scholarly fascination with engagement. Despite their widespread use, a comprehensive assessment of consumer interactions with these smart technologies and their consequences in a smart retail context remains lacking (Roy *et al.*, 2017; McLean, 2018; Grewal, Gauri, Roggeveen, *et al.*, 2021). Previous research has explored the role of smart technology in consumer engagement through various lenses. Existing literature has examined consumer involvement in online brand communities, mobile applications, and social media concerning engagement across various technologies and digital platforms. Studies by Hollebeek, Glynn and Brodie (2014), Baldus, Voorhees and Calantone (2015), Dessart, Veloutsou and Morgan-Thomas (2016), Hollebeek, Juric and Tang (2017), Viswanathan et al. (2017),Pongpaew, Speece and Tiangsoongnern (2017), Marino and Lo Presti (2018),Gong (2018), and more recently, Chahal, Wirtz and Verma (2020), (Morgan-Thomas et al., 2020), Kumar and Utkarsh (2023), and Zou et al. (2023), have all explored this. Recent research in ecosystem scholarship posits that a comprehensive perspective on technology is required. Engagement can occur in diverse digital contexts where individuals and technologies actively contribute to a broader ecosystem's functioning (Brodie *et al.*, 2019; Morgan-Thomas, Dessart and Veloutsou, 2020; Koh *et al.*, 2023; Kumar and Utkarsh, 2023; Zou *et al.*, 2023). According to this viewpoint, engagement is a deliberate yet limited undertaking (Hollebeek et al., 2017; Hollebeek, Sprott, et al., 2019), revolving around generating value among participants, including consumers, brands, corporations, and other entities forming engagement networks (Brodie et al., 2019; Morgan-Thomas et al., 2020). Breidbach and Brodie (2017) and Li et al. (2017) argue that digital technologies promote action and interaction, thereby facilitating engagement.

While there has been notable progress in understanding engagement, the precise function of digital technology within digital ecosystems remains incompletely understood. While it is recognised that smart technologies play a role in engagement, studies by (J. Wirtz et al., 2013) emphasise a scarcity of empirical evidence effectively capturing the significance of smart technology in relation to engagement. Nevertheless, some studies, such as those by (Hollebeek et al., 2014), Vivek et al. (2014), and Li et al. (2017), have attempted to address this gap. In the work of Hollebeek, Sprott et al. (2019), and (Chahal et al., 2020), technologies are perceived as tools for passive engagement, providing contextual backdrops to consumer activity. The prevalence of the metaphor of technological mediation was acknowledged by (Breidbach and Maglio, 2016). The focus on human-centred approaches appears at odds with the current state of engagement, as technological advancements have led to various new engagement practises (Wirtz *et al.*, 2019; Chahal, Wirtz and Verma, 2020; Morgan-Thomas, Dessart and Veloutsou, 2020).

Additionally, the interaction between different technologies influences consumer behaviour (Larivière et al., 2017; Hoffman and Novak, 2018), and artificial intelligence-based algorithms can actively influence the actions and interactions of human actors (Lugosi and Quinton, 2018). For instance, the Snapchat icon known as "Snapstreak" represents the degree of closeness between two individuals on the platform, signifying a continuous and uninterrupted flow of interactions. According to a 2019 BBC report, this functionality has a significant impact on teenagers' behaviour and level of commitment to streak maintenance, to the point where they entrust others with their devices to maintain streaks while they are away. New insights in the field of smart platform research, as presented by Alexander, Jaakkola and Hollebeek (2018), Hollebeek, Srivastava and Chen (2019), and Wajid et al. (2019), may further challenge the dominance of technology-focused research in academia. Existing literature on the engagement of smart platform ecosystems primarily adopts a service dominance perspective, representing a gap that warrants exploration of alternative viewpoints.

2.3.2 Consumer herding behaviour in smart retail settings.

The concept of herd behaviour has gained significant recognition, signifying individuals' tendency to mimic each other's conduct and judgements (Chen, 2008; Xu *et al.*, 2017b; Pavlović-Höck, 2022). This phenomenon is particularly prevalent in digital marketplaces, including smart retail settings, where an overwhelming amount of data is presented, leading to information overload. Unlike physical retail settings (brick-and-mortar stores), virtual or AI-embedded shopping environments exhibit a higher degree of information asymmetry and ambiguity, making it more challenging for consumers to accurately assess the value and quality of products and services they intend to purchase. Consequently, consumers often engage in additional information-seeking behaviours, invest more effort and allocate more resources, including financial resources, to optimise their decision-making process, mitigate potential risks, enhance value and conform to external expectations. As a result, individuals are prone to incorporating external information into their decision-making process, especially when faced with a deluge of asymmetric information (Bonabeau, 2004; Chen, 2008;

Lee et al., 2011; Xu et al., 2017). For instance, previous research (Chiu et al., 2006) has indicated that cutting-edge digital technologies have enabled various avenues for online users to share information with others. Online communities, such as discussion forums and social networking sites, have emerged as primary platforms for consumers to engage in information sharing. Specific online communities, such as TripAdvisor and Yelp, prioritise online consumer reviews as the primary source of information that captures consumers' interest. Electronic word-of-mouth (eWOM) refers to online reviews that encompass consumer assessments and viewpoints on a diverse range of products or services, typically contributed and disseminated by consumers with prior purchasing experience. Individuals within online review communities often use this information to reduce product and purchase ambiguity in their decision-making processes (Chiu, Hsu and Wang, 2006; Shen, Zhang and Zhao, 2016; N. Wang et al., 2022).

It is commonplace for consumers to conform to majority beliefs while ascribing a higher level of knowledge to others (Bonabeau, 2004; Xu et al., 2017). Deutsch and Gerard (1955) identified two distinct forms of influence that individuals derive from others: informational influence and normative influence. Informational influence relates to the extent to which individuals perceive information acquired from external sources as a valid indication of a particular reality (Deutsch and Gerard, 1955). This form of influence can assist in problem-solving or adapting to one's surroundings (Lee et al., 2011; Xu et al., 2017). The impact of online product recommendations and reviews, including sales volume, star ratings, and consumer feedback, on consumer decision-making is substantial (Chen, 2008; Xu *et al.*, 2017a). Normative influence, on the other hand, pertains to the influence of positive expectations from others on an individual's inclination to conform (Deutsch and Gerard, 1955). This form of influence is often associated with social influence, defined as the impact of viewpoints or endorsements from significant individuals that enhance the credibility of information and consequently affect consumer behaviour (Deutsch and Gerard, 1955; Stevenson, Hack-Polay and Tehseen, 2022).

Collective behaviour among consumers, commonly referred to as herd behaviour, emerges as a result of the coexistence of both informational and normative influences.

Venkatesh, Thong and Xu (2012) used the term "social influence" to describe normative influence, positing that the endorsement or advice of esteemed individuals would enhance the credibility of information and subsequently influence individuals’ behaviours. According to findings from existing studies, herd behaviour arises from these two external influences (Cvii and Banerjee, 1992). Consumer purchasing behaviour in smart retail settings undergoes continuous evolution due to the proliferation of technology and the expansion of online shopping, transforming consumer purchasing behaviour within retail settings. Therefore, it is imperative for smart retailers to familiarise themselves with the determinants that influence consumer behaviour in such settings, enabling them to adjust their strategies accordingly. Understanding the determinants that drive collective behaviour can assist retailers in devising more effective marketing tactics. However, the limited number of studies in this area is a notable gap that needs further exploration.

In summary, consumer purchasing behaviour within a smart retail environment can be contextualised by the level of engagement, interaction and enjoyment derived from online shopping experiences. Herd behaviour is often observed among consumers who tend to emulate others, as evident in their engagement, socialisation, and amusement within online social communities. A deeper understanding of the determinants that influence herd behaviour can provide retailers with valuable insights into consumers’ cognitive processes and help in the development of effective marketing strategies. However, the scarcity of studies in this area poses a significant limitation.

2.3.3 Consumer Online Purchase Behaviour and Decision-Making.

The abundance of information available online has transformed the consumer purchase decision-making process into a challenging and often frustrating task (Karimi et al., 2018) To explore the overwhelming choices and the vast sea of information emanating from various smart retail platforms (Hall and Towers, 2017), consumers employ specific decision-making strategies (Bettman and Zins, 1979; Malhotra, 1984; Payne, Bettman and Johnson, 1991; Karimi, Holland and Papamichail, 2018). Consumers continuously adapt their decision strategies in response to new information, resulting in dynamic purchase processes. These purchasing processes evolve through a series of behavioural choices, and distinct decision-making patterns are expected to reflect the characteristics of various consumer demographics.

While studies on online consumer decision-making have indicated that individual traits may influence behaviour (Smith and Rupp, 2003; Darley, Blankson and Luethge, 2010; Karimi, Holland and Papamichail, 2018; Shin, Shin and Gim, 2023), there is limited empirical evidence to support this assertion. Previous research has predominantly focussed on demographic factors (Ranaweera, McDougall and Bansal, 2005; Hall and Towers, 2017) and web experience (Frambach et al., 2007; Scarpi et al., 2014), However, substantial distinctions among online consumers extend beyond demographics and web behaviours (Brengman et al., 2005; Ratchford et al., 2022). These distinctions encompass motivating forces (Morrison et al., 2013), personality attributes, subjective knowledge (Brucks, 1985; Park, Mothersbaugh and Feick, 1994), and decision-making style (Karimi et al., 2015) as illustrated in the *Figure 8*.

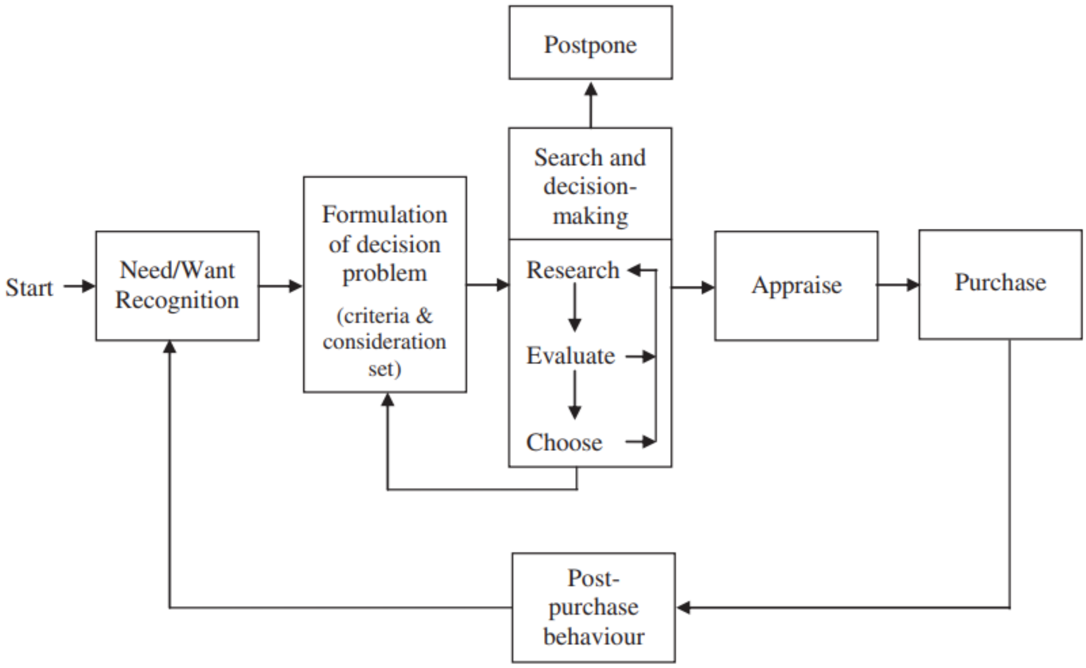


Figure 8: Consumer purchase decision-making model. Source:(Karimi, Papamichail and Holland, 2015).

This model combines different stages of the purchasing process to provide both prescriptive and descriptive perspectives on the decision-making processes involved in online purchases. It transcends conventional linear process models by highlighting internal loops in the process and showcasing its dynamic and iterative nature.

Moreover, it offers a prescriptive viewpoint by enumerating various stages. Consumer purchasing behaviours and decision-making within a smart retail setting entail several stages that significantly influence the likelihood of a successful purchase, as shown in Figure 8. Payne, Bettman and Johnson (1991) assert that decision strategies are shaped by the internal capabilities and motivation of decision-makers. The purchase decision-making behaviours of online consumers is influenced by two individual characteristics: their knowledge of the product and their maximization tendency.

These characteristics are related to their inner capacity and motivation to identify the optimal choice. In a similar vein, prior research (Xiao and Benbasat, 2007) has revealed the varying levels and characteristics, including factors, that impact consumer decision-making processes and outcomes, as illustrated in Figure 9 below.

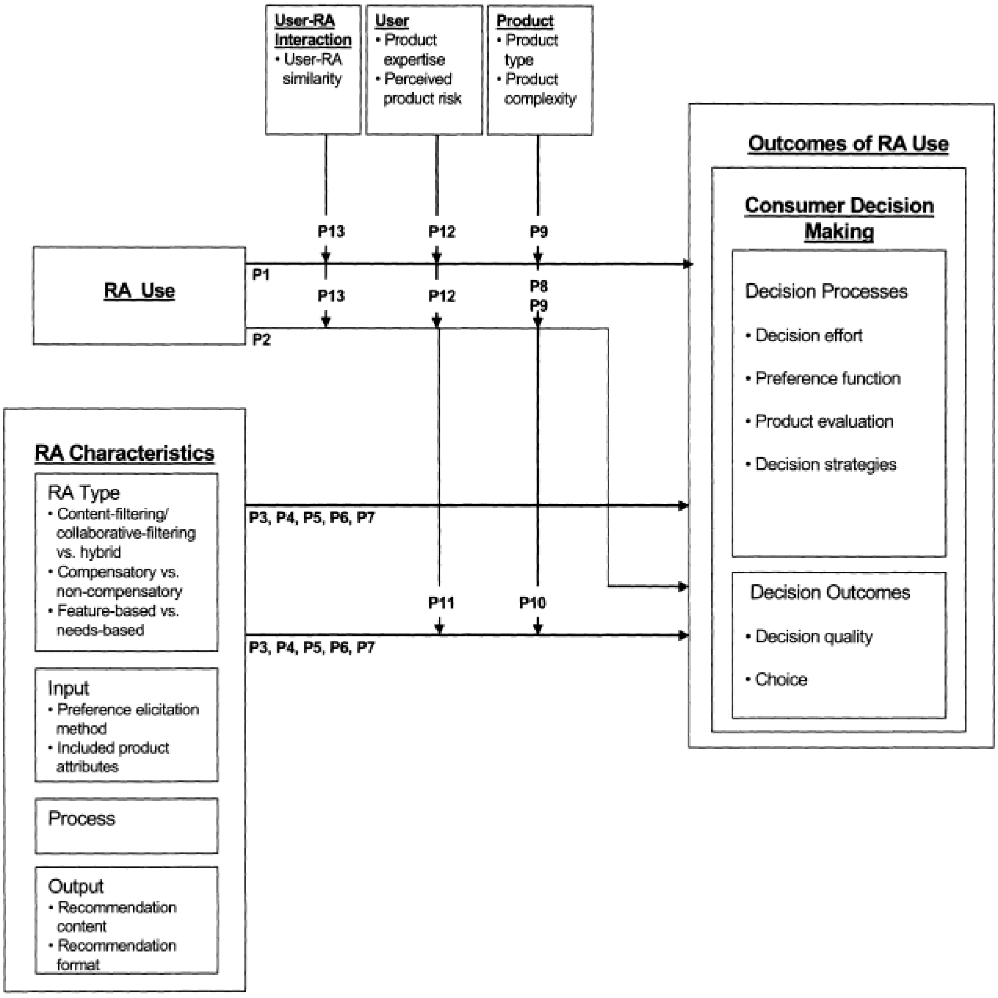


Figure 9: Effects of RA Use, RA Characteristics, and Other Factors on Consumer Decision Making. Source:(Xiao and Benbasat, 2007)

Ultimately, consumer satisfaction with their choice and the decision-making process itself hinge on their purchase decision-making behaviour, as discussed in studies by Heitmann, Lehmann and Herrmann (2007) and Guo et al. (2020). Four distinct consumer archetypes can be delineated on the basis of their decision-making style and level of knowledge: satisficers and maximizers (see diagram below), as well as those with low and high levels of knowledge (Karimi et al., 2018). Previous studies have examined the impact of consumer archetypes on process-related outcomes. Karimi, Papamichail and Holland, (2015) demonstrated that product knowledge and maximisation tendencies significantly influence process-related outcomes, including the number of cycles, duration, number of evaluated alternatives and the number of criteria considered. When making online purchases, individuals who exhibit maximising and satisficing tendencies are required to engage in continuous decision-making throughout the decision-making process. Because of their various motivational objectives, people use various decision-making processes and strategies. Satisficers adopt a decision-making approach that prioritizes ease and streamlining, whereas maximisers strive to attain an optimal choice from among the available alternatives. It is expected that maximisers will exhibit more intricate and repetitive procedures, particularly during the information retrieval and assessment phases. However, the study fails to address the procedural aspects of decision-making, specifically the fundamental mechanisms governing the process for each consumer archetype. The impact of online consumer archetypes on decision-related outcomes, such as consumer satisfaction and experience within smart retail settings, remains largely uncharted territory (Kamis, Koufaris and Stern, 2008; Karimi, Holland and Papamichail, 2018; Barta, Gurrea and Flavián, 2023).

Table 6: Maximizing verses Satisficing based on (Schwartz *et al.*, 2002).

Satisficer	**Maximiser**
• Sufficiently acknowledging what is deemed as satisfactory is adequate.	• Thoroughly searching for the optimal choice.
• Avoiding excessive obsession on alternatives.	• Examining all feasible alternatives.
• Sufficient research and diligent effort are necessary for making a well-informed decision.	• The exertion of an excessive amount of research and effort, irrespective of the potential outcomes.
• A dedication to the process of decision-making that is to be undertaken.	• Interested in making comparisons
Greater Happiness	**Greater Depression**

2.4 Barriers to Delivering Positive Consumer Experience Smart Retailing

Over the past few decades, Inman and Nikolova (2017) have conducted research that underscores the transformative impact of emerging technological breakthroughs on the retail industry. These ongoing innovations and the integration of smart technologies have played a pivotal role in empowering retailers to cultivate stronger consumer relationships and maintain a sustainable competitive advantage (Inman and Nikolova, 2017; Vrontis, Thrassou and Amirkhanpour, 2017). Inman and Nikolova (2017) assert that "new technologies create value by either augmenting revenue through (a) attracting new shoppers, (b) increasing the share of volume from existing shoppers, or (c) extracting greater consumer surplus while simultaneously reducing costs by delegating tasks to consumers." Nevertheless, it is essential to acknowledge that consumers' perceptions of fairness, trustworthiness, attitudinal loyalty, and the potential encroachment upon their personal privacy by these technologies may serve as formidable barriers (Scarpi, Pizzi and Visentin, 2014; Inman and Nikolova, 2017; Roy *et al.*, 2017). Advancements on the Internet and smart technology have empowered consumers to remotely connect with retailers and products. Research has also demonstrated that consumers are reshaping their information-seeking and purchase decision-making processes in profoundly novel ways. After their consumption experiences, they actively share their opinions, frequently with the help of third-party service providers such as Yelp, TripAdvisor, and various social media platforms (Priporas, Stylos and Fotiadis, 2017; Grewal, Gauri, Roggeveen, *et al.*, 2021). However, it is crucial to recognise that consumer ethical concerns represent a substantial hurdle to delivering a positive smart retailing experience (Du and Xie, 2021). Smart retailing hinges on the use of sensitive consumer data, which encompasses purchase history, preferences, and personal information. Mishandling these data can culminate in breaches and consequent erosion of consumer trust (Wu *et al.*, 2023). For instance, in the event of a security lapse leading to the leakage of a consumer's personal information, the resultant loss of trust in the retailer may dissuade them from future patronage, thereby engendering a negative overall experience. Prior research underscores the intriguing phenomenon that, notwithstanding ethical concerns surrounding privacy, consumers occasionally exhibit a willingness to disclose their personal information or simply overlook perceived risks (Higueras-Castillo et al., 2023). This phenomenon, in which consumers behave in a manner contrary to their own ethical apprehensions, is commonly referred to as the "privacy paradox" (Norberg, Horne and Horne, 2007; Dienlin and Trepte, 2015; Du and Xie, 2021; Ying *et al.*, 2023). Consequently, ethical concerns such as privacy remain a formidable obstacle to the widespread adoption of smart retailing practices.

2.4.1 Ethical concerns in SMART Retailing.

The influence of smart technology on the retail sector extends its reach across various dimensions, impacting both online (e-commerce) and offline (brick-and-mortar) stores. The emergence of technologies such as artificial intelligence, the Internet of Things (IoT), and augmented and virtual reality has not only enhanced retail business processes but also ushered in novel approaches to conducting retail operations (Dacko, 2017; Grewal, Roggeveen and Nordfält, 2017; Gauri *et al.*, 2021). For instance, contemporary retailers are increasingly harnessing interactive chat agents as first-tier support to engage with consumers, ranging from e-commerce customer care representatives to well-known AI personalities such as Apple’s Siri and Amazon’s Echo. These chat agents offer a better user experience than static information delivery methods such as frequently asked questions (FAQs) (Go and Sundar, 2019). However, despite the potential advantages of online chat agents in terms of providing swift and efficient support, research indicates that consumers prefer human interaction over chatbot engagements because of scepticism regarding chatbot technology (Roy and Naidoo, 2021; Janson, 2023; J. Zhang et al., 2024).

Existing studies have proposed that imbuing chatbots with anthropomorphic attributes can result in more cost-effective consumer interactions (Araujo, 2018; Roy and Naidoo, 2021). Nevertheless, consumers’ reluctance to embrace these smart technologies persists, primarily due to issues of trust and confidence. A study conducted by the travel search engine KAYAK.co.uk, as part of its Mobile Travel Report, exploring the impact of new technologies on travel, indicates an increasing use of chatbots. However, consumers approach chatbots with caution, with three-quarters (75%) expressing at least one concern, including data security, manipulation, and consumer trust, as depicted in *Figure 10* (Elsner, 2017).

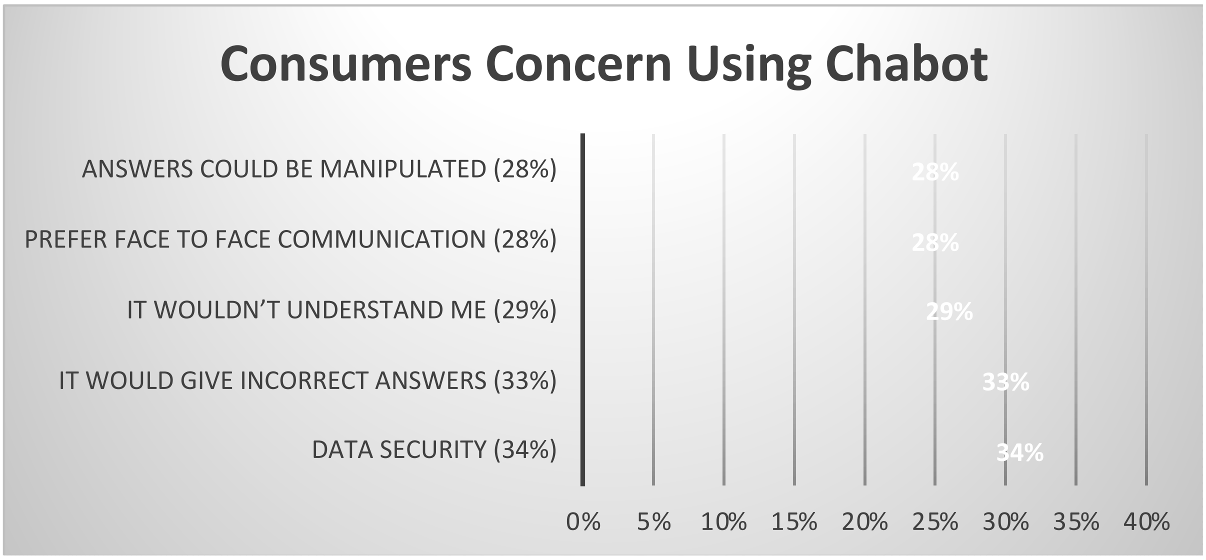


Figure 10: consumer concerns when using chatbot Source:(Elsner, 2017)

The act of purchasing products and services through smart technology-powered internet platforms has become routine for consumers, driven by various motivations. Some opt for online shopping due to its convenience, while others seek low prices, offers, and discounts facilitated by retailers through personalisation and product reviews, among other factors (Ameen *et al.*, 2021; Bijmolt *et al.*, 2021). However, the pursuit of personalisation, while advantageous for businesses targeting specific niches, can occasionally give rise to perceptions of stereotyping and even offense (Harwood and Eaves, 2020; Bijmolt *et al.*, 2021).

In recent years, retailers have witnessed a proliferation of technologies with the potential to significantly enhance retail operations while concurrently engaging consumers (Dacko, 2017). However, as technology's role in retail continues to expand, so does consumer concern about the ethical implications of smart retailing. It is worth noting that much of the earlier academic work in this field has been conceptual in nature and has often centred on consumer privacy concerns (Roman, 2007). While technology, particularly artificial intelligence, is reshaping the retail landscape, questions persist regarding its impact on consumers. This issue extends beyond the domains of academia and society, posing a reputational risk to retail businesses and the entire sector. Retail firms are keen to avoid association with ethical crises similar to those that have affected companies such as Facebook, Amazon, and Google (Martin and Palmatier, 2020; Martin *et al.*, 2020). On the surface, smart technology in retail offers numerous advantages to both consumers and retailers. However, given the impersonal nature of interactions within the smart retailing ecosystem, retailers must allocate resources to address consumer ethical concerns. The acceptance of new technology by consumers hinges on their perceptions of the associated benefits and risks (Inman and Nikolova, 2017; X. Wang et al., 2021). The factors driving consumer ethical concerns will be explored in a subsequent section.

2.4.2 Forces Driving Consumer Ethical Concerns.

As brick-and-mortar retailing reaches its zenith, the smart retailing ecosystem, which encompasses digital platforms and omni-channel retailing powered by smart technology, is ushering in the next wave of competition, business model evolution, and shifts in consumer behaviour. While some of these changes are embraced, others are met with apprehension. Within the extant literature, many academics contend that the deployment of smart technology such as AI in the retail business serves to optimise retail operations and facilitate seamless interactions within the smart retail ecosystem. Nevertheless, counterargument exists, cautioning against potential ethical implications and future perils associated with the use of smart technologies, particularly artificial intelligence. These concerns encompass issues such as consumer trust, digital well-being, adoption, privacy, and the potential for bias in AI-based decision-making. This section investigates the various forces driving these apprehensions.

The potency of self-monitoring, analysis, and reporting technologies (SMART)," encompassing artificial intelligence, the Internet of Things, augmented and virtual reality, robotics, and blockchain, is revolutionising every facet of the retail industry. It replaces intuition with intelligence, offering retailers a glimpse into the future. For instance, Amazon Go and Amazon Go Grocery represent cutting-edge retail technology poised to shape the trajectory of artificial intelligence in retail. At the core of Amazon Go's proposition is the concept of a cashier-less shopping experience. Unlike traditional stores (Polacco and Backes, 2018; Pickard, 2020), Amazon Go outlets operate without cashiers or checkout counters. Shoppers can simply enter, select their desired items, and depart. Amazon dubs this as a "just walk out" shopping encounter. To avail of this convenience, consumers should download the Amazon Go app for iOS and Android before visiting the store. Once at the store, they can enter, make their selections, and exit, with the app seamlessly handling the billing through their linked Amazon account (Pickard, 2020; Calderón - Ochoa, Hernandez and Portnoy, 2021).

Figure 11:How Amazon Go works Source: (Pickard, 2020).

While the concept of "Amazon Go" appears appealing on paper, it has raised concerns regarding the integration of such technological innovations into retail. Research findings indicate that despite the rapid and widespread proliferation of AI-enabled products in consumer markets, consumers and various stakeholders harbour reservations about smart technology, stemming from a myriad of ethical considerations. These concerns encompass issues related to privacy, digital well-being, reliability, safety, transparency, and job security (Martin *et al.*, 2020; Du and Xie, 2021).

2.4.3 Consumer Trust.

Smart technologies, including artificial intelligence, are becoming increasingly integrated into the operations of numerous businesses, particularly within the retail sector. These technologies serve as tools for engaging with a dynamic consumer base, streamlining service delivery, and enhancing efficiency. However, alongside the adoption of these technologies, a pressing concern has arisen regarding their ethical implications.

Consumers have expressed significant scepticism regarding the extent to which smart technology, encompassing artificial intelligence, the Internet of Things, augmented or virtual reality, and big data analytics, benefits retailers while potentially undermining consumer trust, privacy, and overall shopping experience (consumers international and Internet Society, 2019; Kim, Barasz and John, 2019; Martin *et al.*, 2020). Despite the adoption of smart technologies by both retailers and consumers for tasks such as service requests and information exchange, trust is a fundamental prerequisite for these interactions to function optimally. The significance of consumer trust within the smart retailing ecosystem is on the rise (Van Kenhove, De Wulf and Van Waterschoot, 1999; Verhoef et al., 2009; Duhigg, 2012; Kim et al., 2019; Pizzi and Scarpi, 2020; Pizzi et al., 2022).

Existing literature underscores that trust is a pivotal component for the success of smart retailing. For instance, recent high-profile data breaches at major retailers have contributed to a heightened sense of consumer distrust in smart technology. The notorious 2013 Target Corporation data breach exposed personal information, including credit card details, for almost 70 million households (Inman and Nikolova, 2017). Target’s data mining efforts even revealed sensitive information, leading to a public relations debacle (Duhigg, 2012; Inman and Nikolova, 2017). This unfortunate incident was not an isolated case, as other major retailers such as Home Depot (56 million credit card accounts) and Nieman Marcus (1 million credit card accounts) also experienced data breaches, resulting in a loss of consumer trust (Inman and Nikolova, 2017; Martin and Murphy, 2017; Martin and Palmatier, 2020; Pizzi and Scarpi, 2020).

A recent study conducted across various countries revealed that a substantial percentage of consumers find smart technologies creepy because of the data collection practices associated with these devices. Moreover, a significant proportion of respondents expressed concerns about the risk of 'eavesdropping' when using smart technology (consumers international and Internet Society, 2019).

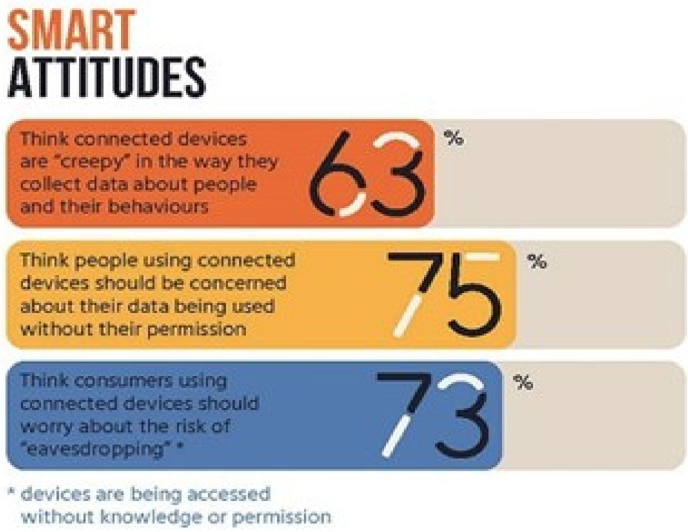


Figure 12:A Study of consumer behaviour (Consumers International and Internet Society, 2019).

Retail technology and related analytics have undeniably transformed the retail landscape over the years. However, research indicates that perceived risk has a substantial influence on consumer trust and behaviour Retailers who overlook this aspect do so at their own peril. Perceived risk exerts its influence across every stage of the consumer decision-making process, posing a challenge for retailers to leverage this knowledge effectively for a competitive advantage (Mitchell *et al.*, 1999; Grewal, Roggeveen and Nordfält, 2017; Roy *et al.*, 2017; Grewal, Noble, *et al.*, 2020; Gauri *et al.*, 2021; Grewal, Gauri, Roggeveen, *et al.*, 2021). Concerns surrounding consumer trust have surged alongside the growing adoption of smart digital technologies by both online and offline retailers. These retailers have heavily invested in smart technologies, and the return on these investments is fundamentally predicated on consumer acceptance and trust in these technologies (Dacko, 2017; Poncin et al., 2017; Appel et al., 2020; Grewal et al., 2021a; Bawack et al., 2022). Trust and risk are intrinsically interconnected, and both are rooted in perceptions (Verhoef et al., 2009). Although some level of risk is inevitable when trust is involved, trust is essentially the belief that an exchange partner will not engage in opportunistic behaviour (Verhoef et al., 2009; Lemon and Verhoef, 2016; Pansari and Kumar, 2017; Roy et al., 2017).

In summary, consumer trust within the smart retailing ecosystem is assuming growing significance. Consumer purchasing behaviour has evolved over time, encompassing individuals who adhere to familiar choices and those who seek to explore new offerings (Inman and Nikolova, 2017; Wang *et al.*, 2021; Guo and Wang, 2023). While categorising consumers into distinct types may be challenging, there exists one unifying factor: the universal desire for trust in their purchases. Trust extends beyond the product or service itself; it encompasses the processes involved both before and after consumption (Kim *et al.*, 2019; Davenport *et al.*, 2020; Guha *et al.*, 2021).

2.4.4 Lack Of Transparency.

Retailers have fully embraced various technologies to engage with their consumers, resulting in a transformative shift in the retail landscape (Grewal et al., 2017). Currently, retailers harness the power of smart technologies, such as artificial intelligence, virtual reality, and augmented reality, to amass copious amounts of consumer data, both online and offline. Products empowered by artificial intelligence, such as Fitbit, voice assistants (Amazon Alexa, Apple Siri, Google Assistant), and smart home systems (Nest Thermostat, Ring doorbells), are instrumental in this data gathering trend (Morey, Forbath and Schoop, 2015; Agrawal, Gans and Goldfarb, 2018a; 2018b; Vimalkumar et al., 2021; Riegger et al., 2022). However, retailers often remain opaque regarding the information they collect and frequently engage in reselling practices, which leave consumers dissatisfied. While this approach might offer a short-term competitive edge, it erodes consumer trust in the long run, diminishing overall competitiveness (Morey et al., 2015; Riegger et al., 2022).

Research underscores that safeguarding privacy and maintaining transparency in consumer data management is a shared objective among academics, retailers, regulators, advocacy groups, and consumers. With such unanimous consensus, ensuring the safety, security, and ethical use of consumers' personal data should be a straightforward endeavour (Martin, Borah and Palmatier, 2017; Martin and Palmatier, 2020). However, research has revealed that transparency and requests for consent are becoming increasingly rare as governments and businesses collect and analyse personal data (Chang, 2021; Vimalkumar *et al.*, 2021). While some retailers are forthright about their data collection and processing methods, a significant majority prefer to keep consumers in the dark, leaving them with no choice over the data shared and seeking forgiveness rather than permission (Morey, Forbath and Schoop, 2015; Cadwalladr and Graham-Harrison, 2018; Oghazi *et al.*, 2020). It is common for retailers to amass consumers' personal data without immediate utility, banking on the hope that it might prove valuable in the future. However, this deluge of data collection also presents significant opportunities for misuse, prompting academics to question how retailers can leverage technological advancements to enhance transparency in their promotional and privacy policies with consumers (Grewal, Gauri, Roggeveen, *et al.*, 2021).

Presently, smart technologies enable retailers from various sectors to access new types of data, encompassing consumers' locations, activities, and behaviours. This data collection empowers retailers to personalise the consumer experience, with continuous adaptation to consumer preferences becoming integral to the product experience. For instance, products such as Google's Nest thermostat automatically adjust heating and cooling based on learned consumer habits (Morey et al., 2015). However, large-scale security breaches, such as the Facebook– Cambridge Analytica scandal in March 2018, which involved improper data gathering from approximately 87 million users' Facebook profiles for psychographically customised advertising, have left consumers more bewildered than assured and more anxious than encouraged about how businesses handle their personal data (Cadwalladr and Graham-Harrison, 2018; Oghazi *et al.*, 2020).

A driving force in smart retailing is the increasing need for a unified consumer shopping experience across all channels. Retailers employ technology to gather more specific data about products and consumer purchasing habits, which can enhance inventory management efficiency and accuracy (Grewal, Roggeveen and Nordfält, 2017; Grewal et al., 2020a; Gauri et al., 2021). However, consumers have grown sceptical of smart retailing because of concerns about data breaches, fake news, and disinformation. Retailers are now actively working to restore consumer trust, with recent research revealing their efforts to introduce transparency into their operations due to trust and transparency concerns (Morey et al., 2015; Vadakkepatt et al., 2021).

Research highlights growing concerns about transparency in smart technology-enabled platforms, as creators often refuse to disclose the types of consumer data they collect and input into these systems. For example, developers of the Google search engine do not divulge the procedures by which search results are ranked, citing them as closely guarded business secrets. Such behaviour contradicts consumers' expectations of transparency in smart or artificial intelligence applications (Mele *et al.*, 2021). The lack of transparency in smart retailing applications raises fundamental questions about how these technologies can genuinely enhance the consumer experience while addressing ethical concerns. Regardless of the arguments presented by creators of artificial intelligence-enabled systems regarding the secrecy of their processes, the time has come for them to embrace greater transparency. Failure to adhere to this straightforward guideline will further erode consumer faith in future smart technologies, including artificial intelligence (Dwivedi *et al.*, 2021). In summary, transparency is a prevailing trend in retail, extending beyond mere marketing rhetoric. It entails retailers informing consumers about how they intend to handle, process, and use their personal information within the smart retail ecosystem.

2.4.5 Increased Data Privacy Concerns

One of the primary concerns associated with the current generation of smart technologies, including applications enabled by smart technology, is their insatiable appetite for consumer data. While machine-learning technologies, driven by artificial intelligence, excel at processing vast datasets to identify patterns, data collection infringes on consumers' privacy. Data extraction should only occur with the explicit consent of consumers. Consumers' desire to control or, at the very least, influence the data concerning themselves is commonly referred to as information privacy (Bélanger and Crossler, 2011). Technological advancements have given rise to concerns about information privacy and its repercussions, prompting scholars and stakeholders to explore further consumer privacy concerns and technical solutions to address them (Bélanger and Crossler, 2011; Okazaki *et al.*, 2020).

Retailers, in their quest to gain profound insights into consumer behaviour and enhance consumer experiences across multiple channels, accumulate vast amounts of data from both current and prospective consumers (Okazaki *et al.*, 2020). Previous research has argued that many consumers are willing to provide their personal information in exchange for benefits such as tailored online offers, increased convenience, and location-specific content (Aguirre et al., 2015b; Rainie and Duggan, 2016; Okazaki et al., 2020). However, existing literature indicates that an increasing segment of consumers is growing concerned about their personal privacy (Cecere, Le Guel and Soulié, 2015; Inman and Nikolova, 2017; Martin and Palmatier, 2020; Patel, Oghazi and Arunachalam, 2023). This growing concern can be attributed to notorious instances of privacy breaches, such as Target's microtargeting of pregnant consumers (Duhigg, 2012) and high-profile data breaches, including the £99 million fine imposed on the Marriott hotel by the U.K. data protection authority in 2018 for exposing the personal data of over 300 million customers (O'Flaherty, 2019; Whittaker, 2019; Gao, Zhang and Wei, 2021). For smart retailers, technological advancements are a double-edged sword. On the one hand, technology has empowered them to customise their products, communications, and services to meet consumers' needs more effectively, resulting in cost-effective advertising and enhanced consumer retention (Deighton, 1996; Inman and Nikolova, 2017).

On the other hand, recent advances in retail technology have significantly amplified consumers' concerns that retailers might exploit and misuse their personal information. Privacy, indeed, ranks among the top concerns for consumers. A survey conducted in the United States revealed that most American consumers believe that the right to privacy is under severe threat, with 52 % believing it is seriously endangered and another 30 % thinking it is already lost. Only 16% believe that it is still intact, as depicted in the figure below. This growing unease stems from the large number of companies collecting personal information (Roberts, 2005). Moreover, retail technologies perceived as invasive of consumers' privacy trigger a backlash that undermines their benefits. Consumers express negative sentiments and resist retailers who collect personal data about them, including information about their purchases, credit histories, and income. Concerns about privacy among consumers often revolve around three distinct dimensions: the collection of personal data, control over the utilisation of personal information by retail businesses, and comprehension of privacy policies and the ways in which personal data are employed. In summary, contemporary smart retailers are inundated with an array of smart technologies, including artificial intelligence, the Internet of Things, augmented reality, and virtual reality (Gauri *et al.*, 2021; Dhiman, Jamwal and Kumar, 2023). Understandably, consumers may feel overwhelmed by these choices and acquire technology without a clear vision of how it fits into their strategy or, more crucially, how consumers will react. However, research indicates that the concept of data privacy is likely to gain even more prominence in the coming years (Bélanger and Crossler, 2011; Martin and Palmatier, 2020). Despite significant technological advancements and improvements in theory and retail practises (Bélanger and Crossler, 2011; Inman and Nikolova, 2017; Gauri *et al.*, 2021), existing literature on consumer privacy issues remains dispersed across academic disciplines, lacking convergence in terms of conceptual breadth and empirical findings (Bélanger and Crossler, 2011). This absence of cohesion underscores the urgent need for a comprehensive synthesis that can serve as a roadmap for future theory development and managerial practises in the domain of consumer privacy issues within the smart retailing settings (Bélanger and Crossler, 2011; Okazaki *et al.*, 2020).

2.4.6 Consumer Perceived Risk

Perceived risk, defined as the anticipated negative consequences of a behaviour (Stone and Grønhaug, 1993; Mitchell, 1999; Laroche et al., 2004; Sohn, 2024), plays a crucial role in consumer decision-making due to the inherent uncertainty in assessing the consequences or severity of a behaviour (Dowling and Staelin, 1994). Consumers naturally tend to avoid losses or adverse outcomes, underscoring the significant predictive power of perceived risk in behavioural responses (Mitchell, 1999). Risk perceptions vary across different entities and behaviours, leading to diverse effects on consumer decision-making. For instance, research has shown that risk perceptions influence consumers' decisions to use (Forsythe and Shi, 2003; Featherman and Hajli, 2016; Rehman, Baharun and Salleh, 2020) or purchase (Stone and Grønhaug, 1993; Rauschnabel, He and Ro, 2018) specific products or services. Despite scholarly efforts, inconsistent findings regarding the role of consumer risk perceptions in smart technology adoption have been reported (Hubert *et al.*, 2017; Mani and Chouk, 2018; Rauschnabel, He and Ro, 2018; Sohn, 2024). One approach to addressing these inconsistencies is to consider different types or dimensions of consumer perceived risk alongside various retail environments when conceptualising risk perceptions (Park and Tussyadiah, 2017; Sohn, 2024). However, current research on smart technology adoption has primarily focused on single types of perceived risk (Pizzi and Scarpi, 2020; Riegger *et al.*, 2022) or utilised a composite measure of risk perceptions (Adapa *et al.*, 2019).

Within the context of smart retailing and consumer behaviour literature, the term "perceived risk" denotes the consequence arising from uncertainty or the perception of potential adverse outcomes associated with a smart technology-enabled product, services or retail environment (Adapa et al., 2019; Rehman, Baharun and Salleh, 2020; Sohn, 2024). Various scholars have endeavoured to theorise perceived risk, with Bauer (1960) being one of the pioneering figures in conceptualising this concept within retailing literature (Hawes and Lumpkin, 1986; Man Hong *et al.*, 2018). According to Bauer (1967), perceived risk can be defined as "a combination of uncertainty and the seriousness of the outcomes."

Alternatively, Dowling and Staelin, (1994) proposed a definition in their study, characterising it as "the consumer's perception of the uncertainty and potential adverse consequences associated with purchasing a product (or service)." Pavlou and Gefen (2004), in their study focusing on online marketplaces, conceptualise perceived risk as "the subjective belief that there is some probability of experiencing a loss while pursuing a desired outcome." Despite various attempts to define perceived risk in the literature, a universally accepted definition of this concept remains elusive. It is widely regarded as a multidimensional construct, encompassing six dimensions: physical/safety, financial, psychological, time, performance, and social risk, particularly in the context of online purchases (Rehman, Baharun and Salleh, 2020; Herzallah, Muñoz Leiva and Liébana-Cabanillas, 2022). Similarly, Ahmed, Ali and Top (2021), contend that perceived risk has a harmful impact on consumers' intentions to engage in online shopping. In contrast, Arora and Rahul (2018) argue that perceived risk does not significantly influence attitudes. This demonstrates the scholarly discourse on perceived risk. Various studies (e.g., Alhumaid, Habes and Salloum, 2021) have illustrated how fear of emerging technology serves as a driving force influencing individuals' willingness to adopt smart technology. Despite the increasing adoption of smart technology by consumers, fear, often referred to as "technophobia" and "technology avoidance," remains a significant challenge for a substantial portion of the global population (Martínez-Córcoles, Teichmann and Murdvee, 2017; Higueras-Castillo, Liébana-Cabanillas and Villarejo-Ramos, 2023). Apprehension about the potential repercussions of using smart technology-embedded retail or smart retailing systems can hinder their adoption, leading to feelings of insecurity and intimidation, which in turn may result in reduced use of these technologies.

Given that consumer risk perceptions are context-specific, it is crucial to develop a smart retail technology-specific understanding of consumer perceived risk. Therefore, this study aimed to establish a multidimensional understanding of consumer perceived risk within a smart retail setting. In this context, a comprehensive exploration of the multifaceted nature of perceived risk provides a nuanced understanding of its implications in consumer behaviour.

The incorporation of multiple dimensions of perceived risk alongside the consideration of various retail environments is crucial for a holistic comprehension of its impact on consumer decision-making processes. Despite extensive research, the complexities surrounding perceived risk continue to pose challenges, particularly concerning its role in smart retail environments. However, by adopting a multidimensional approach and accounting for context-specific factors, this study aims to overcome these challenges and develop a more comprehensive understanding of perceived risk's influence on consumer behaviour.

2.5 Recommendation Systems and Consumer Well-being

Rapid advancements in smart retailing technologies have led to the widespread use of smart technology-enabled recommender systems, which leverage individual preference data to provide automated recommendations to consumers. These platforms facilitate easier product searches and selections by using data tailored to each consumer’s unique preferences. Such digital retail platforms span various consumer domains, including online shopping platforms (e.g., Amazon, eBay, Alibaba), movie platforms (Netflix, Apple TV+, Disney+, Hulu), music selection platforms (Spotify, YouTube Music, Apple Music, Tidal), financial investment platforms (Wealthfront, M1 Finance, Fidelity), and even dating platforms (Tinder, eHarmony, OkCupid). While these smart technology-enabled platforms aim to enhance consumer decision-making and overall experience, they introduce a potential risk: consumers may become overly reliant on algorithmic recommendations, which can impact their digital well-being and perpetuate biases (Banker and Khetani, 2019).

Recommender systems employ various methods to indicate new products to consumers based on their preferences and product ratings (for example, Netflix recommends a new movie based on a consumer's past preferences). These algorithms encompass content-based methods that use consumer preferences and product attributes, collaborative filtering methods that rely on comparisons with similar consumers, and hybrid approaches that combine both (Resnick and Varian, 1997; Adomavicius and Tuzhilin, 2005; Konstan and Riedl, 2012; Banker and Khetani, 2019). Recent literature indicates that these strategies have been further explored in retail contexts (Ansari, Essegaier and Kohli, 2000; Liu and Cong, 2023).

Despite efforts to enhance algorithm quality, findings from the existing literature indicate that consumers often reject algorithm-generated recommendations in favour of following their own intuitions. This phenomenon spans various domains, such as employment decisions (Diab *et al.*, 2011; Castelo, Bos and Lehmann, 2019; Castelo *et al.*, 2023), where participants perceive human interviews as more effective, formal, equitable, individualised, adaptable and accurate than algorithms. In the field of legal decision-making (Eastwood et al., 2012; Yeomans et al., 2019), human decision-making is thought to operate through an enigmatic mechanism known as intuition, with decision-aiding requiring an understanding of the underlying mental processes. Similarly, in medical decisions (Banker and Khetani, 2019a; Longoni, Bonezzi and Morewedge, 2019), individuals tend to prefer the advice of medical practitioners over technological devices. Moreover, consumers exhibit reactance towards recommender systems when presented with substandard product recommendations, actively avoiding such suggestions (Fitzsimons and Lehmann, 2004; Lettinga and Lettinga, 2011; Volpert and Michel, 2022; Cuesta-Valiño *et al.*, 2023). This aversion to algorithms often results in persistent scepticism and a preference for relying on personal intuition or human guidance when making decisions. Conversely, evidence indicates the opposite trend (Banker and Khetani, 2019), where consumers' excessive reliance on algorithm-generated recommendations poses a potential threat to their digital well-being and contributes to the propagation of systemic biases that can affect other consumers. This study underscores the importance of comprehending and acknowledging the potential hazards associated with recommender systems, given their widespread use across various consumer domains. Recent research has led scholars to theorise that consumers "surrender to technology" in today's modern digital landscape, as they place unwavering trust in online information exchange platforms, often inadvertently divulging sensitive personal information (Walker, 2016a; Martin and Murphy, 2017; Martin and Palmatier, 2020).

This framework of "surrendering to technology" has influenced policymakers' approach to addressing privacy risks, emphasising that users are most vulnerable when factors related to the complexity (e.g., user cognitive limitations) and context (e.g., marketplace asymmetries) of information exchange converge. In addition, past research has not come to a clear conclusion about how smart technology-powered recommender systems affect consumers. This study adds to the theory by saying that "surrendering to technology" happens in more digital interactions than just exchanging information. This is especially common when using algorithmic recommender systems in smart retail settings to help people decide what to buy. Given the complexity of decision-making environments and the limitations of human cognitive abilities to effectively process vast amounts of information, consumers may become vulnerable to potential harm, ultimately affecting their overall digital well-being. The following discussion explores further these complex factors. The experience of shopping for products and services online is increasingly becoming an overwhelming endeavour. According to (Dellaert and Stremersch, 2005; Dellaert *et al.*, 2020), consumers face difficulties when making purchasing decisions because of the expanding variety of product offerings, customizable attributes, available retailers, ratings, and reviews. Limited attentional resources may hinder consumers from thoroughly evaluating every product, despite the abundance of accessible information. Similar to the phenomenon observed in (Simons and Chabris, 1999) study, individuals may fail to notice critical information while searching for a product that meets their requirements. Additionally, according to Louro, Pieters and Zeelenberg, (2007), juggling multiple goals at once may exacerbate attentional biases. Consequently, individuals may rely on condensed data and recommendations when engaging in online shopping.

2.5.1 The precision and reliability of recommendation systems

In the ever-evolving landscape of digital commerce, the quest to refine AI-enabled recommender systems persists, yet consumers frequently encounter a precarious digital marketplace rife with partial and substandard recommendations. Expressing consumer preferences is not a straightforward task (Bettman, Luce and Payne, 1998b; Senecal and

Nantel, 2004; Goh, 2020; Oosthuizen, 2021; Xu *et al.*, 2021), and retailers often grapple with the elusive measurement of these preferences (Mullainathan and Obermeyer, 2017; Korneeva *et al.*, 2023). The outcome of this conundrum is suboptimal recommendations due to incomplete or inadequate inputs. Empirical evidence underscores the disconcerting tendency of several smart retail platforms to guide consumers toward more expensive products and services by prominently featuring financially lucrative items at the forefront of recommended product lists, sometimes irrespective of their quality (Mullainathan and Obermeyer, 2017; Hufnagel, Schwaiger and Weritz, 2022; Korneeva *et al.*, 2023). Furthermore, investigations have unveiled discriminatory inclinations within recommendations, as manifested by the provision of fewer high-income job recommendations to women (Datta, Tschantz and Datta, 2015; Banker and Khetani, 2019) and a noticeable surge in the display of arrest record ads for names disproportionately associated with black individuals in search results (Sweeney, 2013). A recent study underscored the pivotal role of race in shaping marketplace actions and their underlying ideologies, emphasizing that this aspect remains underexplored in the domain of online consumer interactions (Azer *et al.*, 2023).

It is imperative to note that these outcomes were not the intended consequences of the algorithm developers. The unintended repercussions of recommendation systems underscore the pressing need for more stringent regulations to safeguard consumers. Presently, the use of these systems is subject to minimal regulations, and even those in place, such as those governing digital advertising (Trade Commission, 2013; Goodman and Flaxman, 2017) and the application of algorithms in automated decision-making, may warrant fortification to address potential vulnerabilities. Recommendation systems exert a profound influence over the daily decisions of digital-native consumers, spanning domains from music and films to shopping and social media. However, the algorithms underpinning these systems can inadvertently reinforce biases or create filter bubbles that constrict exposure to diverse viewpoints. Consequently, consumers become susceptible to deception and exploitation. The proliferation of recommender systems across online retail interfaces, interactive agents, and smart devices heralds an escalation in associated risks.

As elucidated earlier, the unbridled use of recommender systems to automate demand, bereft of appropriate oversight, can significantly compromise consumer welfare. This study explores the impact of these retail systems on consumers, making a valuable contribution to current literature aimed at shielding consumers from potential harm and promoting a more equitable and robust digital ecosystem for all.

Chapter 3: Systematic Literature Review

Technological transformation and AI advancement have reformed many sectors today (Alcácer, Cantwell and Piscitello, 2016), and the retail sector is no exception to this rapid technological development. The implementation of artificial intelligence (AI) in retail is often described as "human progress" (Stahl *et al.*, 2021) which is transforming the stakeholders including consumers experiences and relationships (Shankar *et al.*, 2021), particularly in retail setting. The substantial literature on this area has made remarkable contribution on exploring the relationship between the consumers experience and their repurchasing behaviour, organisational performance, and business productivity. Many existing literatures emphasise on different views that how consumers experience, and satisfaction could impact on their repurchasing behaviour (Blut *et al.*, 2015; Gao, Zhang and Wei, 2021; Gao *et al.*, 2022) and their relationship with organisations (Plangger *et al.*, 2022).

However, the technological advancement changes the way that consumers interact with producers (Reinartz et al., 2019; Tabaghdehi, 2022) particularly retailers for online purchasing. Hence, retailers use a variety of digital strategies to improve consumer experiences this includes: self-checkouts using smart phones and handheld scanners that enable consumers to instantly bag their purchases after scanning their groceries as they shop (Grewal, Noble, *et al.*, 2020); anthropomorphic voice assistants (e.g., Google Assistant, Amazon Alexa) and natural-language voice commands which allow consumers to control “smart” objects or perform a variety of tasks, including accessing the internet for information, shopping, and entertainment (McLean, Osei-Frimpong and Barhorst, 2021; Bahmani, Bhatnagar and Gauri, 2022). Furthermore, the rise of online shopping through various platforms and websites has improved consumers experience as they can make instant comparison about the products, services, quality, and prices before taking any purchasing decision (Song and Kim, 2022).

Furthermore, the ease of one-click ordering, personalised recommendations, and smart speakers revolutionise the online shopping experience. As a result, numerous brick-and-mortar retailers have seen their consumers abandon them for better shopping experiences offered by new tech-driven innovations (Xiao and Benbasat, 2007; Shankar *et al.*, 2021). Retailers are increasingly promising to provide their consumers a pleasurable experience to build a competitive edge (Agarwal *et al.*, 2020). Hence, they need to understand their consumers' personal experiences if they want to succeed (Puccinelli et al., 2009). Agarwal et al. (2020) argues that retailers may be able to leverage technology-driven privacy protection measures to build trust with their consumers by identifying what matters most to their consumers while equipping them with the resources to help them to make informed decisions. Hence, consumers' online behaviour is mostly collected by retailers to provide personalised services for their consumers. Greater personalisation usually results in increased service relevance (e.g., while looking for a new product, the best pricing, etc.) and better consumer adoption. However, it may also result in increased consumers' feelings of vulnerability and decreased adoption rates in the longer term (Aguirre et al., 2015b; Davenport et al., 2020).

In today's society with AI advancement, retail technologies are more autonomous, capable of making decisions and completing activities on behalf of consumers. The outsourcing of choices and responsibilities to technology has challenged the psychological incentive of consumption and entrenched human–machine connections (Grewal et al., 2020). This makes consumers more concerned about the ethical implications such as trust, privacy, information transparency, digital wellbeing, surveillance, and discrimination in smart retail setting. (Martin and Palmatier, 2020; Okazaki et al., 2020; Pazzanese, 2020; Du and Xie, 2021). Yet, the literature on online consumer behaviour and decision making is still in its infancy (Davenport *et al.*, 2020; Gauri *et al.*, 2021). However, some theories have supported the lack of academic research on exploring the adoption and ethical implication of extensive use of technology in retail setting (Rese, Ganster and Baier, 2020; McLean, Osei-Frimpong and Barhorst, 2021).

Whereas much is known about the use of AI in retail and its accuracy, cost-efficiency, and optimisation including scalability, but little is known about consumers' receptivity to its widespread use of technology and its ethical implications in terms of privacy, trust, and fairness. There is an increasing level of concerns about the ethical use of technologies and accumulated digital information by smart retailers. There is lack of research on understanding how consumers' digital data should be approached and implemented in a socially responsible way. With smart retailers' ability to track consumers' online-shopping activity has concerned consumers on how retailers collect and use their consumers' personal information. For example, the revelation that retailers were furtively tracking consumers' in-store movements using mobile phone data sparked controversy in the mass media and beyond (Kim, Barasz and John, 2019). More generally, and unbeknownst to many consumers, the sharing of consumer digital information among businesses is pervasive. For example, Facebook purchased data on millions of households, which enables the company to customise their advertisement strategy based on consumers' purchasing behaviour (Wasserman, 2012; Kim, Barasz and John, 2019). Consequently, an unethical practice by smart retailers even large organisation may undermine the effectiveness of their sales and marketing strategies while damaging their reputation (Maroufkhani *et al.*, 2022). Given how invasive these practises are, there is a growing need for greater transparency and privacy protection of consumers' digital data (Martin *et al.*, 2020).

This study aims to explore further that how retailers collect and use consumers' digital information for behavioural and content creation while improving consumers' experience and ensuring a fair advertising practice (Kim, Barasz and John, 2019; Cambier and Poncin, 2020; Baabdullah et al., 2022; Riegger et al., 2022; Wang et al., 2023). Consumers have mixed views regarding the use of smart technologies in retail because of the various ethical issues in relation to their digital data and privacy (Du and Xie, 2021). However, in recent years, several smart retailers have attempted to implement ethical digital advertising strategies. For example, Facebook created a feature that informs users why they have been shown a specific advertisement (Kim, Barasz and John, 2019).

Although currently many retail websites telling their consumers when tracking software like cookies is being used and show the "privacy seals" logo to specify the privacy standards for their users (Alzaidi and Agag, 2022). Hence academic research should address and focus on this perceived relevant gap. The implementation of AI in retail faces a number of challenges as a research area. First, researchers sought a wide range of publication outlets for their findings, resulting in a corpus of literature published in a range of relevant academic and retail journals. This has resulted in a fragmented, disjointed body of literature of varying quality. However, this pattern of varied publication quality is not exceptional for a growing field of study (Kelly *et al.*, 2009). As a result, this study draws attention to these flaws and emphasises the need to expand the scope of current research. One advantage of this systematic literature review is that it employs a "replicable, scientific, and transparent process" (Tranfield, Denyer and Smart, 2003; Denyer and Tranfield, 2009; Macpherson and Jones, 2010) to assess the current state of the field and synthesise the diverse studies that characterise the use of AI in retail and the shenanigans in this research space.

Thus, the goal of this study is to review and organise the present empirical and theoretical literature on the use of AI in the smart retail space in a systematic manner and build on existing research into the impact of artificial intelligence on consumer-brand outcomes via smart shopping channels. We explore further the constituents of the digital consumer experience within smart retail settings. We included theoretical papers that were frequently cited and had a significant impact in the field based on the Academic Journal Guide 2021 rankings.

The SLR was guided by the following research questions:

1. how AI development assists or challenges consumers' ethical concerns such as privacy, information transparency, and accountability when engaging in smart retail settings through various platforms and applications.

2. How do AI bias and security concerns shape consumer adoption and further impact their wellbeing when interacting with AI-enabled applications?

This paper begins with a summary of the process used to select and analyse the literature, followed by a description of our search strategy, analysis, and evaluation of the quality of the reviewed studies. We then give our conclusions regarding the SLR of the reviewed studies. Next, we examine future directions for theory development, methodology, and subject matter. In conclusion, we evaluate the strengths and drawbacks of our review and emphasise the paper's contributions to future research on the use of AI in the smart retailing settings.

3.1 METHODOLOGY AND RESEARCH DESIGN

3.1.1 Methodology

We analysed 1192 articles in English that were published or available in press from 1974 to August 2021 in 271 journals. This list is based on publications that have a history of publishing retailing, emerging technology and/or consumer behaviour research and have varied levels of impact based on the Academic Journal Guide 2021. Using Science Direct as the main database, Google Scholar, Web of Science-indexed journals, and the Scopus database, we adhered to the SLR method recommended by Denyer and Tranfield (2009) and Macpherson and Jones (2010). A description of the SLR procedure used to preparing this paper is shown in *Figure 13*.

3.1.2 Literature Search and Preparation

Following Denyer and Tranfield's (2009) recommendation, we started the SLR process by defining the research objectives and conceptual boundaries. In each repository, we searched for three key terms related to smart retailing, artificial intelligence, and ethics from four academic repositories: Science Direct, Google Scholar, Web of Science, and Scopus. A total of 933 articles were retrieved from Science Direct as the main database, and 233 articles from Google Scholar, 13 articles from Web of Science-indexed journals, and another 13 papers from the Scopus database. The searches were limited to articles written in English only. In total, 1192 articles from 271 journals from the above four academic repositories were selected.

3.1.3 Defining the scope of the research

A preliminary examination of the 1192 articles indicated that they are widely dispersed throughout a wide range of publications and themes. To ensure the study's rigour, we applied elimination filtering on selected articles and all materials other than research articles and review papers were removed from the selected sample. The final database with 760 research articles and review papers, provided attributes such as article titles, publication dates, journal titles, keywords, citations, references, abstracts, and for these papers.

Data review and extraction

The focus of the sample process was on papers in the relevance-gap debate that paid attention to the effects of using AI in retail. A data extraction template was developed based on the inclusion criteria as shown in *Table 7*.

Inclusion criteria

Following Wang and Chugh, (2014) recommendations, three types of inclusion criteria were used to choose the papers that would be included in this literature review process. These included setting the search boundaries, phrases, and specifying the time that the search was to be conducted. We first started by searching for the following keywords: smart retailing, Artificial Intelligence (AI), ethics, and consumer that were published in Science Direct, Scopus, and Web of Science databases, in addition to Google Scholar, due to the comprehensive range of articles, dating up to the 31st of August 2021. These academic repositories were chosen for the search because they are the most comprehensive for scholarly work and cover thousands of academic publications.

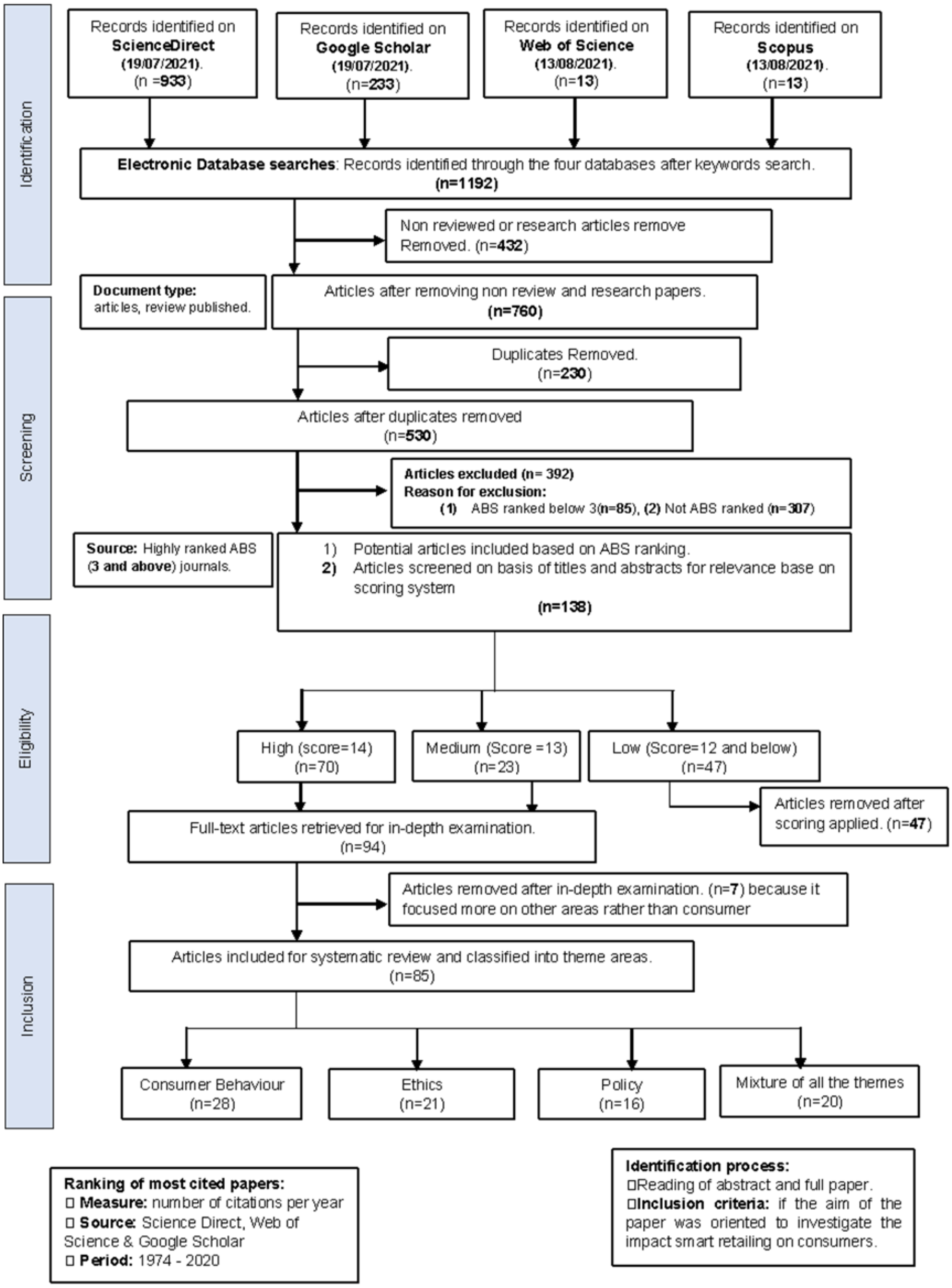
Exclusion criteria (Removing all duplicates)

To avoid evaluating publications that have already been reviewed, further screening was carried out by the means of an exhaustive manual search of the review and research articles (n=760) for duplicates. The search process revealed that there were 230 duplicated articles that were removed, and the remaining 532 articles were narrowed down for further eligibility screening.

Sourcing for High Impact Journals

In order to enhance the credibility and trustworthiness of the study, the extracted 530 articles were further analysed and ranked by impact factors against the Academic Journal Guide 2021 (Association of Business Schools list (ABS), 2021). The Academic Journal Guide, formerly referred to as ABS-list, details a variety of subject matter and quality of the journals, published by business and management academics (Wang and Chugh, 2014). Articles that were not listed on the Academic Journal Guide 2021 were removed from the selected sample. Furthermore, we only focused on 138 articles that were published in journals ranked Grade 3 and above. Furthermore, we narrowed down the search criteria to those articles that were particularly related to Smart Retailing, Artificial Intelligence, Ethics and consumer in the Social Science domain including Business Management and Accounting, Decision Science, Economics, Econometrics and Finance, Psychology, Social Science, Computer Science, Law, Arts and Humanities, Engineering, Healthcare, Agricultural and Biological Sciences. The review period spans the years 1974 to 2021 (47 years).

Figure 13:Summary of the systematic literature review methodology.



3.1.4 Data Analysis and Synthesis

A manual content analysis method was adopted to process and analyse the sample articles (Miles and Huberman, 1994). This is a qualitative systematic review technique, as indicated by (Siddaway et al., 2019), because the debate regarding the use of smart technology in retail, including ethical concerns is conceptualised and operationalised in several ways in the existing literature. All the research and review articles have been screened based on the relevance of their title and the review of the relevant abstract as shown in *Table* 7.

Table 7:Summary of inclusion and exclusion scoring

No	CRITERION	INCUSION	EXCLUSION	SCORING SYSTEM		
		Reason for inclusion	Reason for exclusion	Score (**1**)	Score (**2**)	Score (**3**)
1	Type of Publication	Review or Research articles: Captures credible and important findings from studies on smart retailing, artificial intelligence, and ethics	Non review or research articles (e.g. books chapters, news, Encyclopaedia, etc)	Non review or research paper	Review or research paper	N/A
2	Study focus	Focus on organisation or individuals (consumer)		Studies not focusing on organisation or consumer	Studies focusing on organisation or consumer	N/A
3	Research domain	Business and management, economic, physiology, social science, computer science, law		Outside the selected research domain	Relevance to selected research domain	N/A
4	Research themes	consumer experience, customer behaviour and ethical concerns		Not relevant to the theme(s)	Partially relevant to one or more of the selected themes	Relevant to one or more of the selected themes
5	Academic Journal Guide 2021 (ABS ranking)	ABS ranked (3 and above) To ensure relative quality of the studies	Non-ABS ranked papers and ABS ranked papers (1 and 2)	Non-ABS ranked	ABS ranked 1or 2	ABS ranked 3 and above
6	Language	English	Non-English papers	Non-English studies	English studies	N/A

Following a subsequent evaluation, we found 94 research and review articles that were ultimately deemed very relevant and included in the inquiry. In accordance with the final selection criteria, which included publication type, study topic, research domain, themes, Academic Journal Guide 2021, and language, the remaining papers were assessed and divided into three groups: A (High), B (Medium), and C (Low). Articles in Class A (High) are extremely relevant; articles in Class B (Medium) are indirectly related to smart retailing; articles in Class C (Low) have little relevance to smart retailing, artificial intelligence, and ethics; and articles in Class D have no relevance to the key research themes. There were 138 articles; 68 were categorised as class A, 23 as class B, and 47 as class C; however, only 91 were maintained for full-text and comprehensive review.

This study's content analysis was performed by hand to identify and include all pertinent studies pertaining to retailing, smart technologies, ethics, consumer behaviour, consumer experience, digital wellbeing, artificial intelligence-bias, artificial intelligence adoption, algorithm fairness, privacy and security, transparency, trust, government regulation and policy, design, and artificial intelligence development. After completing the final phase of the SLR procedure, six further articles were eliminated due to their lack of relevance to smart retailing, AI, ethics, and consumers. Consequently, 85 publications were analysed and manually coded according to Wang and Chugh (2014). Manual coding was then employed, resulting in 28 (33 %) articles focusing on consumer behaviour in smart retailing; 21 (25 %) research articles focusing on ethics in smart retailing; 6 (7%) studies relating to policy and regulation in smart retailing; and the remaining 30 (35 %) articles classified as having mixed themes.

3.2 RESULTS: THE STATE OF THE EMPIRICAL LITERATURE

Following Tranfield et al. (2003), this section summarises the findings from the systematic literature review, utilising descriptive statistics to map the research for academics interested in the subject. This review discusses the papers published; their citations; the publishing time; the journal of publication; the authors' origins; research methodology; and ultimately, a narrative content analysis, including a cluster analysis of research streams.

3.2.1 Key trends in Smart Retailing Literature

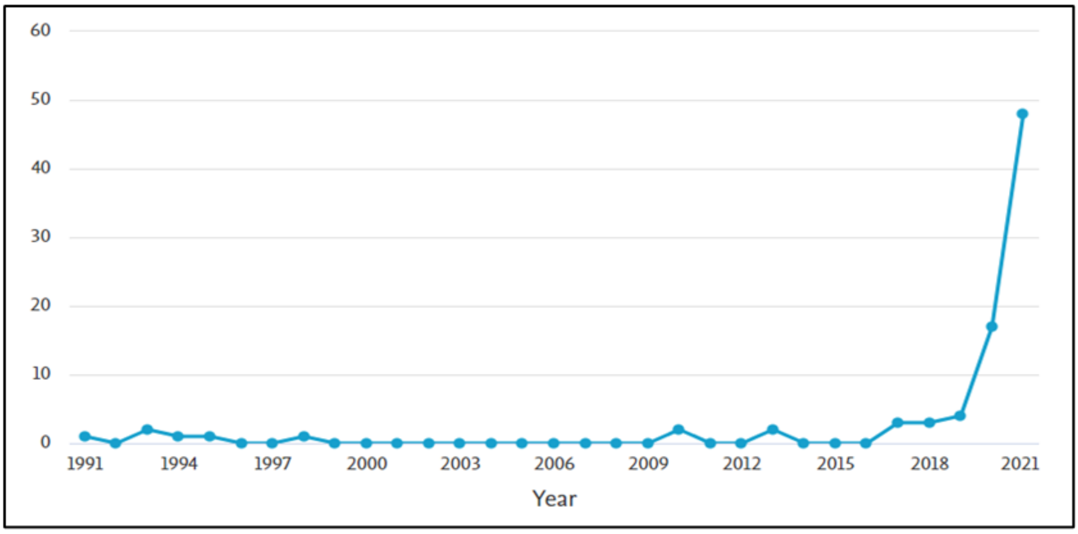
Table 2 depicts the distribution of papers on smart retailing, AI, ethics, and consumers published in 24 different journals on the topic. Some of the topics covered by the journals that have been published and included in the study analysis are as follows: Decision Science, Economics, Psychology, Social Sciences, Computer Sciences, Law, Arts and Humanities, Engineering, Marketing, Healthcare, Strategy, and Innovation.

Table 8:Summary of journals, journal ranking and articles per journal included in the review

Journal Title	ABS Journal Ranking 2021 grade	Total article Count
Journal of international business studies	4*	1
Annals of Tourism Research, European Journal of Operational Research, International Journal of Research in Marketing, Journal of Corporate Finance, Journal of Retailing, Tourism Management	4	13
Decision Support Systems, Government Information Quarterly, Human Resource Management Review, IEEE, Industrial Marketing Management, Information and Management, International Journal of Contemporary Hospitality Management, Journal of Business Research, Journal of Interactive Marketing, Long Range Planning, Omega: The International Journal of Management Science, Psychology and marketing, Technological Forecasting and Social Change, Technovation, The Journal of Strategic Information Systems, Transportation Research Part A: Policy and Practice, Computers in Industry	3	71
Grand Total		**85**

Based on the articles retained and included in this study, the issue of consumer ethical concerns, especially privacy in smart retailing, was first discussed in the Government Information Quarterly journal in 1991. The research argued that the emergence of retail products containing comprehensive compilations of personal information coupled with rising consumer ethical concerns underscores the importance of establishing a data protection board to implement safeguard measures to protect individual privacy (Rotenberg, 1991). The number of published articles has been relatively flat up to the year 2010, whilst there were no publications recorded for the years 1992, 1996, and 1997. The publications then began to steadily climb over time (see *Figure 14*).

Figure 14:Publication distribution in relation to Smart Retailing, Artificial Intelligence and Ethics by year



This study established that about one-fourth (0.25%) of the 85 publications retained in the review sample were published before 2018. In addition, a recent upsurge was noticed, with over three quarters (76%) of the publications in the sample having been published between 2020 (19%) and 2021 (57%) (see Figure 3). Most of the studies, on the other hand, are published in the Journal of Business Research (27) and Technological Forecasting and Social Change journal (19), as shown in *Table 7*.

Figure 15::Publications distribution by year

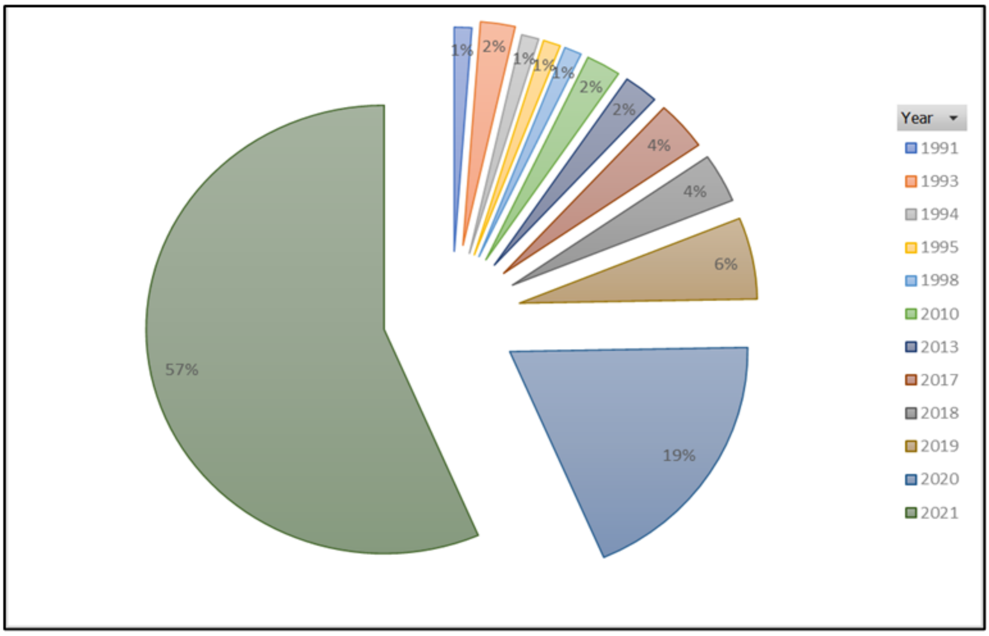


Figure 16:Publication distribution by subject area.

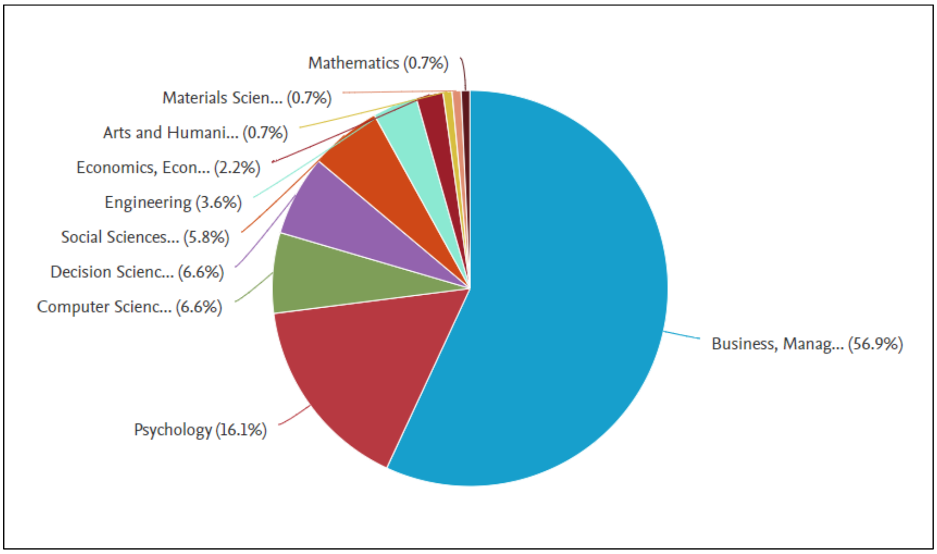
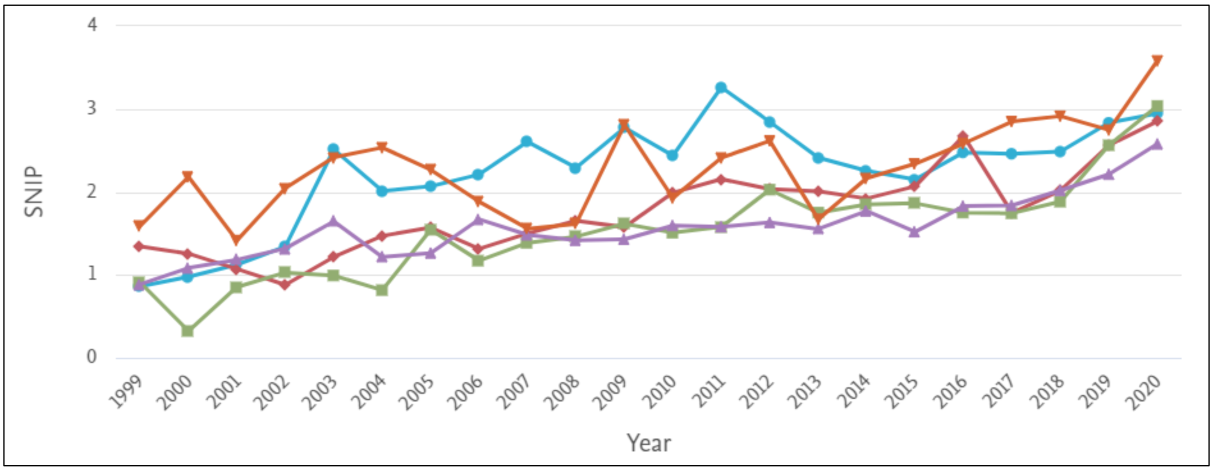


Figure 17: Source normalised impact (SNIP) per paper by year.

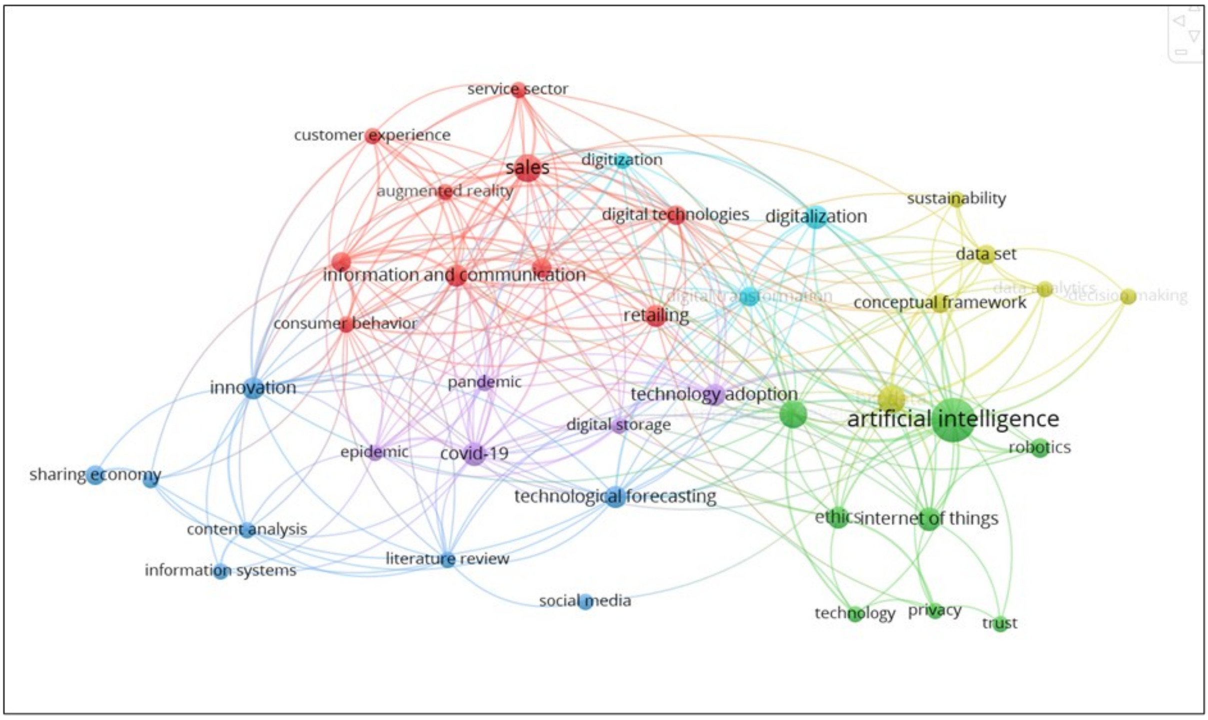


3.2.2 Keywords Analysis

In the keyword analysis using the Vosviwer analytical tool, broad thematic themes of smart retailing research were identified. Figure 6 demonstrates the connected network of the most common keywords (keywords with three or more occurrences) used by academics and indexed in the relevant research databases. The words that describe smart technologies used in retail, like artificial intelligence and the internet of things, were naturally in the middle of the word map. The map shows that various subdomains that came up in the analysis are technological development, technological forecasting, information and communication technology, digitalization, and so on. All these subdomains are clustered around artificial intelligence. The cluster of artificial intelligence methods is made up mostly of the words "machine learning," "robotics," "virtual reality," and "algorithm aversion”. The cluster also shows a focus on consumer experience and ethical concerns related to the use of AI in retail, such as privacy, bias, and trust. The key observation that could be drawn from this bibliometric analysis is the dynamic of the line of work aimed at understanding the impact of the use of technology on the consumer. The map, on the other hand, does not reflect how important consumer ethical concerns were in the previous studies (Bélanger and Crossler, 2011; Aguirre et al., 2015b; Bleier and Eisenbeiss, 2015b, 2015a; Martin and Murphy, 2017; Shankar, 2018; Rajavi, Kushwaha and Steenkamp, 2019; Martin and Palmatier, 2020; Du and Xie, 2021; Guha et al., 2021; Sembada and Koay, 2021; Vimalkumar et al., 2021; Wieringa et al., 2021; Bawack et al., 2022).

Arguably, this dynamism could in part be explained by the urgent nature of consumer ethical concerns, which may lead to consumers' resistance to the adoption of emerging technologies (Inman and Nikolova, 2017; Mansoori, Sarabdeen and Tchantchane, 2018; de Bellis and Venkataramani Johar, 2020; Fernandes and Oliveira, 2021b; Ko, Kim and Kim, 2021; Chatterjee, Khorana and Kizgin, 2022). Apart from the dynamic of the field, a recurrent observation throughout this analysis indicates the need for further investigation into the focus on ethical use of AI to understand more about the reasons behind this trend and calls for the attention of academics for further research and direction. This was based on the analysis of the review sample and the clusters that were found in the keyword analysis.

Figure 18:The Keyword density heat map of final sample (85 articles)



3.2.3 Key Methodologies in Existing Literature

This section summarises the methodology used in the relevant articles. The table below summarises the most used methodologies. It is evident whilst conducting this review that the authors of the articles included in the review sample utilised a variety of terminology for smart retailing. In addition, the study shows heterogeneity attributes; the sample studies varied in terms of methodological and contextual perspective. Qualitative research accounts for most of the study. It is almost certain from the sample that smart retailing research is shifting more towards qualitative phenomenological studies than toward quantitative theory-based analyses in empirical articles. Most of the articles included in the review sample utilised qualitative approaches (n = 54) rather than quantitative approaches (n = 24), with a few mixed-method research (n = 6). It is evident that the analysis with mixed methods or mathematical analysis were rare.

3.2.4 Theoretical Underpinnings

There are various theories that have been used to explore this subject area. As seen in Table 3, these theories emphasise the critical nature of theoretical contributions in the sphere of the relevant knowledge. Most studies used a variety of theories, including theory of planned behaviour, technology acceptance model, theory of reasoned action, unified theory of acceptance and use of technology, uncanny valley theory, stakeholder's theory, self-determination theory, institutional theory, among others. A brief description of the top four of these highly used theories has been explored in this review process.

The theory of planned behaviour: The theory of planned behaviour is a widely used social-psychological model for behaviour prediction (de Kervenoael *et al.*, 2020; Tussyadiah, 2020; Huang, Jin and Coghlan, 2021; Attié and Meyer-Waarden, 2022). The origins can be traced back to Ajzen and Fishbeins' (1980) theory of reasoned action. It was created in reaction to the apparent disjunction between general inclinations and observed behaviour (Ajzen, 1985; 1991).

The theory of reasoned behaviour: The theory of reasoned action is one of the most frequently used technology adoption theories in the review sample (de Kervenoael et al., 2020; Tussyadiah, 2020; Huang, Jin and Coghlan, 2021). According to the theory of reasoned action (TRA) (Fishbein and Ajzen, 1975), consumers think about the effects of their actions and want to act in line with what they think is best (Lee and Green, 1991).

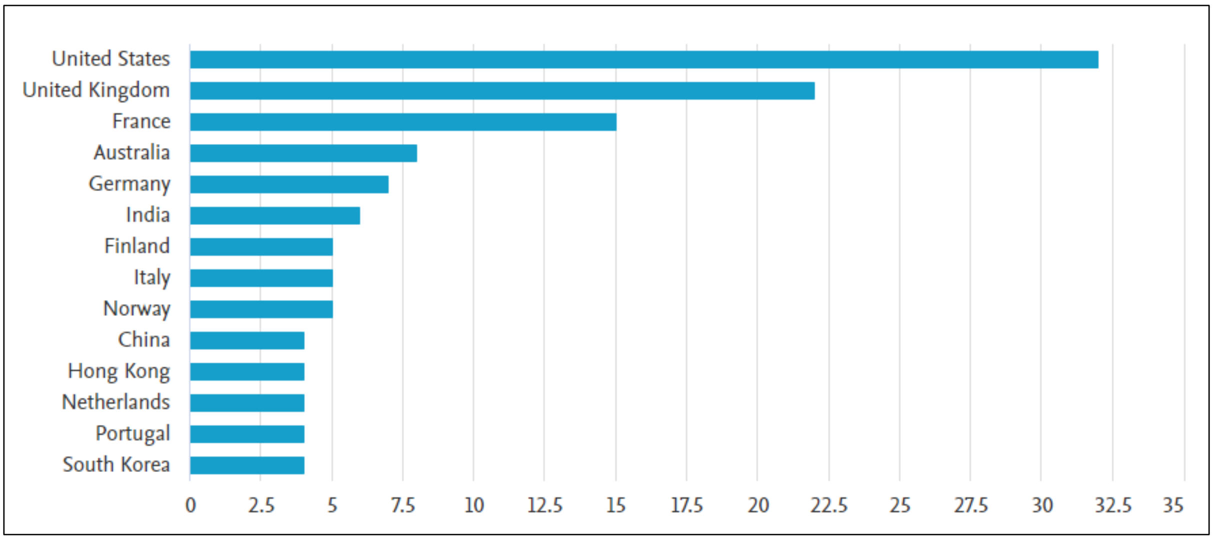
Technology acceptance model: The Technology Acceptance Model (TAM; Davis, 1989) is one of the most important models of technology acceptance, positing that two key elements influence an individual's intention to utilise new technology: perceived ease of use and perceived utility.

Unified theory of acceptance and the use of technology: New technology acceptance and user research are well-established (Venkatesh et al., 2012), with applications in a variety of industries and products and services. The Unified Theory of Acceptance and Use of Technology (UTAUT), originally established by Venkatesh et al., (2003) as a merger of eight separate ideas, is one of the theoretical foundations (see below). UTAUT is one of the most widely recognised baseline models of technology acceptance and use. UTAUT is comprised of four core factors (effort expectancy, performance expectancy, social influence, and facilitating conditions) and four moderating variables (effort expectancy, performance expectancy, social influence, and facilitating conditions) (age, experience, gender, and voluntariness of use) (Schmitz et al., 2022).

3.2.5 Cross-countries and industries review

The systematic literature has expanded the scope of recognised contexts by incorporating emerging sectors or industries and countries. Although past research collected data from a variety of industrial sectors, the technology/big data (n = 19), retail (n = 16), and marketing (n = 14) sectors were the most prevalent. In terms of country focus, the United States (n = 22) has significantly more research than the United Kingdom (n = 17) and France (n = 14), as shown below.

Figure 19:Top 14 publication by country or territory.

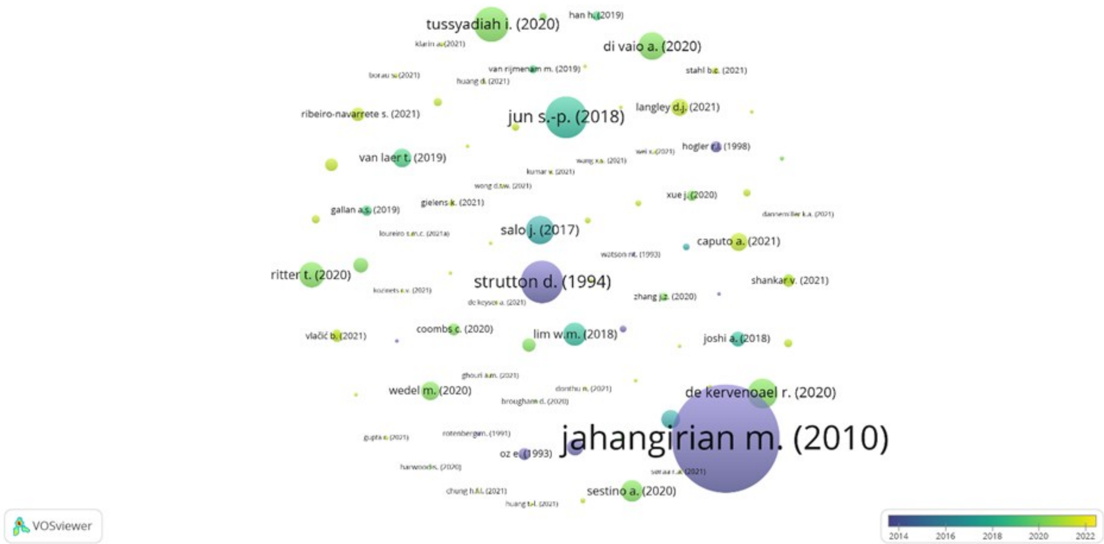


3.2.6 Citation Overview

The top 30 most frequently cited papers were selected from among the (n = 85) review samples and included in this report. While this study's primary objective is to determine key research areas regarding smart retailing, this initial analysis of authors' citations provided an overview of the intellectual structure, including providing an early insight into the nexus of influences underlying the smart retailing research domain. The highly cited study was conducted by Jahangirian et al., (2010) on the evaluation of simulation applications published in peer-reviewed journals between 1997 and 2006 to present an overview of simulation techniques' relevance in manufacturing and business. Their findings were published in the European Journal of Operational Research and had the highest number of citations of 401.

The next highly cited study was by Strutton, Vitell and Pelton, (1994) on consumers' justifications for inappropriate behaviour in retailing environments. It was published in the Journal of Business Research and had the second highest citations of 124. Next, the study by Jun, Yoo and Choi, (2018) had the third highest citation of 81, and they determined how public use of Big Data derived from web searches has impacted research, as well as analysed the implications of Google Trends for Big Data usage and application. Furthermore, Poncin et al., (2017) was the next highly cited study with 61 citations from the journal of Technological Forecasting and Social Change (see *Figure 20*).

Figure 20:The visualisation of the studies based on their citation number.



3.3 Discussion

The analysis of the results of our study indicates that researchers and other stakeholders urgently require a better understanding of the ethical challenges and opportunities associated with artificial intelligence-enabled value creation given the rapidly growing number of smart technologies, including artificial intelligence-enabled products and services, that are currently available in today's smart retail ecosystem, as well as the profound impact that these products and services have on consumers and societal wellbeing. This review also explored and highlighted how smart retailers could help make sure that artificial intelligence is ethically used to avoid consumer harm while examining how the ethical challenges in smart retail settings are currently managed. First and foremost, our study showed that the usage of smart technology and artificial intelligence in retail has a considerable impact on the extrinsic values associated with a smart consumer experience (Strutton, Vitell and Pelton, 1994; Bai *et al.*, 2017; Poncin *et al.*, 2017; Salo, 2017; Foroudi *et al.*, 2018; de Kervenoael *et al.*, 2020; Grewal, Kroschke, *et al.*, 2020; Huang, Jin and Coghlan, 2021; Jiang and Stylos, 2021; Krishen *et al.*, 2021; Ribeiro-Navarrete, Saura and Palacios-Marqués, 2021; Shankar *et al.*, 2021).

Existing reviews state that consumers who have a positive perception of retailers that use technology (such as chatbots, voice control, augmented and virtual reality) believe that these businesses are forward-thinking (Porter and Heppelmann, 2015; Foroudi *et al.*, 2018; Shankar, 2018; Kumar, Nim and Agarwal, 2020; Dannemiller *et al.*, 2021; Shankar *et al.*, 2021). This accession is shared by Shankar et al., (2021), who strongly believed that "the success of technologies in the retail context depends on adoption by relevant stakeholders, such as shoppers." Shankar et al. (2021) analyses the drivers and consequences associated with the usage of new retail technology across a broad range of applications. They predict that consumer adoption of these technologies may result in increased purchases, satisfaction, and loyalty. Evidence from the review shows that smart retailing is growing in popularity, and digital technology enables new forms of engagement amongst retail actors. In fact, digitization has made a lot of things more efficient and cut down on distances in a global village environment, all at a lower cost (Grégoire *et al.*, 2009; Jiang and Stylos, 2021; Shankar *et al.*, 2021).

Moreover, the COVID-19 pandemic has unquestionably accelerated technological advancement and transformed the way consumers shop. Physical stores were already declining, with some calling it the "death of the high street," and the situation was exacerbated when governments around the world imposed a series of lockdowns and social distance measures (Dahlke *et al.*, 2021; Huang and Liu, 2021; Jiang and Stylos, 2021; Ribeiro-Navarrete, Saura and Palacios-Marqués, 2021; Shankar *et al.*, 2021). Furthermore, as countries and major economies begin to reopen for business or emerge from COVID restrictions, the retail industry will be compelled to undergo further digital transition regardless of the size of the retail business.

In a nutshell, retail technologies that get good usability ratings make consumers feel comfortable and valued, solve their problems, and make them think the retailers are new and interesting. Smart technologies like chatbots can also have a big impact on the value of the customer experience because they are very responsive, which means that customers can get a lot of benefits with little effort whilst also getting more information from the chatbot (Borau *et al.*, 2021). The comprehensive search, screening, and extraction method, which was undertaken independently by the authors at each stage, enabled the review process to identify all applicable studies that met our inclusion criteria. The most recent search (31st August 2021) ensures that the process has captured the evidence base as it exists now across a diverse range of academic journals. The retail landscape is continually developing as systems, processes, information, and communication technologies become more integrated (Grewal, Roggeveen and Nordfält, 2017; Grewal et al., 2020; Guha et al., 2021). The data shows that retailers are rapidly adopting new technology to stay profitable, relevant, and consumer-focused (Grewal et al., 2017; Grewal, Hulland, et al., 2020; Guha et al., 2021). Due to the intensity of technological advancement and implementation, consumers have become accustomed to smart retailing. This comfort with smart retailing has risen dramatically throughout the COVID-19 pandemic (Gauri *et al.*, 2021). While smart retailing has experienced significant growth in recent years, consumers' concerns, and perceptions about the ethical implications of online shopping have also increased (V. Chang, 2021; Du & Xie, 2021; Roman, 2007). The key ethical concerns and other challenges in a smart retail setting are presented in *Table 9*.

Table 9:The Key Challenges faced by consumers when engaging smart retailing.

ETHICAL CONCERNS	SOURCE
Privacy	(Aguirre et al., 2015b; Bélanger & Crossler, 2011; Bleier et al., 2020; Cecere et al., 2015; V. Chang, 2021; A. De Keyser et al., 2021; Du & Xie, 2021; R. Gupta et al., 2021; Hann et al., 2007; K. D. Martin et al., 2020; K. D. Martin & Murphy, 2017; K. D. Martin & Palmatier, 2020; Okazaki et al., 2020; Ribeiro-Navarrete et al., 2021; Rotenberg, 1991; V. Sharma et al., 2020; J. Z. Zhang & Watson IV, 2020)
Trust	(Chatterjee et al., 2022; V. Sharma et al., 2020; T. Ying et al., 2021)
Adoption	(Batat, 2021; Chatterjee et al., 2021; Dannemiller et al., 2021; Ghouri et al., 2021; Guha et al., 2021; Hopkins, 2021; Krishen et al., 2021; V. Kumar et al., 2020; Sestino et al., 2020; Shankar et al., 2021; Tussyadiah, 2020; Vlačić et al., 2021; X. Wang et al., 2021)
Ai bias	(Borau et al., 2021; A. De Keyser et al., 2021; Du & Xie, 2020; Haenlein & Kaplan, 2021; D. Huang et al., 2021; Ritter & Pedersen, 2020; Vlačić et al., 2021)
Consumer wellbeing	(Burr et al., 2020; Du & Xie, 2020, 2021; Orben & Przybylski, 2019; Robeyns, 2020)

Furthermore, there are limited studies that focus particularly on the privacy concerns that affect consumer adoption, behaviour, and experience with smart retail technologies. The advantages of smart retail are not without their own set of possible dangers, uncertainties, and negative effects. Consumers' expressed doubt about utilising a given technological product or service is a result of the possible negative repercussions that are projected to result from their adoption or usage of that technological product or service, which is referred to as perceived risk (Mitchell *et al.*, 1999; Hassan *et al.*, 2006; Cecere, Le Guel and Soulié, 2015). Hence, consumers' willingness to adopt a particular technological advancement may be harmed by their perceived risk aversions (Adapa *et al.*, 2019). Furthermore, it was highlighted that some security concerns shape consumers' behaviour when interacting with AI-enabled applications and machine learning. Consumers may be concerned with time-related risks such as psychological risk, financial risk, performance risk, and social risk (Rapp *et al.*, 2015; Chung *et al.*, 2021; Karpoff, 2021; Lyngdoh *et al.*, 2021; Bawack *et al.*, 2022). For example, consumers may be hesitant to spend an excessive amount of time learning a new retail technology (i.e., time risk), may be nervous about the smart retail technology (i.e., psychological risk), or may be concerned about fraud when utilising the smart retail technology (i.e., money risk) when engaging with smart retailing settings (Adapa *et al.*, 2019).

Some scholars have shown that the recent data breaches have damaged consumers' confidence in smart retail technology's security (Cadwalladr and Graham-Harrison, 2018; Whittaker, 2019; Gao, Zhang and Wei, 2021) An essential component of any innovation is its novelty, its newness or freshness in the adopter's perspective (Adapa et al., 2019; Attié & Meyer-Waarden, 2022; Burke, 2002). While previous research has frequently assumed that novelty is inherent in smart technology innovations, it is also possible that individuals' perceptions of novelty vary widely (Shankar, 2018; Martins et al., 2019). Consumers have both positive and negative feelings when they think of new things as novel and innovative (Adapa et al., 2019). In conclusion, the findings from this study indicate that perceived novelty is a salient emotive notion that has a substantial impact on the adoption of smart technologies such as artificial intelligence.

Developing and using smart technology is not straightforward, and it presents a slew of ethical issues and concerns that must be addressed. Consumers' intents to engage with the smart retailing ecosystem related to their attitudes toward the employment of technology in general, such as artificial intelligence, in retail. This research reveals that consumers' willingness to make purchases using smart technology is mostly determined by their positive attitude towards these technologies. Despite being a precursor to such an intention, consumers' sentiments toward smart retailing are mediated by their attitudes concerning artificial intelligence. There is growing criticism and debate about what role smart technology, particularly artificial intelligence, should and should not play in larger society. It is vital for merchants, researchers, and other stakeholders to recognise that, while emerging technologies may result in beneficial outcomes, they also carry a high risk of misuse, manipulation, and exploitation. To emphasise the need for an ethical and efficient understanding of the impact of AI advancements on consumer behaviour and experiences, the following are some of the major obstacles to the development, deployment, and impact of smart technology on consumer behaviour and experiences. For future studies, we emphasise the focus on data gathering and use; personal privacy and security; data storage and security; and four-inclusiveness and bias. While outlining each of these obstacles, we also suggest numerous critical topics for future study and practise.

The systematic literature review enabled this study to concentrate on a manageable but large number of studies to compile an unbiased (as opposed to simple judgmental evaluations) and transparent picture of current research on the use of smart technology, including artificial intelligence, in retail. This study acknowledges that adhering to the methodology may exclude some important studies. This is even more difficult if the search criteria are limited to titles, abstracts, and keywords, not the entire text. Another limitation is that this analysis only focused on top publications based on the Academic Journal Guide 2021 (ABS Ranking) ranking of three or above. While it is believed this approach is warranted based on previous literature evaluations, it is also acknowledged that there is a risk of missing relevant literature that is published in journals below ABS Grade 3 or published in other publications that are not ranked by the Academic Journal Guide. As a result, the report may have been biased because the articles were not published in high-ranked journals.

3.4 Conclusion

This study was driven by a broad interest in gaining a better understanding of how consumers interact with smart retail and has concentrated on the constituents and consequences of a smart consumer experience in retail. These included the relationships between consumer satisfaction, perceived risk, behavioural intentions, loyalty, shopping effectiveness, and consumer well-being toward smart retailing. Digital technologies are becoming more integrated into consumers' lives, and retail businesses are attempting to capitalise on these new opportunities to engage each consumer on a more personal level by offering more relevant and engaging products, services, and advertising messages. Given that the nature of information technology has shifted significantly, we advocated the importance of emphasising holistic experiences when it comes to smart retail technologies.

While the fourth industrial revolution is well underway, a huge surge of modern technology is forcing businesses to change rapidly to stay competitive, and the retail sector is no exception. The use of smart technology, especially artificial intelligence, is the key to the future of retail. The way retailers research products, price them, and keep track of their inventory will become increasingly dependent on artificial intelligence, as will the way consumers interact with the smart retail ecosystem. Technological advancements have made it easier to collect a range of information to facilitate smart retailers in personalising their products and services for consumers via new media. The review samples have indicated that smart retail requires the development of better, new, and distinctive competencies and dexterity. To do this, you need to use the power of data and make it work seamlessly across the retail value chain. This can only be done by doing this. In the same way, several artificial intelligence disasters that have led to biases, stereotypes, and actions that are hard to understand have shown how important it is for the global community to guide the ethical development of artificial technology in both present and future technologies.

This study through content analysis has established that industries, policymakers, and governments have agreed on core artificial intelligence concepts, but there is still a lack of clarity and disagreement over how to put them into practice. The paradox of privacy in our hyperconnected world is that consumers want more data privacy but tend not to take steps that are adequate to protect their data. Because of this, some retailers might be of the view that most consumers are unconcerned about data privacy. But the begging question is, does the consumer have an actual support mechanism? Whether or not they can do something is a question, or if there are barriers. Despite recent advancements, retailers and intermediaries tend to bear the primary responsibility for adopting privacy measures. Pseudonymization and basic rule-based data anonymization solutions are frequently insufficient to secure sophisticated, dynamic, multidimensional retail consumer data.

The use of smart technology and artificial intelligence in retail will require more research. To do this, we developed a conceptual framework called "Unified Framework for Understanding Adoption", which covers the entirety of consumers' experience with emerging retail technologies and is solidly anchored in earlier research in cognitive and social psychology (Affordance theory). This new construct, on the other hand, adds to the body of work on intrinsic motivation variables in technology acceptance by adding the dimension of temporal dissociation, which has been missing from operational definitions of related constructs until now. This dimension, which is present in conceptual definitions of related constructs, has been missing from operational definitions until now.

The main purpose of this research was to improve our understanding of how smart retail consumers react to and engage with the use of artificial intelligence in retail and the level of negative impact this has on the consumers' experience. To aid future research, we proposed a conceptual framework termed "unified framework for understanding adoption". Given the undeniable fact that the use of technology in retail is pervasive in both commercial and personal contexts, such study is valuable for both theory development and practice. The pragmatic examination of the digital shift brought about by artificial intelligence in retail, as well as the developed conceptual framework, might serve as documented resources for future studies on prospective long-term deployments of artificial intelligence in retail. Further study might strive to deepen and broaden the new framework application scenarios, as well as analyse trends in the maturity of artificial intelligence technologies and their influence on retail and consumers.

3.4.1 Policy implications

Consumers have shown increased concern about data privacy over the last two decades, particularly over their inability to regulate the types of their personal information gathered and shared with others, when they interact with any smart retail ecosystem (Martin and Murphy, 2017). As a result of this growing momentum considering privacy as a fundamental of the human's right, firms and governments are required to develop potential principles that includes the laws and regulations that could restrict the firms' access to consumer data (e.g., the European Union's the General Data Protection Regulation (GDPR), California's AB 375 bill) (Appel et al., 2020).

3.4.2 Limitations

This review focuses exclusively on articles published in ABS-ranked journals, a deliberate choice to ensure the inclusion of high-quality, peer-reviewed research with established methodological rigour and theoretical depth. However, this approach inevitably narrows the scope by excluding non-ABS-ranked journals, industry reports, and conference proceedings. Such exclusions may omit timely and applied insights, particularly those emerging from practitioner-led innovations or interdisciplinary approaches that have not yet been formalised within academic discourse. For instance, industry-driven advancements in smart retailing technologies or region-specific adaptations may not be captured in this review.

This focus also limits the contextual diversity of the analysis, as high-impact journals often emphasise universalizable theories over regionally nuanced or practice-specific findings. Consequently, this review may under-represent emerging trends or innovations occurring outside the mainstream academic lens. Future research should address this limitation by adopting a broader inclusion strategy, integrating diverse sources through systematic reviews or mixed-method approaches. Such efforts would provide a more comprehensive understanding of smart retailing, bridging theoretical advancements with practical applications and enriching the academic discourse with context-specific insights.

Chapter 4: Conceptual Framework and Hypothesis Development

The previous chapters extensively discussed the development and application of smart technology in retail, including its impact on consumer experiences, satisfaction, purchasing behaviour, perceived risk, and ethical concerns. However, limitations in the existing literature regarding consumer experience and satisfaction and digital ethical perception, trust, decision-making, and risk tension were identified. This chapter explores the limitations discussed above by examining emerging and contentious topics, including consumer awareness, expectations, perceived risks in smart retail, consumer experience with smart technology, satisfaction, and ethics. Taking an affordance theory perspective and drawing upon extant literature, a conceptual framework was developed that encompasses various elements of consumer perceptions related to digital ethics (such as privacy protection, fairness, and brand trust), attributes of perceived risk, smart consumer experience, satisfaction, and (re)purchasing behaviour including brand loyalty and digital well-being. This chapter provides new insights into the impact of smart technology adoption in the retail industry, specifically focussing on its influence on consumer pre-purchase, purchase, and post-purchase intent. This study examines these influences through the lens of affordance theory, considering affordance, interactions, and realisations within smart retail environments.

The subsequent section of this chapter is organised as follows: it begins by explaining the exposition and background of affordance theory and then critically analyses its inherent limitations. Following this, the research model is presented, along with an explicit discussion of the hypotheses developed, the conceptual model, and a comprehensive review of pertinent literature. These discussions provide a robust justification for the construction of the model. Finally, this chapter concludes with a summary highlighting the key findings and insights derived from the analysis.

4.1 EXPOSITION OF AFFORDANCE THEORY

This study draws upon affordance theory to develop a conceptual framework that explores the relational processes in smart technology-embedded retailing. The framework explicitly considers various elements of consumer perceptions related to digital ethics, perceived smart retail risk, smart experience, smart satisfaction, consumer (re)purchasing behaviours, loyalty, and digital well-being.

Affordance, as defined by Gibson (1977), refers to an individual's perception of how the environment or objects can be used. Combining principles of perception and value, affordance theory offers a structured framework for understanding the interaction between features of the information technology (IT) environment and actions required in specific contexts. This theory elucidates how individuals perceive their surroundings and how these perceptions subsequently drive their actions (Gibson, 1977). Unlike theories primarily centred on psychological factors, affordance theory incorporates IT artefacts into its conceptual framework (Gibson, 1977). It has emerged as a prominent and widely embraced theory within the field of information systems (IS).

Donald Norman (1988) introduced an additional perspective in his book titled "The Psychology of Everyday Things," focussing on perception and integrates the concept into the domain of design and human-computer interaction studies (Norman, 1988; Soegaard, 2010; Evans *et al.*, 2017). In this context, affordance pertains to the design elements of an object that indicate how the object should be used; it serves as a visual indicator of the object's intended purpose and functionality (Norman, 1988). Therefore, affordance is dynamic and context-dependent, adapting to an individual's circumstances, capabilities, and objectives. For instance, an open window might afford the opportunity for a burglar to "climb through" and commit theft, but this affordance does not apply to a child who cannot reach the window and lacks the necessary action potential (Soegaard, 2010). This definition emphasises that an object influences how it should be utilised. Furthermore, current research demonstrates that affordance can arise through direct interaction with technologies, often leading to processes of experimentation and adaptation that impact individuals' behaviour.

Researchers have leveraged this theory to explore a diverse range of information technologies (Markus and Silver, 2008; D. Wang et al., 2023), investigated the influence of IT features on consumer engagement behaviours (Sun et al., 2019; D. Wang et al., 2023), and contribute to design science (Karahanna *et al.*, 2018).

In recent times, scholars have turned to affordance theory to examine how the functionalities of technology-enabled retail platforms influence consumer behaviour (Sun et al., 2019; D. Wang et al., 2023). For instance, Sun et al. (2019) applied this theory to e-commerce and identified affordance such as visibility, meta-voicing, and guidance shopping. They established that these affordances exert a significant impact on consumers' purchase intentions. However, it is worth noting that the definitions and dimensions of the e-commerce affordance are still rooted in traditional social commerce paradigms (Dong and Wang, 2018; D. Wang et al., 2023), thereby overlooking the real-time and intermediary-free nature of e-commerce. Unlike other affordances within the Gibson (1977) context, e-commerce affordances can also be perceived as specialised interfaces through which smart retailers engage with their consumers. By leveraging these e-commerce affordances, consumers can efficiently access authoritative recommendations and product or service details, which, in turn, can influence their perceptions of information reliability and credibility (Filieri, Hofacker and Alguezaui, 2018; Wang et al., 2023; Li et al., 2023), ultimately impacting their final purchasing decisions. Additionally, given that e-commerce affordances offer varied cues, different affordances can lead to distinct information processing mechanisms (Davis and Tuttle, 2013; Wang et al., 2023; Frauenstein et al., 2023). Even though affordance theory confirms the link between IT affordances and consumer actions, the underlying mechanisms require more research. Consequently, this study focuses on the identification of specific IT affordance within smart retail settings and the subsequent elucidation of their impact mechanisms, drawing upon the pre-, during-, and post-purchase experiences of consumers.

In sum, most technology-enabled retail research has only explored consumer-related factors in engagement, experience, and purchasing behaviour from the value/motivation perspective, ignoring the effects of platform-related factors, including consumer ethical perspective, and overall perceived risk. How different types of consumers engage, process information, and make decisions in the smart retailing context remains largely unknown. Additionally, existing studies have tested only the effects of different factors individually. Whether and how the environmental factors of smart retailing platforms collectively affect consumer decisions remain unexplored. Most importantly, the existing definitions and dimensions of e-commerce affordances are still based on traditional social commerce. Further exploration of specific platform-enabled IT affordances in smart retailing is required.

4.1.1 The Origin and Development of Affordances

The concept of affordances, which refers to the functions and capabilities offered by objects or environments, presents a multifaceted history characterised by issues of overuse, misuse and various interpretations (Gibson, 1977). Despite criticisms of the theory (Dings, 2021; M. Oliver, 2005; Volkoff & Strong, 2013), this concept remains a fundamental analytical tool across multiple academic disciplines, including design, science and technology studies, media studies, and everyday discourse (Evans *et al.*, 2017; Sun *et al.*, 2019; Bayer, Gimpel and Rau, 2021; Xu, Jia and Tayyab, 2023). Its enduring relevance stems from its capacity to elucidate the dynamic interplay between technological artefacts and human users, recognising both as active and influential agents in interaction.

In 1966, J.J. Gibson, an ecological psychologist, laid the foundation for the concept of affordances in his work "The Senses Considered as Perceptual Systems." Gibson initially defined affordances as the functionalities that objects provide, whether beneficial or detrimental, albeit offering limited elaboration (Gibson, 1966). In 1977, J.J. Gibson published, "The Theory of Affordances," this work explores his influential ecological psychology theory, outlining how individuals perceive and interact with their environments. He introduces the concept of "affordances," focussing on the functional properties of objects and how they offer opportunities for actions and interactions within the context of perception (Gibson, 1977). Further development occurred in 1979, when Gibson published "The Ecological Approach to

Visual Perception." In this seminal work, Gibson investigated the variations in the flight skills of World War II military pilots, elevating the environment as an active agent in his analysis. He refined the definition, emphasising that affordances are relative to the perceiving organism and asserting their existence independently of actual use. He posited that objects and environments possess inherent properties that may be exploited by a particular organism (Gibson, 1979; 2014).

In 1984, William H. Warren quantified affordances, with stair climbing serving as a salient example. Warren investigated the relationship between organisms and the opportunities provided by the environment. His research identified the optimal and critical thresholds at which stairs afford climbing, contingent on the leg-length-to-rise ratio. He demonstrated that stair climbing is optimally feasible with a ratio of 0.26 and unfeasible after reaching a ratio of 0.88. Respondents accurately perceived these ratios when evaluating their ability to ascend specific sets of stairs (Warren, 1984). In 1988, Donald A Norman introduced the concept of affordances to human– computer interaction (HCI) and design communities through his book "The Psychology of Everyday Things, which was later republished as "The Design of Everyday Things." Norman's work challenged Gibson's presumption that affordances inherently exist in objects or environments. He argued that affordances are products of human perception. Norman's perspective postulated that the environment offers what the individual perceives it to provide. This distinction led to varied interpretations, with researchers adhering to Gibson and Norman's views or attempting to reconcile the two (Norman, 1988). In 1999, Norman distinguished between real and perceived affordances, emphasising the centrality of perception as a variable of interest for designers (Norman, 1999, 2016). In 2003, Keith Jones, facilitated a comprehensive debate concerning the ongoing relevance of affordances. Scholars predominantly retained Gibson's relational and ecological approach but diverged from the presumption that objects inherently possess certain properties, instead stressing the need for affordances to consider the potentialities of the organism (Jones, 2003). Martin Oliver made a strong case in 2005 for his work on affordance; he critically analysed the concept's extensive use and ambiguous definitions.

He proposed a literary analysis approach to technology, emphasising the understanding of both the design and use of technology. Oliver argued that due to the term's varied interpretations, it had become virtually meaningless and advocated for a more nuanced perspective, but the theory has since found use. (Oliver, 2005). In 2012, Tarleton Gillespie's exploration of affordances explored the nuanced dynamics of human and technological agency within technology and communication studies. The dialogue addressed the multifaceted nature of affordances and the need for a more precise theorisation considering how these concepts apply across different user experiences in the rapidly evolving landscape of technology and media (Neff *et al.*, 2012).

Notwithstanding the criticisms and multifaceted interpretations that have characterised the concept of affordances, it remains an invaluable tool for comprehending the intricate dynamics between technology and its users. Scholars recognise the necessity of refining its usage and advocating for rigorous theorisation. The concept's enduring vitality attests to its persistent relevance and utility in academic discourse. Eminent ecological psychologist James Gibson (1979) fundamentally contributed to the development of affordance theory, offering insights into the dynamic relationship between an individual or organism and their surroundings or other objects (Gibson, 1986). According to Gibson, individuals perceive affordances as attributes of objects rather than physical objects themselves. These perceived affordances represent the opportunities for actions that objects facilitate for individuals. Thus, the perception of affordances may vary among individuals based on their unique circumstances, competencies, and objectives (Gibson, 2014).

Current research indicates that affordances can emerge through direct interactions with technologies, often leading to processes of experimentation and adaptation that influence the behaviours individuals exhibit with these technologies (Sun *et al.*, 2019; Mora, Kummitha and Esposito, 2021; Xu, Jia and Tayyab, 2023). Academics can better understand how consumers perceive and use emerging information technology systems, such as smart technologies in retailing, by using the affordance lens (Pozzi et al., 2014).

Since the inception of affordance in the domain of ecological psychology, Gibson's (1979) theory has found application and extension across various domains. These diverse areas encompass design (Norman, 2013), human– computer interactions (HCI), autonomous robotics, and artificial intelligence (Kim *et al.*, 2010; Lee and Li, 2023; Leung *et al.*, 2023), as well as neurophysiology (Luyat and Regia-Corte, 2009; Thill *et al.*, 2013). Remarkably, the field of marketing has seen limited use of this theory.

The concept of affordance has undergone a notable evolution, expanding its scope beyond the original definition put forth by Gibson (1979), where it was conceived as the bridge connecting an organism's perception to its subsequent actions. The contemporary understanding of affordance encapsulates various conceptualisations across different disciplines, as outlined in *Table 10*.

Table 10:Summary of key definitions of affordance. Adapted from (El Amri & Akrout, 2020)

Field	References	Definitions	Key words
Ecological psychology	Gibson (1979)	"The affordance of the environment is what it offers the animal, what it provides or furnishes, either for good or ill" (p. 127).	- Affordances are the potential actions that an object offers an organism within an environment. - They are dependent on the subject, the environment and the specific context.
	Turvey (1992)	"An affordance is a particular kind of disposition; one whose complement is a dispositional property of an organism." (p. 179)	- Affordances are real possibilities and dispositions and are complemented by effectivities. - Defines affordance as a property of the environment only. - Approach criticized by Stoffregen, 2003, Chemero, 2003

Field	References	Definitions	Key words
	Stoffregen (2003)	“Affordances are properties of the animal–environment system, and they exist only at the level of the animal–environment system” (p.124)	Unlike Turvey, Stoffregen places affordances in an entire organism-environment system; that is, it concerns emergent properties that are not inherent to either the environment or to the animal.
	Chemero (2003)	“Affordances are relations between the abilities of organisms and features of the environment” (p.189)	Affordances are both real and perceptual but are not properties of either the environment or the organism.
Cognitive psychology	Zhang & Patel (2006)	“In distributed cognition, affordances can be considered as distributed representations extended across the environment and the organism.” (p. 337)	The conjunction or the disjunction of the internal level (the perceived organism) and the external level (the environment), representations which means that affordances can be described respectively as a space for possible actions or as spaces for constraints.
	Morgagni (2011)	“Affordances can be seen as dispositions to act and patterns of expectation that are from the beginning, intrinsically, linked to the social and cultural dimensions of the human world.” (p.242)	- Affordances are a manifestation of readiness for action. - Affordances are articulated between information and capabilities. - Affordances are dynamic, meaning it is possible to create new affordances.

Field	References	Definitions	Key words
Design	Norman, 1999, Norman, 2002	"Affordance refers to the perceived and actual properties of a thing, these fundamental properties that determine just how the thing can be used." (2002: 8)	- The author distinguishes subjective perceived affordances from Gibson's actual affordances. - "Perceived affordances are not at all the same as real ones… The designer cares more about what actions the user perceives to be possible than what is true." (1999: 39)
IT	Ortmann and Kuhn (2010)	"Affordances are perceived by agents and may lead to actions, just like qualities are perceived and may lead to observations." (p.1)	- Affordance is determined by the capacity for interaction and depends on perception, observation and action. - Humans do not perceive properties or objects objectively.
Robotics	Sahin, Cakmak, Dogar, Ugur and Ücoluk (2007)	"The affordances in this ecology can be seen from three different perspectives: • agent perspective; • environmental perspective; and • observer perspective" (p.457)	Affordances are tripartite relationships between the agent (or robot), the environment and the observer. It is important to take all three perspectives of affordance into account.

4.1.2 Affordance theory as a lens

The advent of smart retailing, driven by remarkable advancements in digital technology, has undeniably revolutionised the field of consumer experiences and shopping behaviours as discussed earlier. Within this transformative context, the theory of affordance, initially developed by James Gibson and subsequently expanded upon by the influential work of Donald A. Norman, offers a compelling conceptual framework for comprehending the intricate interaction between technological affordances and consumers within the dynamic domain of smart retailing (Gibson, 1966, 1977, 1979, 1986, 2014; Norman, 1988, 1999, 2013, 2016; Sun et al., 2019; Mora, Kummitha and Esposito, 2021; Xu, Jia and Tayyab, 2023). This exploration study investigates affordance theory as an illuminating framework for investigating the multifaceted effects of smart retailing on consumers, encompassing several dimensions: ethics, perceived risk, experience, satisfaction, digital well-being, purchase intention, and loyalty.

The theory of affordances found its roots in the groundbreaking work of J.J. Gibson (1966) revolves around the fundamental concept that the environment, with a specific focus on technology in this context, presents individuals with a rich tapestry of possibilities and functionalities. According to Gibson's pioneering insights, individuals perceive affordances rather than merely perceiving the physical object itself. These perceptions are not uniform but are significantly influenced by a myriad of factors, including an individual's unique circumstances, competencies, and goals. Building upon these foundations, Donald A. Norman extended the theory to encompass the design element, placing particular emphasis on the notion that affordances offer valuable visual indicators regarding the intended purpose and use of an object.

In the field of smart retailing, the application of affordance theory is an invaluable framework that allows us to comprehensively examine how consumers actively engage with the affordances provided by smart retail technologies and the subsequent impact of these engagements on consumer behaviour Affordance theory provides a nuanced lens through which we can dissect the intricate relationship between technology and consumers, shedding light on various key dimensions (Dong and Wang, 2018; Sun *et al.*, 2019).

4.1.3 An Evaluation of Affordance Theory

In comparing the impact of affordance theory in smart retailing, it is crucial to consider alternative theories and frameworks commonly applied in this context. Two prominent alternatives that have garnered significant attention in the field of technology adoption and usage are the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Gefen, Karahanna and Straub, 2003; Lawson-Body *et al.*, 2018; Hollebeek and Belk, 2021; Adu-Gyamfi *et al.*, 2022; AlKheder *et al.*, 2023). While these frameworks offer valuable insights into consumer behaviour and technology adoption, they have distinct focuses and may not fully address the multifaceted dimensions of smart retailing.

The Technology Acceptance Model often considered a foundational theory in the study of technology adoption (Marangunić and Granić, 2015; Granić and Marangunić, 2019; Al-Qaysi, Mohamad-Nordin and Al-Emran, 2020), centres around the relationship between perceived ease of use and perceived usefulness in shaping user intentions and actual technology usage. TAM indicates that users are more likely to accept and use a technology if they find it easy to use and perceive it as valuable in achieving their goals (Davis, 1989; Venkatesh et al., 2003b). While TAM provides valuable insights into the initial adoption of technology, it primarily concentrates on the usability and utility of technology, which are important but do not encompass the entire smart retailing landscape.

In the context of smart retailing, TAM's emphasis on ease of use and usefulness is particularly relevant for understanding how consumers initially engage with digital retail technologies. For example, if an AR shopping app is intuitive to use and provides a genuinely enhanced shopping experience, consumers are more likely to adopt it (Xu, Jia and Tayyab, 2023). However, TAM's scope is somewhat limited in terms of delving into ethical considerations, experiential aspects, and digital well-being, which are increasingly pivotal in the era of smart retailing.

The Unified Theory of Acceptance and Use of Technology (UTAUT) extends the foundation of TAM by incorporating additional factors such as social influence, facilitating conditions, and performance expectancy (Venkatesh, James Y L Thong and Xu, 2012; Tamilmani et al., 2021). UTAUT takes a more comprehensive approach to understanding technology acceptance and usage by acknowledging the role of various determinants.

While UTAUT's expanded framework is beneficial, it primarily focuses on the acceptance and use of technology, similar to TAM. This study explores how factors such as consumer digital ethical perception, perceived risk and expected performance impact technology adoption and usage. However, UTAUT does not explicitly examine the intricate dimensions of ethics, consumer experiences, or digital well-being, which are central concerns in the context of smart retailing.

Affordance theory, as applied in the context of smart retailing, emphasises the inherent functionalities and capabilities of technology in shaping user perceptions and experiences. It highlights the pivotal role of perceived affordances in the entire process. By focussing on how consumers perceive and interact with the affordances of technology, affordance theory provides a valuable lens through which to analyse the multifaceted nature of smart retailing (Bayer et al., 2021; Volkoff & Strong, 2017).

Affordance theory not only focuses on the initial acceptance and use of technology but also extends to ethical considerations, the richness of consumer experiences, digital well-being, and various dimensions of consumer behaviour, including purchase intention and loyalty. Affordance theory is particularly relevant in examining the dynamic and evolving nature of the smart retailing environment, where technology continually shapes and reshapes consumer interactions (Bayer et al., 2021). Moreover, affordance theory can complement elements of TAM or UTAUT for a more comprehensive analysis of smart retailing.

Researchers and practitioners can use these theories in tandem to understand not only the initial adoption of technology but also its ongoing impact on consumers, considering the broader ethical, experiential, and well-being aspects of smart retailing. In doing so, they can gain a holistic understanding of how technology shapes the evolving retail landscape and consumer behaviour.

Within smart retail settings, affordance is fundamentally rooted in the intricate interplay between consumers and the information technology features at their disposal (Dong and Wang, 2018). When consumers engage in smart retailing, they inevitably encounter distinctive features associated with this mode of shopping, subsequently forming perceptions about these features. It is, therefore, our contention that affordance provides a unique vantage point for considering the technical features and the corresponding perceptions of consumers as a cohesive whole rather than treating them as discrete components (Leonardi, Huysman and Steinfield, 2013; Treem and Leonardi, 2013; Parchoma, 2014; Tamilmani *et al.*, 2021). Consequently, the primary objective of this study is to elucidate the way smart technology/retailing exerts its influence on consumers' purchasing behaviour through the lens of IT affordance.

4.1.4 IT Affordance and Smart Retailing

In their 2018 publication, Dong and Wang proposed a thought-provoking viewpoint regarding the impact of information technology affordance in the field of smart retailing. This perspective has significant implications for different aspects of consumer experience, particularly ethical considerations such as privacy, trust, and fairness. This academic inquiry examines the advantages and benefits of a certain subject based on the initial research conducted by Dong, Wang and Benbasat (2016) and incorporates perspectives from additional researchers. The primary objective of this study is to provide a thorough understanding of these consumer-focussed aspects in the realm of intelligent retailing.

Dong, Wang and Benbasat (2016) argue that information technology affordance fulfils consumers' essential requirements to obtain extensive product information during smart commerce. This agrees with ethical considerations, as consumers are increasingly requesting openness and data privacy when engaging with smart retailing technologies. To maintain privacy and cultivate trust, strong data protection protocols are crucial in conjunction with the technological functionalities of smart retail platforms that offer transparent and readily accessible product information (Martin, Borah and Palmatier, 2017; Wieringa *et al.*, 2021). Technological advancements like augmented reality and virtual reality applications not only change the way consumers engage with products but also raise ethical concerns regarding data security and reliability (Shankar, 2018; Meißner *et al.*, 2020; Shankar *et al.*, 2021). These developments are in line with Dong, Wang, and Benbasat's (2016) understanding of IT affordance, which highlights the significant impact of technology on consumer experiences and the development of trust in the context of smart retail.

Within the realm of smart commerce, the use of information technology raises concerns regarding fairness. This is because it requires the development of transparent and unbiased smart platforms that promote equal consumer participation. Interactive platforms and chatbots in smart retail environments enable consumers to ask questions and provide feedback in real time. Smart retailers must ensure that they treat consumer input without bias. This is supported by studies conducted by Chung et al., 2020; Pantano and Pizzi, 2020; Adam, Wessel and Benlian (2021). This interactive process enables consumers to actively search for and acquire relevant product information, thereby substantially contributing to their overall pleasure. Hence, the affordance of information technology is a crucial factor that encompasses ethical considerations while improving the smart shopping experience.

In addition, Dong, Wang, and Benbasat (2016) contend that the fundamental nature of information technology affordance is to provide customers with tailored and cooperative services that assist them in finding products that match their tastes. In this particular situation, the primary issues revolve around digital well-being and the intention to repurchase.

The core technical competency that enables the utilisation of information technology is the provision of personalised advisory functions (Sun et al., 2019). AI-driven recommendation systems and data analytics are utilised in smart retailing to attain a high degree of personalisation (Guha *et al.*, 2021; Frauenstein *et al.*, 2023). Although personalisation enhances the smart shopping experience, it also raises concerns about digital well-being, such as information overload and excessive dependence on technology (Lindecrantz et al., 2020). The ethical aspect in this context is achieving a harmonious equilibrium between customisation and the welfare of consumers (Banker and Khetani, 2019; Hu, Pantano and Stylos, 2023), while ensuring that consumers are not exposed to excessive digital pressure. Moreover, customised services have a direct effect on customer satisfaction, thus influencing the likelihood of repeat purchases. This discourse, elaborated by Lin et al. (2019) and Yan et al. (2023), deepens the comprehension of IT affordance, encompassing the core of intelligent retailing in the wider framework of customer worries and encounters. This synthesis emphasises the crucial significance of these capabilities in building a smart commerce environment and highlights their combined impact on ethical considerations, perceived risk, consumer satisfaction, digital well-being, and repurchase intention.

4.1.5 IT Affordance and Perception-action links in Technological Environments

In the evolving landscape of smart retailing (Cukier, 2021; Shankar *et al.*, 2021; Maroufkhani *et al.*, 2022; Marder, Angell and Boyd, 2023), Pea's (1993) groundbreaking exploration of designs for distributed learning finds relevance, offering a framework to comprehend technological affordances in this dynamic sector (Parchoma, 2014). Smart retailing, characterised by the integration of cutting-edge technology and digital innovation into conventional retail practices (Priporas, Stylos and Fotiadis, 2017; Pantano and Dennis, 2019), is a context in which affordances play a pivotal role. In this discourse, Pea's insights can be applied and extended to the smart retailing domain.

Within the context of smart retailing, the concept of technological affordances is of heightened significance (Yan *et al.*, 2023). It encompasses the potential of technological tools, devices, and platforms to provide not only functional features but also opportunities for both retailers and consumers to engage in more sophisticated and personalised ways (Chen *et al.*, 2022). For example, the deployment of augmented reality and virtual reality applications in smart retailing elevates consumers' perceptual experiences (Nikhashemi *et al.*, 2021). These technologies deliver immersive, real-time access to product information, enabling consumers to visualise and interact with products virtually (Chen *et al.*, 2022; Ho *et al.*, 2022; Sun *et al.*, 2022). This transcends mere product recognition and engenders a deeper level of engagement by reshaping how consumers perceive and interact with items in a smart retail environment. Pea's emphasis on the interplay between perception and action aligns with this transformation (Parchoma, 2014), emphasising the profound impact of technology on customer experiences in the context of smart retailing.

Furthermore, Norman (1988) concept of perceived affordances is highly relevant in the smart retailing landscape. In this setting, the way consumers perceive affordances profoundly influences their shopping experiences. Even meticulously designed smart retailing tools, such as virtual product catalogues or AI-driven shopping assistants, may fall short of delivering value if novice consumers do not comprehend or perceive these affordances as intended. Hence, it is not merely the existence of these affordances that matters; it is also the effectiveness of communication and comprehension by consumers. The imperative for smart retailing is to bridge the gap between the inherent affordances of technology and users' perceptions and actions. Consequently, Pea's redefined concept of affordances as objects linking perception and action takes centre stage in this discussion.

Pea's work also underscores the relational and socially constructed nature of affordances in learning environments (Parchoma, 2014). A parallel can be drawn to smart retailing, where affordances are shaped not only by the technology itself but also by the interactions and relationships among consumers, retailers, and the technological ecosystem. For instance, how consumers perceive affordances within a smart retailing environment may depend on their interactions with knowledgeable store employees, online reviews, or recommendations from peers. The idea that affordances are not static but rather influenced by context and social dynamics resonates within the smart retail setting.

In sum, the insights on technological affordances, although originally rooted in the context of ecological psychology, find valuable parallels and applications in the domain of smart retailing. As smart technologies continue to redefine the retail industry, comprehending the nuanced relationship between technology and consumer perception and action assumes paramount importance. Pea (1993) and Parchoma (2014) serves as a foundational framework upon which to construct a more comprehensive understanding of how affordances function within the dynamic and multifaceted landscape of smart retailing.

4.2 RESEARCH MODEL AND HYPOTHESIS DEVELOPMENT.

This study aims to comprehensively understand consumers' relationships with smart retailers and their associated digital ethical concerns. To achieve this, a model has been developed that explores the impact of smart technologies in retail on consumer behaviour and experience, encompassing aspects of both cognitive and affective digital well-being. The objective is to gain a more profound understanding of consumer behaviour and their preference to embrace smart technology-themed products and services.

A significant gap in the smart retailing literature is the lack of a theoretical framework to conceptualise and understand the dynamics between smart retailing platforms and consumers (Ostrom, Fotheringham and Bitner, 2019; Giroux *et al.*, 2022; Kamoonpuri and Sengar, 2023; Sharma *et al.*, 2023). In this context, affordance theory, as discussed in the previous section, can offer fresh perspectives and facilitate a comprehensive understanding of the relational dynamics between consumers and smart retail platforms.

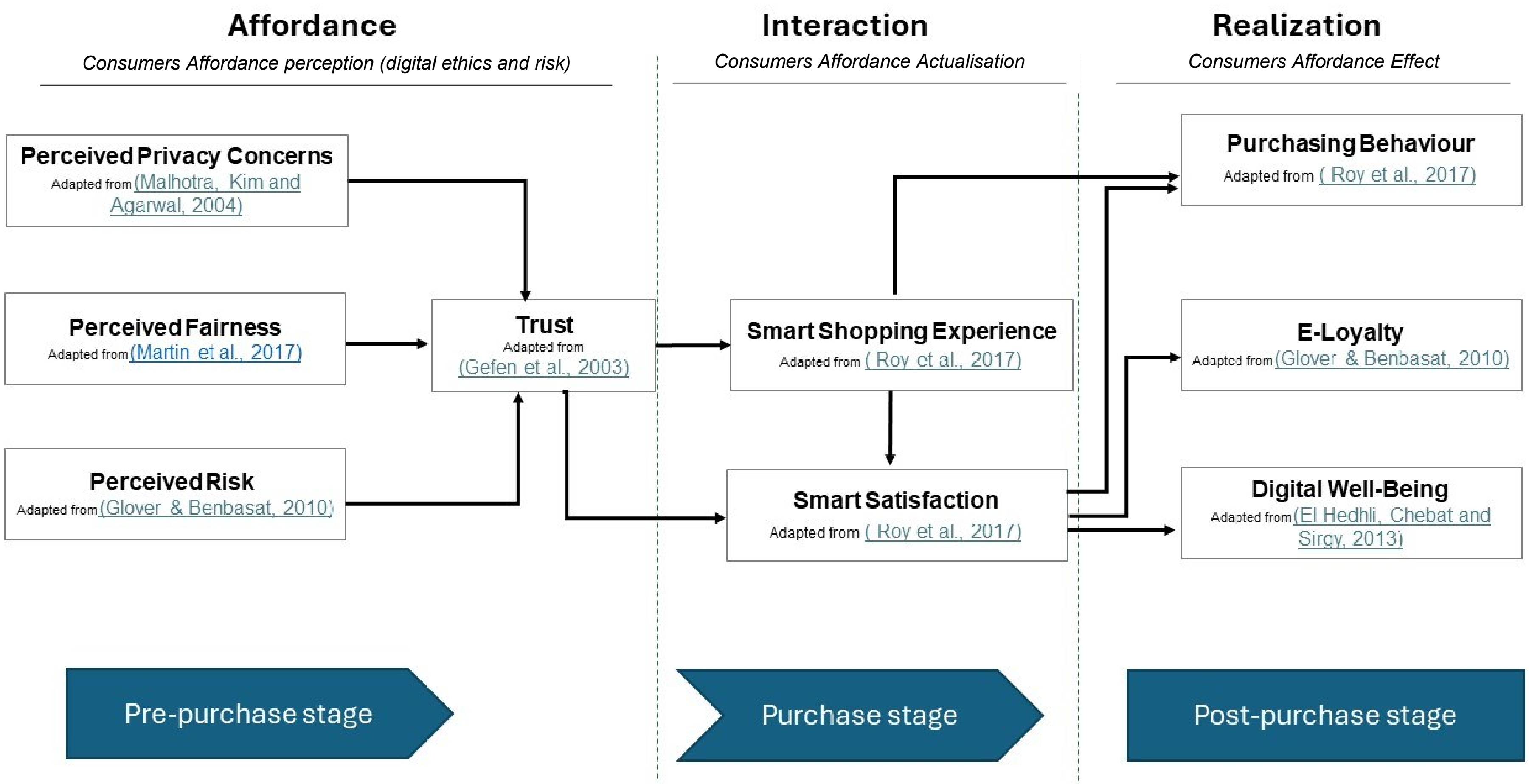
In the ever-evolving landscape of smart retailing (Davenport *et al.*, 2020; Cukier, 2021; Shankar *et al.*, 2021), the concept of repurchase intention takes centre stage, signifying consumers' deliberate choices to endorse a specific brand while disregarding alternative options. In the past, the level of service provided by salespeople was the predominant factor influencing consumer experiences and satisfaction. However, the paradigm shift brought about by the widespread adoption of smart technologies has fundamentally reshaped the role of consumers and emerging digital retail platforms(Shankar *et al.*, 2021). These retail platforms have evolved into central repositories of information for potential consumers. This transformation has profound implications for consumers and their purchase intentions, accentuating the pivotal role of consumer digital interfaces in instigating purchase intent and thereby exerting a substantial impact on the overall financial performance of retailers operating within the digital retail landscape.

Furthermore, consumer ethical digital perceptions and attitudes towards perceived risks exert significant influence on repurchase behaviour within smart retail settings (Agag, 2019; Yang *et al.*, 2019). This influence becomes particularly pronounced in the absence of traditional salesperson interactions. Factors such as the convenience of round-the-clock shopping, click-and-collect alternatives, the global nature of online shopping, and online payment options have assumed critical importance for consumers. Paradoxically, these conveniences inadvertently amplify their perception of risk and underscore concerns related to privacy, fairness, and trust (Cath, 2018; Pazzanese, 2020; Chang, 2021; Du and Xie, 2021). Consequently, the absence of these ethical safeguards has emerged as a substantial hurdle in the online business sphere. Research consistently underscores that the perceived level of consumer ethical digital perception is a pivotal determinant in the consumer decision-making process regarding online purchases. Ethical concerns now occupy a prominent place in the minds of prospective consumers. Authentication mechanisms implemented by smart retailers play an instrumental role in establishing trustworthiness and nurturing consumer confidence (Bart *et al.*, 2005; Schlosser, White and Lloyd, 2006; Trivedi and Yadav, 2018; Cuong, 2023).

Scholarly inquiries into the domain of smart retailing consistently reaffirm trust as a foundational element that shapes consumer behaviour in the domain of online purchasing (Jai, Burns and King, 2013; Thatcher *et al.*, 2013; Yang *et al.*, 2019; Wu *et al.*, 2023).

Furthermore, numerous studies have probed consumer privacy concerns and their subsequent impacts on purchase intentions (Dienlin and Trepte, 2015; Martin and Murphy, 2017; Martin *et al.*, 2020; Wieringa *et al.*, 2021; Zhang *et al.*, 2022). This line of research seeks to identify the attributes, including fairness and privacy, of online platforms that effectively mitigate perceived risks for consumers. Additionally, it explores the strategies that smart retailers can employ to effectively address these attributes on their smart retail platforms. These measures aim to enhance consumer trust, elevate overall experience and satisfaction, and ultimately fortify repurchase intentions (Dayal, Landesberg and Zeisser, 1999) Below is the proposed conceptual framework for this study.

Figure 21:Proposed conceptual framework.



4.2.1 Privacy concerns

Affordance theory, which is rooted in the concept of perceived and actual capabilities of a system or object influencing consumer behaviour (Trepte et al., 2020), provides a valuable lens for understanding and addressing online privacy concerns in the context of smart retailing. The affordance perspective allows the analysis of how design features and functionalities influence users' ability to shape their accessibility levels through self-disclosure or privacy regulation. Online privacy, as a concept, is an individual consumer's assessment of their exposure while interacting with others and institutions or businesses in a digital setting (Trepte and Reinecke, 2011; Sevignani, 2016; Martin and Murphy, 2017; Martin et al., 2020; Masur and Trepte, 2021; Kim et al., 2023; Kim, Seok and Roh, 2023). Importantly, it includes the consumer's ability to actively shape this level of accessibility through self-disclosure or privacy regulation (Masur and Trepte, 2021). It is important to acknowledge that what constitutes a privacy violation is highly context-dependent and can vary depending on the situation and the online environment. Different digital platforms and settings significantly affect how consumers perceive and manage their privacy, making the management of privacy boundaries complex (Chellappa and Sin, 2005; Palmatier and Martin, 2019; Wieringa *et al.*, 2021). This complexity arises from disruptions such as intentional violations of established rules, misinterpretation of rules, the emergence of ambiguous boundaries, differing rule orientations due to various socialisation processes, and privacy dilemmas. These privacy dilemmas and concerns are not confined to specific platforms but extend across various online contexts. For instance, on social media, sharing personal information within interconnected networks is an integral aspect of the user experience, highlighting the intertwined nature of personal data in the digital age. Privacy breaches or violations in such settings can include actions such as stalking, harassment, spreading harmful rumours, and the unwanted sharing of personal information (Masur and Trepte, 2021). This demonstrates the intricate relationship between privacy concerns and online interactions in interconnected spaces.

In contrast, smart retail settings prioritise buying and selling, requiring consumers to provide personal information such as addresses and credit card details. However, this results in a different set of privacy concerns, primarily related to the continuous collection of personal data and metadata by commercial entities. Such privacy invasions often go unnoticed, leaving consumers uncertain about the extent of concern they should have, as these violations are typically invisible (Martin et al., 2020; Masur and Trepte, 2021; Kim et al., 2023). Consumer privacy concerns, which encompass individuals' beliefs, attitudes, and perceptions regarding their privacy, have been extensively used to assess consumer privacy in various contexts (Martin and Murphy, 2017; Martin *et al.*, 2020). This construct has been investigated as an antecedent (Kim et al., 2023), consequence (Xu *et al.*, 2008), mediator (Hu and Min, 2023), and even moderating factor in consumer behaviour (B. Lu & Yi, 2023). Various studies have explored the multifaceted relationship between privacy concerns and trust, which are often conceptualised as opposing forces in the consumer's decision-making process regarding data sharing (Dinev & Hart, 2006; Milne & Boza, 1999; Rodríguez-Priego et al., 2023; Swani et al., 2021). While privacy concerns are negatively correlated with trust, the precise nature of this relationship varies depending on the individual's attitudes, situational characteristics, and shopping habits (W. Hong et al., 2021; Phelps et al., 2000). Trust, defined as an individual's willingness to rely on an exchange partner despite potential risks, is a critical factor that influences privacy concerns(McKnight and Chervany, 2001; Gefen, Karahanna and Straub, 2003; Mofokeng, 2023). High levels of trust can mitigate privacy concerns by assuring consumers that their data will remain secure and free from exploitation (Bleier and Eisenbeiss, 2015b; Lwin, Wirtz and Stanaland, 2016; Cai and Mardani, 2023). However, individual consumers with elevated privacy concerns may exhibit lower levels of trust, perceiving the situation as more fraught with risk (Malhotra, Kim and Agarwal, 2004; Martin *et al.*, 2020). The existence of trade-offs between perceived benefits and privacy concerns (Milne and Gordon, 1993; Martin, 2017, 2018), as well as conflicting expectations (Martin, 2018; Martin and Nissenbaum, 2020), significantly affects consumers' willingness to share their information. Yet, studies have consistently shown that consumers often prioritise the perceived benefits of direct and online marketing despite their privacy concerns, giving rise to the "privacy paradox" (Norberg et al., 2007). This phenomenon highlights the divergence between individuals' expressed privacy concerns and their actual online behaviours and choices. It remains the subject of ongoing debate within the academic community (Kokolakis, 2017; Butori and Lancelot Miltgen, 2023). Drawing from the existing evidence of the privacy paradox in related contexts and the empirical observation that consumers continue to engage in smart retailing despite harbouring privacy concerns, it is reasonable to anticipate a significant impact of privacy concerns on consumers' trust in smart retailing environments. Therefore, understanding the intricate interplay between privacy concerns and trust is vital in the context of smart retailing, as it can significantly influence consumer behaviour, purchase decisions, and the overall success of smart retailing strategies. This study anticipates a significant effect of privacy concerns on consumers' trust, leading to the following hypothesis:

Hypothesis 1a

Attributes of the perceived smart retail privacy concerns impacts on consumers' trust in smart retailing platforms.

4.2.2 Perceived Fairness

Research across various domains consistently examines consumer fairness concerns. This study explores their implications in the context of smart retailing and their potential influence on trust, incorporating the affordance theory perspective. Previous studies have primarily focused on supply chain management, with investigations into consumer fairness concerns focusing on their impact on perceived product value, pricing strategies, and distribution channels.

In examining perceived product value, several studies (Pizzi and Scarpi, 2020; Hamzah and Pontes, 2022; Zhao, Guan and Zhang, 2023) have explored the relationship between consumer fairness concerns and how consumers perceive the value of products.

Affordance theory, rooted in the concept of perceived and actual capabilities influencing consumer behaviour, provides a valuable lens for understanding this relationship. Notably, these concerns are associated with consumer loyalty, satisfaction, and trust in retailers. These factors, in turn, affect how consumers perceive the value of products and their purchase intentions. This indicates that fairness concerns play a significant role in shaping consumer behaviour and attitudes towards products and retailers (Hamzah and Pontes, 2022; Zhao, Guan and Zhang, 2023).

The impact of consumer fairness concerns on pricing strategies has also garnered attention. Chen and Cui, (2013) and Li and Jain (2016) have shown that concerns about fairness lead to uniform pricing, which in turn reduces price competition and enhances firm profits. Affordance theory allows the study to analyse how design features influence consumers' ability to shape their accessibility levels through self-disclosure or privacy regulation. Guo and Jiang, (2016) indicated that strong aversion to unfairness among consumers can diminish consumer surplus and harm inefficient businesses. Fairness concerns can have far-reaching implications for pricing dynamics in retail environments. Furthermore, distribution channels are not immune to the effects of consumer fairness concerns. Yi et al. (2018),Yu, Wang and Liu (2022) and Zhao, Guan and Zhang (2023), explored how fairness concerns influence consumer behaviour in transactions and the subsequent impact on retailers. The results indicate that fairness behaviour can negatively affect a retailer’s profits and drive them to lower retail prices, highlighting the significance of these concerns in distribution channels.

Some studies have also considered alternative strategies to address strong consumer fairness concerns, such as altering selling formats (Yi *et al.*, 2018) or introducing price ambiguity (Allender *et al.*, 2021) to enhance retailers’ profits. Despite the valuable insights from these studies, most of the research has concentrated on traditional retail supply chains rather than smart retail supply chains, overlooking the potential impact of fairness-concerned consumers in the smart retail landscape. Therefore, this study examines fairness through an ethical lens, aligning with the approach of Martin et al. (2017).

Research in the field of consumer privacy within smart retailing indicates potential strategies to mitigate the adverse effects of vulnerability, particularly concerning trust and violations. Martin et al. (2017) explored the roles of perceived fairness and value in moderating the impact of vulnerability on trust and violations. This analysis employed a partial least squares model, introducing product-term interactions that examined how changes in vulnerability interacted with value and fairness. The findings indicate that neither value nor fairness had a moderating effect on the relationship between vulnerability and violations. However, both value ($\beta = -.44$, $p < .01$) and fairness ($\beta = -.70$, $p < .01$) significantly moderated the vulnerability-trust relationship. In the context of smart retailing, this indicates that both perceived value and fairness play crucial roles in enhancing a customer's trust in a firm, especially when addressing issues such as data breaches. These factors positively impact trust primarily through cognitive mechanisms, rather than exacerbating emotional reactions related to violations. Consequently, this underscores the potential benefits of using rational appeals when communicating with customers to emphasise the positive aspects of their relationship with the firm. Although the study did not investigate deeply into the intricate workings of perceived fairness and value within the context of smart retailing, these findings open intriguing avenues for future research. Understanding how these factors influence customer behaviour and their perception of trust within the unique landscape of smart retailing holds promise for both researchers and businesses operating in this evolving and dynamic environment, leading to the following hypothesis:

Hypothesis 1b

Attributes of the perceived smart retail fairness impacts on consumers' trust in smart retailing platforms.

4.2.3 Perceived Risk

Perceived risk, a concept in consumer psychology, involves consumer's subjective assessment of uncertainties and potential adverse consequences associated with product or service purchases (Bauer, 1960; Stone and Grønhaug, 1993; Faqih, 2012, 2022). In the context of smart technology adoption, especially within online environments such as online shopping, the relationship between trust and risk perceptions is intricate and entangled. However, research findings have exhibited inconsistency, leading to ongoing discourse among academics and practitioners on integrating trust and risk perceptions into consumer decision-making processes (Dowling and Staelin, 1994; Faqih, 2012, 2022; Ahmed, Ali and Top, 2021; Guo *et al.*, 2023). Affordance theory, which is rooted in the concept of perceived and actual capabilities that influence consumer behaviour (Bayer et al., 2021), provides a valuable lens for understanding the dynamics of trust and risk perceptions in technology adoption. Affordance theory indicates that the design features and functionalities of a system influence consumers' ability to shape their accessibility levels through self-disclosure or privacy regulation (Trepte et al., 2020).

Empirical research indicates that trust and risk perceptions are subjective and intricate, resisting facile categorization and quantification (Taylor, 1974; Horton, 1976; Peter and Ryan, 1976; Pavlou, 2003; Kim, Ferrin and Rao, 2008). Notably, a salient aspect emerging from this relationship is that risk inherently precedes trust, as trust becomes relevant and significant only in the presence of associated risk (Pennanen, 2006; Faqih, 2022). Researchers continue to explore how these perceptions and their interplay shape individual adoption behaviour concerning technology in online settings. Lim (2003) provided a pioneering overview of how trusting behaviour and perceived risk mutually influence one another and subsequently impact the adoption process. Lim (2003) provided an insightful overview of how trusting behaviour and perceived risk mutually influence each other and impact the adoption process. Lim's work outlines specific relationships among trust, risk, and behavioural intention, contributing to a more comprehensive understanding of the intricate nexus between these two factors.

Studies, such as the one conducted by Ahmed, Ali and Top (2021), have shown that perceived risk factors negatively influence behavioural intent related to online shopping adoption. Similarly, Kamalul Ariffin, Mohan and Goh (2018) affirmed the adverse impact of perceived risk on behavioural intention. Numerous researchers have demonstrated that perceived risk hinders the intention to adopt online shopping (Qalati *et al.*, 2021; Faqih, 2022).

In the context of the perceived risk and trust relationship, numerous empirical investigations have established that perceived risk plays a substantial role in hindering trust development in Internet-based purchase activities. These studies have consistently indicated that perceived risk negatively impacts trust (Mahliza, 2020; Citaningtyas Ari Kadi and Surya Amalia, 2021; Faqih, 2022). This exploration, which incorporates the affordance theory perspective, highlights the significance of design features in shaping consumers' perceptions of risk and trust in online environments. Affordance theory indicates that the design of online platforms, with their perceived and actual capabilities, plays a crucial role in influencing consumer behaviour in the context of technology adoption and online shopping. Consequently, this study offers further clarification regarding how the interaction between risk and trust may influence behaviour in the domain of smart retailing, leading to the following hypothesis:

Hypothesis 1c

Attributes of the perceived risk impacts on consumers' trust in smart retailing platforms.

4.2.4 Consumer Trust

Trust, a fundamental concept in the sphere of online interactions, can be effectively explored through affordance theory. Affordance theory, which is rooted in the perceived and actual capabilities of a system or object that influence consumer behaviour (Trepte et al., 2020), provides valuable insights into the dynamics of trust in the context of smart retailing. In the digital landscape, trust is commonly defined as the willingness of one party to be vulnerable to the actions of another, based on the expectation that the other will perform a particular action important to the trustor (Mayer et al., 1995). Affordance theory indicates that the design features and functionalities of online platforms play a crucial role in shaping consumers' perceptions of trust and their willingness to engage in vulnerable actions such as online transactions. Trust is a pivotal element in online retail environments, influencing consumer relationships and serving as a key factor in attracting and retaining consumers, especially in the evolving landscape of smart retailing (Doney and Cannon, 1997; Gefen, Karahanna and Straub, 2003; Pavlou and Gefen, 2004; Chiu, Huang and Yen, 2010; Shiau and Luo, 2012). Affordance theory posits that the design of digital platforms affords consumers the capability to perceive and establish trust through various features, such as secure payment gateways, transparent communication channels, and reliable product information (Kankanhalli, Tan and Wei, 2005; Bianchi and Andrews, 2012; Patel *et al.*, 2023).

Trust's significance is evident in human behaviour, especially when individuals face risks and cannot control others' actions. This importance is highlighted in the successful adoption of both old and emerging technologies, such as e-commerce and smart retailing platforms (Hoffman, Novak and Peralta, 1999; Kim, Ferrin and Rao, 2008; Wu *et al.*, 2023). In online retail environments, trust is essential for building and maintaining retailer– consumer relationships (Gefen, Karahanna and Straub, 2003; Pavlou and Gefen, 2004). It is considered a key factor in attracting and retaining consumers, particularly in the early stages of online retailing (Hoffman, Novak and Peralta, 1999; Chang, Cheung and Lai, 2005; Chen, Lan and Chang, 2023). Moreover, trust becomes even more critical in smart retailing, impacting consumer purchasing intentions, experience, satisfaction, and loyalty (Ba and Pavlou, 2002; Li, Browne and Wetherbe, 2006; Lim *et al.*, 2006; Shiau and Luo, 2012). Affordance theory emphasises that the design affordances of smart retail platforms, including seamless experience, personalised recommendations, and secure data handling, contribute to building and enhancing trust among consumers (Sun *et al.*, 2019; Bayer, Gimpel and Rau, 2021).

In the context of smart retailing, trust extends beyond mere transactional activities to encompass a wide spectrum of consumer experiences, interactions, and communications. Affordance theory suggests that the design features of smart retail platforms afford users the capability to engage meaningfully with brands, online platforms, and fellow consumers. Trust, as an affordance, empowers consumers to actively participate in various actions without fear of exploitation. Furthermore, trust collectively affects the overall service quality and consumer satisfaction of online shopping, along with other factors such as design and reliability (Lee *et al.*, 2009; Zhang *et al.*, 2018; Pagani, Racat and Hofacker, 2019; Suh and Moradi, 2023). Consumer motivations for online shopping are strongly linked to distributive, procedural, and interactional fairness, perceived risk, and ethical concerns such as privacy, which are potent predictors of trust (Zhang *et al.*, 2018; Pagani, Racat and Hofacker, 2019).

Research indicates that trust is intrinsically linked to engagement in smart retailing, where online retailers invest efforts in fostering meaningful conversations and continuously integrating features to enrich consumer experiences (Hsu et al., 2012). Affordance theory underscores the role of design in facilitating and enhancing the trust-engagement relationship within the smart retail domain. The empirical findings strongly support the idea that trust is a substantial predictor of experience. In summary, the affordance theory perspective illuminates how the design features and functionalities of smart retail platforms afford consumers the capability to perceive, establish, and benefit from trust. Trust, as a multifaceted and pervasive concept, is intricately tied to the affordances provided by digital platforms, influencing various aspects of consumer behaviour, and ultimately impacting the success of smart retail transactions. Understanding the role and dimensions of trust is essential for researchers and businesses operating in the digital age, leading to the following hypothesis:

Hypothesis 2

Attributes of trust in smart retail platforms impacts on consumers' smart shopping experience.

4.2.5 Smart Shopping Experience

The impact of smart consumer experiences on consumer satisfaction is a critical area of study in the context of smart retailing, where technological advancements have reshaped how consumers interact with smart retail platforms (Inman and Nikolova, 2017; Roy *et al.*, 2017; Hess *et al.*, 2020; Riegger *et al.*, 2022). In this study, smart consumer experience is defined as an integral aspect of smart retailing, specifically focussing on technology-mediated retail experiences facilitated by connected technologies such as AI, VR, and AR. Affordance theory, which is rooted in the concept of perceived and actual capabilities influencing consumer behaviour, provides a valuable lens for understanding and evaluating the elements that constitute a smart consumer experience (Sun *et al.*, 2019). The affordance perspective allows an analysis of how design features and functionalities influence consumer experiences.

Previous studies have identified key components that encapsulate the essence of smart consumer experiences, including the relative advantage, perceived control, perceived interactivity, perceived enjoyment, and personalisation (Roy *et al.*, 2017). The relative advantage, as a cognitive facet of smart consumer experiences, relates to how consumers perceive smart retail technologies and platforms as superior to their brick-and-mortar counterparts. This perception encompasses technological advancements, convenience, quality, and functionality. Fundamentally, it is about whether consumers see smart retailing as a better way to shop (Priporas et al., 2017; Zou et al., 2023). Perceived enjoyment, on the other hand, explores the emotional aspect of smart consumer experiences. It measures the pleasure and satisfaction consumers derive from using smart retail technologies, going beyond mere functionality (Roy *et al.*, 2017; Roy, Balaji and Nguyen, 2020; Nguyen and Llosa, 2023). Personalisation, a behavioural dimension, pertains to the ability of smart retail technologies to offer customised services (Roy *et al.*, 2017; Riegger *et al.*, 2022). This study addresses the behavioural aspects of smart consumer experiences, focussing on how consumers can tailor their shopping experiences to their preferences. Perceived controls, another behavioural element, centre around consumers' feelings of control in their interactions with smart retail technologies.

It encompasses consumers' ability to influence and engage with these technologies to achieve their shopping goals and desired outcomes. Perceived interactivity, a cognitive aspect, evaluates the overall interaction between consumers and smart retail technologies. It assesses the extent to which these technologies facilitate interaction and support consumers in achieving their shopping objectives and tasks. These elements collectively form the intricate landscape of smart consumer experiences, shaping how consumers perceive and engage with smart retail platforms (Roy *et al.*, 2017). Retailers have begun to recognise the pivotal role of smart consumer experiences in influencing consumer satisfaction. Recognition is rooted in enhanced engagement, ease of use, responsiveness to consumer needs, and real-time feedback and monitoring. Consumer satisfaction, within smart retailing setting, is the result of consumers' evaluations and impressions regarding the performance of smart technologies and retail platforms. The accumulation of these experiences with smart retail platforms significantly contributes to consumer satisfaction. Building upon previous research, this study anticipates that the use of smart retail technology stimulates smart consumer experiences, which in turn can foster consumer satisfaction, leading to the following hypothesis:

Hypothesis 3a

Attributes of Smart consumer experience will have a positive direct impact on smart satisfaction.

Smart experiences have emerged as distinctive positive emotions, separate from emotions such as happiness, joy, and pride, and are specifically related to the feelings of amazement provoked by a variety of stimuli (Septianto, Kemper and Choi, 2020; Kim, Bang and Campbell, 2021; Kautish and Khare, 2022). Encounters with aesthetically pleasing objects, such as smart products and services, can evoke these smart experiences in consumers (Septianto et al., 2020). The impact of this experience, akin to the "wow" effect, is a direct result of exposure to such products, which challenge existing mental frameworks and compel consumers to encounter novel experiences (Hinsch et al., 2020).

This, in turn, triggers an intention to purchase these products (Guo *et al.*, 2018; Guo and Wang, 2023). The same holds true for smart retail technologies and platforms, as previously exemplified. Kautish and Khare (2022) proposed that smart retail technologies and platforms can instigate smart experiences among consumers. Using smart technologies necessitates that consumers adjust their preconceived notions, resulting in smart experiences that subsequently lead to various behavioural outcomes (Hinsch et al., 2020), including purchase intentions (Guo *et al.*, 2018; Chen *et al.*, 2023; Guo and Wang, 2023). This phenomenon, in which smart experiences influence consumers' decision-making processes, has been substantiated by previous research (Guo et al., 2018). Smart experiences provoke curiosity and foster learning among consumers, thereby increasing their willingness to try a product (Septianto et al., 2020). The significant impact of smart experiences on generating purchase intentions has been well documented in prior studies (Guo et al., 2018). As posited by Septianto et al. (2020), smart experiences serve to diminish purchase risk, making them a substantial catalyst for an augmented intention to purchase, leading to the following hypothesis:

Hypothesis 3b

Attributes of Smart consumer experience will have a positive direct impact on consumer purchasing behaviour.

4.2.6 Smart Satisfaction

Examining smart consumer satisfaction through affordance theory offers invaluable insights into the design features and functionalities that mould consumers' perceptions and overall contentment with digital platforms (Roy *et al.*, 2017; Sun *et al.*, 2019). Affordance theory, which is deeply rooted in the concept of perceived and actual capabilities that influence consumer behaviour, enables a nuanced exploration of how smart retailing platforms afford consumers opportunities for satisfaction. Consumer satisfaction reflects a consumer's sense of contentment with the products or services they have obtained (Bridges and Vásquez, 2018).

It can be perceived as a subjective assessment linked to the experience of either gratification or disappointment. Typically, consumers assess a product's performance in comparison with their initial expectations (Oliver, 2013, 2014).

In the context of smart retailing, affordances encapsulate the perceived opportunities and actions that users believe they can perform with digital platforms. (Kujur and Singh, 2018; Xu, 2020; Camilleri and Filieri, 2023). These affordances, which are precisely aligned with consumers' expectations and preferences, significantly contribute to their overall satisfaction. For instance, affordances such as a user-friendly interface, personalised recommendations, and seamless transaction processes enhance the entire smart consumer experience. Affordance theory posits that the design of smart retail platforms shapes users' perceptions of what they can achieve and how easily they can accomplish their goals. When consumers find that a smart retail platform offers clear affordances, including intuitive encounter, personalised features, and efficient transactional capabilities, it profoundly influences their satisfaction.

An extensive body of research on online retailing and self-service retail technology consistently affirms the robust relationship between affordances and consumer satisfaction. For instance, Lin and Hsieh (2007) demonstrated a positive relationship between consumer satisfaction and behavioural intentions regarding self-service technologies. Similarly, Tseng (2015) provided evidence that consumer satisfaction with web-based self-service is positively correlated with their intention to continue using the technology. In line with previous studies (Tseng, 2015), Robertson et al. (2016) extended these findings by establishing a connection between customer satisfaction and the continued use of self-service technology, both online and through interactive voice-responsive systems. In the e-retailing context, Rose et al. (2012) affirmed that consumer satisfaction, stemming from cognitive and affective experiential states, significantly influences their intentions to repurchase from the retailer. Thus, elevated levels of consumer satisfaction are intrinsically linked to platforms that afford users a profound sense of control, customisation, and ease of use. Affordance theory adeptly identifies the design elements and functionalities that contribute to positive consumer experiences.

For example, a precisely designed smart retail platform that seamlessly affords consumers the ability to locate products, customise preferences, and enjoy an intuitive checkout process is unequivocally more likely to evoke heightened levels of satisfaction. Affordance theory, therefore, is an indispensable framework for comprehending the intricate relationship between design features, user perceptions, and overall satisfaction within the domain of smart retailing.

In sum, the examination of smart consumer satisfaction through the lens of affordance theory underscores the pivotal role played by the design and functionalities of digital platforms in shaping user experiences. The theory not only reveals the affordances that foster positive consumer perceptions and contentment but also exerts a profound influence on consumers' intentions to consistently reuse and engage with smart retailing platforms. This comprehensive discussion reinforces the significance of affordance theory in the context of smart consumer satisfaction, offering a holistic understanding of the intricate dynamics at play.Drawing from extensive research in the fields of self-service technology and online retailing, this study postulates that consumers' smart satisfaction with smart retailing platforms will similarly impact their behavioural intentions towards this emerging technology, leading to the following hypothesis:

Hypothesis 4a

Attributes of Smart Satisfaction will have a positive direct effect on consumer purchasing behaviour.

4.2.7 E- Loyalty

In today's fiercely competitive business landscape, building and sustaining consumer loyalty has become a paramount objective for businesses, transcending the traditional boundaries of commerce into the domain of smart retailing, affordance theory provides a valuable lens to understand the dynamics at play (Camilleri and Filieri, 2023; Chen *et al.*, 2023; Mofokeng, 2023). Affordance theory, which is rooted in the concept that the perceived and actual capabilities of a system influence consumer behaviour, offers insights into how smart retail platforms create opportunities for consumers to engage, connect, and form loyalty (Neff *et al.*, 2012; Lin *et al.*, 2019; Bayer, Gimpel and Rau, 2021). Affordances in smart retailing platforms refer to the features and functionalities that these digital environments provide, influencing consumers' ability to explore, make informed choices, and ultimately derive satisfaction from their experiences (Norman, 1999, 2013). The affordance perspective allows us to dissect the intricate relationship between the functionalities offered by smart retailers and the resulting consumer satisfaction and loyalty. The affordances provided by smart retail platforms shape perceived acquisition value, a crucial component in the loyalty chain. These platforms, through features such as personalised recommendations, seamless experience, and real-time information, enhance the perceived value of products and services compared with their price (Fornell et al., 1996; Lam et al., 2004). Affordances enable consumers to extract maximum utility from their interactions, fostering satisfaction and influencing loyalty towards the smart retailer. Remarkably, Shankar, Smith and Rangaswamy (2003) accentuated the heightened significance of the relationship between consumer satisfaction and loyalty, particularly within the dynamic milieu of online retail environments as opposed to the more conventional offline settings.

To lay the foundation for this discussion, this study defines smart satisfaction as the consumer's sense of contentment derived from their previous purchasing encounters with a specific smart retailer, in line with the conceptualisation put forth by Anderson and Srinivasan (2003). Existing research has successfully uncovered a clear chain of events that goes like this: perceived acquisition value (how useful the product is compared to its price) → satisfaction → loyalty, with consumer satisfaction playing a key role (Fornell et al., 1996; Lam et al., 2004b). However, it is noteworthy that empirical studies exploring the nexus of smart consumer satisfaction and loyalty are still relatively scarce. Existing literature has predominantly focused on perceived transaction value, often overlooking the intricate affordances that contribute to user satisfaction and subsequent loyalty.

This gap presents an opportunity for scholars to examine the specific affordances that drive satisfaction and loyalty within the context of smart retailing. For example, Grewal, Monroe and Krishnan (1998) demonstrated that both acquisition and transaction values exhibit a positive correlation with a consumer's inclination to make purchases from a specific retailer. However, an exception to this prevailing trend is evident in the work of Darke and Dahl (2003), which elucidates how discounts can augment purchase satisfaction. This augmentation is driven by nonfinancial rewards that are closely associated with perceptions of fairness. The concept of "smart purchase" scenarios emphasised in the literature aligns with affordance theory. Smart retail platforms, by providing features such as real-time pricing information, comparison tools, and personalised deals, afford consumers the opportunity to make informed and advantageous purchase decisions (Mano and Elliott, 1997; Chen et al., 2023; Mofokeng, 2023). The affordances embedded in these platforms not only facilitate transactions but also contribute to the overall satisfaction and, consequently, loyalty of consumers.

As we traverse the evolving landscape of modern retailing, characterised by smart technologies and digital experiences, affordance theory prompts us to scrutinise the functionalities and features offered by smart retail platforms. Understanding how these affordances influence consumer satisfaction and loyalty is imperative for shaping effective strategies and practices for the future of smart retail. Scholars should explore the nuanced affordances that underpin the satisfaction-loyalty relationship, paving the way for a more comprehensive understanding of consumer behaviour in the dynamic domain of smart retailing (Zeithaml, Berry and Parasuraman, 1996; Nguyen, de Leeuw and Dullaert, 2018). In essence, consumers who derive satisfaction from smart retail environments are more inclined to be loyal (Kaya *et al.*, 2019; Rodríguez *et al.*, 2020), leading to the following hypothesis:

Hypothesis 4b

Attributes of Smart Satisfaction will have a positive direct effect on consumer E-Loyalty.

4.2.8 Digital Well-being

In the dynamic landscape of smart retailing, the spotlight on consumer digital well-being has intensified, drawing considerable attention from scholars and businesses alike (Roy *et al.*, 2017; Barr and Ozturk, 2020; Ovani and Windasari, 2022). This concept, intricately tied to happiness, life satisfaction, and overall quality of life, has evolved into a central concern for retailers, mirroring a broader societal shift towards prioritising individual well-being in the digital age. Esteemed scholars, including Dagger and Sweeney (2006), Jones and Comfort (2013) and Su et al. (2022), underscore the pivotal role of products and services in enhancing consumers' quality of life. This academic underpinning adds depth to our exploration, emphasising the enduring significance of consumer well-being in transformative service research. The acknowledgement of major businesses, with approximately 70% incorporating consumer well-being into their vision and mission statements, not only highlights the zeitgeist but also underscores the tangible impact and strategic alignment that well-being holds in contemporary service transactions (Nataraajan and Angur, 2014; Roy *et al.*, 2017; Burr, Taddeo and Floridi, 2020).

This recognition elevates the discussion beyond theoretical abstraction, emphasising its practical relevance in the corporate domain. Consumer well-being, within the precincts of smart retailing, intimately intertwines with service quality and satisfaction. Dagger and Sweeney's (2006) assertion that service satisfaction directly influences an individual's quality of life becomes a pivotal bridge, elucidating the symbiotic relationship between positive retail experiences and enhanced well-being. This linkage forms a cohesive narrative that fosters a nuanced understanding of the subject. Affordances inherent in smart retail technologies encapsulate the potential actions and experiences that they enable for users. For instance, an intelligently designed user interface can afford seamless experience, enhance user satisfaction, and contribute positively to digital well-being. Conversely, a lack of transparency in data practices may lead to feelings of mistrust, negatively impacting well-being. When dissecting the digital aspect of consumer well-being, specify elements such as user interface design, personalised recommendations, or data privacy measures.

Elaborating on these specifics offers a more nuanced understanding of how digital interactions shape consumers' perceptions of well-being. Illustrating theoretical concepts using real-world examples enhances comprehension. For instance, elucidate how a smart retail platform's user-friendly interface affords a pleasant shopping experience, positively influencing digital well-being. Conversely, an intrusive data-sharing policy may cause discomfort and negatively contribute to well-being. This study ponders potential future implications or unexplored avenues within the intersection of consumer digital well-being and affordance theory. This forward-looking perspective stimulates curiosity and invites scholars to embark on further research endeavours. The premise of this model is that the quality of life can be predicted based on the level of satisfaction consumers derive from their retail transactions and experiences, leading to the following hypothesis:

Hypothesis 4c

Attributes of Smart Satisfaction will have a positive direct effect on consumer digital well-being.

Table 11: Research Hypotheses

Number	Research Hypotheses
H1a	Attributes of the perceived smart retail privacy concerns impacts on consumers' trust in smart retailing platforms.
H1b	Attributes of the perceived smart retail fairness impacts on consumers' trust in smart retailing platforms.
H1c	Attributes of the perceived risk impacts on consumers' trust in smart retailing platforms.
H2	Attributes of trust in smart retail platforms impacts on consumers' smart shopping experience.
H3a	Attributes of Smart consumer experience will have a positive direct impact on smart satisfaction.
H3b	Attributes of Smart consumer experience will have a positive direct impact on consumer purchasing behaviour.
H4a	Attributes of Smart Satisfaction will have a positive direct effect on consumer purchasing behaviour.
H4b	Attributes of Smart Satisfaction will have a positive direct effect on consumer E-Loyalty.
H4c	Attributes of Smart Satisfaction will have a positive direct effect on consumer digital well-being.

4.2.9 The Proposed Model

The eight hypotheses presented above form the model appearing in *Table 11*. This study tests the relationship between the constructs of perceived privacy concerns (adaptation to e-commerce of the scale by Malhotra, Kim and Agarwal (2004), perceived fairness (adaptation to e-commerce of the scale by Martin, Borah and Palmatier, 2017), perceived risk (adaptation to e-commerce of the scale by Glover and Benbasat, 2010), and consumer trust (adaptation to e-commerce of the scale by Gefen, Karahanna and Straub, 2003) being mediated by the construct of smart shopping experience (adaptation to e-commerce of the scale by Roy et al., 2017) and smart satisfaction (adaptation to e-commerce of the scale by Roy et al., 2017). Purchasing behaviour (adaptation to e-commerce of the scale by Roy et al., 2017), E-Loyalty (adaptation to e-commerce of the scale by Glover and Benbasat, 2010) and consumer digital well-being (El Hedhli, Chebat and Sirgy, 2013) The theory of affordance serves as the foundational framework for this model. It suggests that consumers' digital ethical perceptions, encompassing factors like perceived privacy concerns, perceived fairness, and perceived risk, during the pre-purchase of smart retailing create affordances. These affordances significantly influence the level of trust consumers place in the process, subsequently shaping their overall smart shopping experience and, ultimately, their satisfaction with online purchases during the purchase stages. The smart shopping experience and the degree of smart satisfaction achieved during the purchase stage function as crucial mediators. They play a pivotal role in shaping consumers' post-purchase behaviours, including their purchasing behaviour, level of E-Loyalty, and their overall sense of digital well-being.

4.2.9.1 Relating The Proposed Model To Research Objectives And Questions

The proposed conceptual model effectively addresses the study's research objectives and research questions by integrating constructs such as perceived privacy concerns, fairness, risk, trust, smart shopping experience, smart satisfaction, purchasing behaviour, e-loyalty, and digital well-being. This research is grounded in affordance theory, which provides a lens through which to examine how digital affordances in smart retail technologies influence consumer perceptions, experiences, and post-purchase behaviours. This section presents the framework in alignment with the study's aims and offers critical insights into its theoretical underpinnings, construct relationships, and measurement approaches.

The framework aligns with the study's objectives by linking each hypothesis to the following research question:

RQ1: How does the integration of smart technology in retail influence consumers' perceptions of privacy, fairness, risk, and trust?

H1a: Perceived privacy concerns negatively impact trust in smart retailing platforms.

H1b: Perceived fairness positively impacts trust in smart retailing platforms.

H1c: Perceived risk negatively impacts trust in smart retailing platforms.

These hypotheses focus on pre-purchase perceptions and address how consumers' ethical concerns influence trust, a key enabler of engagement in smart retail environments.

RQ2: How does trust shape the smart shopping experience and satisfaction for consumers using smart retail technologies and platforms?

H2a: Trust mediates the relationship between digital ethical perceptions (privacy, fairness, risk) and the smart shopping experience.

H2b: Trust mediates the relationship between digital ethical perceptions (privacy, fairness, risk) and the smart shopping satisfaction.

This hypothesis examines trust as a critical intermediary, enabling positive consumer engagement and satisfaction.

RQ3: In what ways does the smart shopping experience contribute to smart satisfaction among consumers?

H3a: The smart shopping experience positively impacts consumer satisfaction.

H3b: Consumer satisfaction positively impacts purchasing behaviour.

These hypotheses address the transition from the shopping experience to satisfaction and purchasing decisions.

RQ4: To what extent does satisfaction impact consumer purchasing behaviour and contribute to e-loyalty and digital well-being in smart retailing?

H4a: Satisfaction positively impacts consumer repurchase intention in smart retailing environments.

H4b: Satisfaction positively impacts e-loyalty in smart retailing environments.

H4c: Satisfaction positively impacts digital well-being in smart retailing environments.

These hypotheses explore critical post-purchase outcomes by linking satisfaction to e-loyalty, digital well-being, and repurchase intention. Together, they provide a comprehensive understanding of how consumer satisfaction drives long-term engagement and purchasing behaviours, highlighting its central role in fostering sustainable relationships between consumers and smart retail platforms.

4.2.9.2 Application of Affordance Theory

Affordance theory provides a robust theoretical foundation for examining how perceived possibilities for action influence consumer behaviour across various stages of the journey (Gibson, 1977). Affordances are not merely technological features but relational properties emerging from consumers' interaction with digital platforms (Norman, 1999). In the context of smart retailing, digital affordances shape trust, satisfaction, and long-term consumer outcomes by enabling or constraining specific behaviours. This study applies affordance theory to analyse the consumer journey across pre-purchase, purchase, and post-purchase stages.

Pre-purchase stage: In the pre-purchase stage, affordances, such as data transparency and secure payment systems, play a pivotal role in mitigating privacy concerns and perceived risks. For example, clear and accessible explanations of data collection practises enhance consumer trust by signalling ethical behaviour (Pappas et al., 2017). Similarly, secure payment affordances, such as two-factor authentication, reduce risk perceptions and encourage initial engagement with smart retail platforms (Lu et al., 2022). These affordances address critical barriers to trust formation, creating a foundation for positive consumer-platform interactions.

Purchase stage: During the purchase stage, affordances, such as real-time personalisation and customer support systems, facilitate seamless engagement with the platform. Personalisation affordances, enabled by AI-driven algorithms, tailor product recommendations and user interfaces to individual preferences, thereby enhancing perceived convenience and relevance (McLean and Osei-Frimpong, 2019). Additionally, real-time support mechanisms, such as chatbots and virtual assistants, reduce friction during the transaction process, fostering a positive shopping experience (Pantano *et al.*, 2021). Trust mediates this stage by ensuring that consumers feel secure and valued, thus enabling them to engage more confidently with the platform (Gefen, Karahanna and Straub, 2003).

Post-purchase stage: In the post-purchase stage, reflective affordances, such as feedback mechanisms and ethical data handling practices, influence satisfaction, e-loyalty, and digital well-being. Feedback affordances allow consumers to share their experiences and voice concerns, which can enhance satisfaction by demonstrating the platform's commitment to continuous improvement (Turel and Serenko, 2020). Ethical data handling affordances, such as transparency in data usage and adherence to privacy regulations, contribute to long-term trust and digital well-being by fostering a sense of control over personal information. These affordances also strengthen e-loyalty by reinforcing a platform's reliability and ethical stance (Kumar and Kashyap, 2018; Kumar, Ramachandran and Kumar, 2021). This application of affordance theory provides a systematic lens through which to understand how smart technologies shape consumer perceptions and experiences throughout the customer journey. By contextualising affordances within specific stages, the framework captures the nuanced ways in which digital features enable trust, enhance shopping experiences and influence post-purchase outcomes.

This approach ensures that the dynamic interactions between consumers and smart technologies are critically examined, offering valuable insights for both academic research and practical applications in smart retailing. The conceptual framework identifies and elaborates on the key relationships between constructs, emphasising their interdependencies and roles in shaping consumer behaviour within smart retail environments. These relationships are critical for understanding how pre-purchase perceptions influence subsequent stages of the consumer journey, ultimately driving post-purchase outcomes such as e-loyalty and digital well-being.

4.2.9.3 Construct Relationships

The conceptual framework articulates and examines the critical relationships between constructs, emphasising their interdependencies and roles in shaping consumer behaviour across the smart retail journey. These relationships are pivotal for understanding how digital affordances, consumer perceptions, and behavioural outcomes interact, providing a foundation for both theoretical advancements and practical applications in smart retailing environments.

Trust as a Mediator: Trust is a pivotal mediator in the framework, bridging pre-purchase perceptions—namely privacy concerns, fairness, and perceived risk, with the smart shopping experience. Trust reduces the uncertainty inherent in online environments, enabling consumers to engage with confidence (Gefen, Karahanna and Straub, 2003).

Privacy Concerns and Trust: Transparency in data collection and usage fosters trust by addressing consumer fears of data misuse (Pappas *et al.*, 2017; Lu, He and Ke, 2023). For instance, platforms that clearly articulate their data privacy policies are perceived as trustworthy, which encourages engagement.

Fairness and Trust: Perceived fairness, including equitable pricing and ethical practises, enhances trust by signalling the platform's integrity (Bolton *et al.*, 2022). Fair treatment reassures consumers that their interests are respected, fostering a sense of commitment to their relationships.

Perceived Risk and Trust: Reducing perceived risks, such as financial fraud and product misrepresentations, is essential for building trust (Cheung *et al.*, 2003). Features like secure payment systems and customer reviews mitigate risks, which positively influences trust.
By mediating these pre-purchase perceptions, trust serves as a foundation for a seamless and satisfying shopping experience.

Satisfaction as a Driver: Satisfaction acts as both a mediator and an outcome variable in the framework, highlighting its dual role in driving consumer behaviour. Satisfaction arises from positive shopping experiences and trust, which reinforce consumer confidence in the platform (Oliver, 2014). Satisfaction and purchasing behaviour: High satisfaction levels are directly linked to increased purchasing intentions and repeat behaviour (Anderson and Srinivasan, 2003). Satisfied consumers are more likely to revisit and make additional purchases, thus contributing to retailer profitability.

Satisfaction and Post-Purchase Outcomes: Satisfaction drives long-term post-purchase outcomes, such as e-loyalty and digital well-being. Consumers who are satisfied with their experiences are more likely to consistently engage with the platform and report positive digital well-being (Turel and Serenko, 2020). This dual role underscores satisfaction's centrality in the consumer journey, influencing immediate behaviours and long-term consumer-platform relationships.
Sequential Impact: The framework captures a sequential progression from pre-purchase perceptions to post-purchase outcomes through trust and satisfaction, illustrating the cumulative nature of consumer experiences.

Pre-Purchase Perceptions Influence Trust: Constructs such as privacy concerns, fairness, and perceived risk shape consumers' initial trust in the platform (Lu and Yi, 2023). This trust acts as a gateway to further engagement.

Trust Shapes the Shopping Experience: Trust enhances the perceived value of the shopping experience by reducing uncertainty and fostering positive interactions with the platform ((Gefen, Karahanna and Straub, 2003; McLean and Wilson, 2019). For example, trust in personalised algorithms ensures that recommendations are accepted as relevant and helpful.

Shopping Experience Drives Satisfaction: A seamless and personalised shopping experience directly contributes to consumer satisfaction (Pantano *et al.*, 2021). The satisfaction reflects the extent to which the platform meets or exceeds consumer expectations.

Satisfaction with Fuels Post-Purchase Outcomes: Satisfaction sequentially influences post-purchase behaviours, including e-loyalty, digital well-being, and repurchase intentions (Kumar and Kashyap, 2018; Turel and Serenko, 2020). For instance, satisfied consumers are more likely to recommend the platform to others, contributing to its long-term success. This sequential impact highlights the interconnectedness of constructs and demonstrates how early perceptions can cascade into long-term outcomes. By articulating these relationships, the framework provides a comprehensive understanding of the consumer journey in smart retailing.

4.2.9.4 Positioning Digital Well-Being

In this framework, digital well-being is conceptualised as a post-purchase construct reflecting consumers' cumulative evaluation of their experiences with smart retail platforms. This positioning acknowledges that digital well-being is influenced by perceptions of ethical practices and the satisfaction derived from the shopping experience. For example, platforms that transparently handle consumer data and adhere to ethical guidelines foster a sense of security and trust, contributing positively to consumers' digital well-being (Bolton *et al.*, 2022). Satisfaction with seamless navigation, personalised services, and ethical engagement further enhances these evaluations. While digital well-being is primarily a post-purchase outcome, its antecedents can emerge during earlier stages of the consumer journey. For instance: Pre-Purchase Stage: Real-time interactions, such as nonintrusive personalisation and clear communication about data usage policies, may shape consumers' initial perceptions of digital well-being.

Purchase Stage: Features such as transparent pricing, smooth payment processes, and responsive customer support reinforce these perceptions by ensuring a stress-free and ethical transaction experience. Recognising digital well-being's potential influence across all stages provides an opportunity for future research to explore its development throughout the consumer journey. Additionally, as digital well-being encompasses psychological, emotional, and behavioural dimensions, a comprehensive approach to its measurement and analysis is vital for understanding its broader implications (Turel and Serenko, 2020).

4.2.9.5 E-Loyalty in the Digital Context

E-loyalty, distinct from traditional loyalty, pertains exclusively to the digital context, focusing on sustained engagement and repeat transactions within online environments. This construct is becoming increasingly significant in smart retailing, where digital interactions dominate consumer-brand relationships. The framework identifies three defining aspects of e-loyalty:

Channel specificity: E-loyalty is confined to digital platforms such as websites, mobile apps, and virtual environments. Unlike traditional loyalty, which spans both physical and digital channels, e-loyalty captures behaviours unique to online interactions, such as revisiting a retailer's website or engaging with its app-based features (Anderson and Srinivasan, 2003).

Technology-Driven Antecedents: E-loyalty is driven by technological affordances that enhance consumer experiences. These include:

Usability: Intuitive and user-friendly interfaces encourage repeat usage by reducing friction during user journeys.

Personalisation: AI-enabled features that adapt to consumer preferences foster a sense of relevance and convenience, strengthening loyalty (McLean and Wilson, 2019).

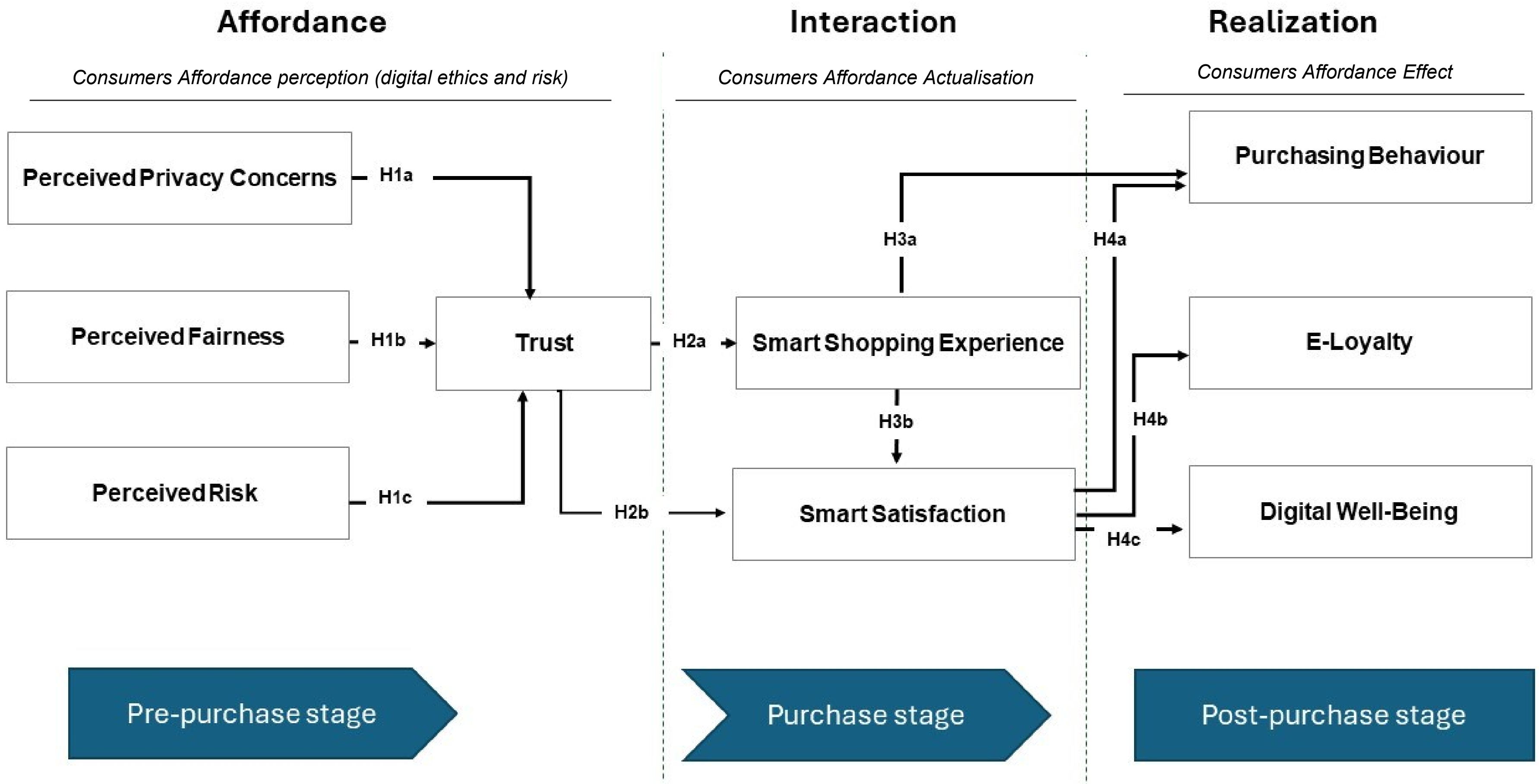
Secure Payment Systems: Robust security measures, such as encryption and multi-factor authentication, build trust and ensure consumer confidence in online transactions (Cheung *et al.*, 2003).

Measurement Constructs: E-loyalty is measured using trust and satisfaction metrics adapted to the smart retailing context. For example:

Trust: The confidence consumers place in a platform's ability to deliver on promises and safeguard their data (Gefen, Karahanna and Straub, 2003; Gefen, Rigdon and Straub, 2011).

Satisfaction: The extent to which the platform meets or exceeds consumer expectations during the shopping experience (Oliver, 2014). By focusing on e-loyalty, the framework underscores the importance of e-loyalty as a strategic objective for smart retailers. High e-loyalty levels translate into increased customer retention, higher lifetime value, and stronger advocacy, all critical in a competitive digital landscape.

Figure 22: Proposed Model



Chapter 5: Methodology

The previous section provided a comprehensive explanation of the methodology employed in developing a conceptual framework and a list of hypotheses by rigorously examining the extant scholarly literature. This chapter elucidates the research methodology that forms the foundation of this empirical study. First, the empirical study setting and the impact of smart technology applications in the retail industry are discussed. Subsequently, the research design and sampling approach are explored. The methodology employed for recruiting study participants is then outlined, followed by a brief biographical overview of the participants. The subsequent section outlines the data collection method. Following that, a description of how the data were analysed is provided. In the final section, the methodological limitations of this study are addressed. The primary aim of this study was to determine the most effective approach for validating the conceptual framework proposed in this research. To ensure the reliability of our findings, it is imperative to understand the correct methods of investigation and the rationale behind the selection of specific techniques in this study.

5.1 Research Philosophy

Žukauskas, Vveinhardt and Andriukaitienė (2018) argued that research philosophy is the main idea behind using scientific and logical methods to choose the best ways to obtain accurate and useful information in the field of research. Research philosophy serves as the compass by which researchers establish the core principles of a scientific discipline (Collis and Hussey, 2021). The acquisition of knowledge is of paramount importance in comprehending inevitable phenomena within a specific research context (Bell *et al.*, 2019). This section discusses two pivotal philosophies in the domain of social scientific research: positivism and interpretivism. Positivism embodies an epistemological standpoint that advocates the application of methodologies derived from the natural sciences to explore the intricacies of social reality. However, it is noteworthy that the concept extends beyond this basic tenet, with nuances existing among different scholars (Bryman and Bell, 2011, 2015; Bell *et al.*, 2019). Collins and Hussey (2021) contend that positivism is grounded in notions such as the existence of social science facts and the establishment of causal relationships. Consequently, positivism represents a quantitative approach in the social sciences, effectively employed to scrutinise hypotheses and theories, thereby augmenting our comprehension of human cognition and behaviour (Bryman and Bell, 2011). While positivism posits that models and quantitative analysis can elucidate all phenomena, interpretivism, in contrast, advocates the interpretation of each event in its unique context (Bryman and Bell, 2011; Bell *et al.*, 2019). Interpretivism acknowledges the diversity inherent in both individuals and objects in the fields of the social and scientific sciences (Bryman and Bell, 2015). Moreover, it is necessary for research to acknowledge the subjectivity that pervades the social sciences to elucidate these variations (Collis and Hussey, 2014, 2021). This implies that individuals engage in dialogue with their subject matter, thereby collectively constructing knowledge through collaborative interactions (Bryman, 2016). Within this paradigm, scholars predominantly employ qualitative methods to elucidate social experiences. However, because this research focuses on the analysis of a phenomenon based on a theoretically established framework of hypotheses, interpretivism, as expounded in the subsequent section, is deemed unsuitable for this study.

Table 12 below compares the key characteristics of these two philosophies. Both ideologies wield substantial influence in the domain of research (Collis and Hussey, 2021). Consequently, it is imperative to deliberate on both philosophies in order to make an informed selection that best aligns with the objectives of this study.

Positivism tends to:	Interpretivism tends to:
Use large sample	Use small samples
Have an artificial location	Have a natural location
Be concerned with hypothesis testing	Be concerned with generating theories
Produce precise, objective, quantitative data	Produce ‘rich’, subjective, qualitative data
Produce results with high reliability but low validity	Produce findings with low reliability but high validity
Allow results to be generalised from the sample to the population	Allow findings to be generalised from one setting to another similar setting

Table 12:The key characteristics of the two major paradigms (Positivism vs Interpretivism) according to Collins and Hussey (2021, p.46)

5.1.1 Justification for Implementing Positivism

After a thorough examination of the arguments surrounding positivism and interpretivism, this study adopts a positivist philosophical stance. The rationale underpinning this choice is firmly grounded in the researcher’s overarching aim of evaluating the influence and repercussions of smart retailing on consumer-perceived privacy concerns, perceived fairness, and perceived risk. Additionally, it investigates how this, in turn, impacts consumer trust and, subsequently, the influence of this trust on mediators related to smart shopping experiences, satisfaction, and their subsequent effects on dependent variables such as purchasing behaviour, loyalty, and digital well-being, using affordances as a lens. To achieve this, this study uses empirical data for measurement. Consequently, a positivist approach is adopted, emphasising an objective evaluation of data and highlighting causal relationships among various constructs. This approach begins with the formulation of a theoretical framework (in this case, affordances) that elucidates the interrelationships between constructs, subsequently subjecting these relationships to empirical scrutiny to either substantiate or refute hypotheses.

Aliyu et al. (2014) emphasised that a positivist researcher subscribes to the belief that the universe adheres to immutable laws and principles of cause and effect. Furthermore, positivism operates on the premise that complexity can be resolved through reductionist methods that prioritise principles of impartiality, measurement, objectivity, and repeatability. However, these fundamental tenets of positivism can also represent potential vulnerabilities. In a positivist approach, the researcher typically maintains a degree of independence and limited interaction with individuals during the data collection phase. This lack of profound engagement in the data collection process can be viewed as a limitation.

Nonetheless, the choice of research method, whether involving direct researcher interaction or not, is contingent on the specifics of the research problem statement, research objectives, and research questions. In the context of this study, causal relationships between variables were illustrated based on a conceptual framework derived from existing literature and a comprehensive literature review. Subsequently, the collected data were subjected to rigorous statistical analysis to establish causality using a logical, systematic approach. In essence, generalisation in this positivist approach is achieved through statistical probability. To attain generalisation, a researcher must accumulate data from a diverse and representative population. In this context, the researcher relies on empirical data and factual evidence, treating organisations and other social entities as natural and tangible entities (Aliyu *et al.*, 2014).

5.1.2 Research Approach

Given the adherence of this thesis to the positivism paradigm, it becomes crucial to establish the central research approach guiding its analysis. Methodology embodies the methodological standpoint adopted for conducting research (Collis and Hussey, 2014). Its raison d'être lies in delineating the research procedures best suited for the collection and analysis of data, which should align with the philosophical foundations of the chosen paradigm. As noted by Collis and Hussey (2014), the terms "quantitative" and "qualitative" are more frequently employed to describe methods of data collection rather than to characterise various research paradigms. Embedded within this contextual landscape are two primary research approaches: (1) quantitative analysis and (2) qualitative analysis.

The retail industry, by its very nature, is dynamic and necessitates the assimilation of technological advancements to ensure success in the marketplace. Among the array of technologies, the ascendency of smart technology, such as artificial intelligence, stands resolute, heralding its indispensable role in the future of retail (Shankar, 2018; Davenport *et al.*, 2020; Collis and Hussey, 2021; Guha *et al.*, 2021; Shankar *et al.*, 2021). The ubiquity of evidence of smart technology's transformative potential highlights its inexorable integration into the retail landscape (Shankar, 2019; Shankar et al., 2021). Evidently, smart technologies such as AI systems have been nurtured through vast datasets, and the retail sector, perceived as fertile ground, has burgeoned as a domain for both harnessing and nurturing these AI systems. Nevertheless, the convergence of smart technology and retail raises ethical dilemmas that demand thoughtful consideration (Scherer, 2016; Tech, Scherer and Matthew, 2016; Kopalle et al., 2021).

A blend of qualitative and quantitative research has begun to explore how the use of advanced technology in retail impacts the smart retail ecosystem (Mägi, 2003; Grewal, Levy and Kumar, 2009; Inman and Nikolova, 2017; Priporas, Stylos and Fotiadis, 2017; Martin and Palmatier, 2020; McKinsey & Company, 2020; Shankar *et al.*, 2021). However, among this scholarly chorus, a noticeable gap emerges: a scarcity of empirical investigations probing the consequences of smart technology implementation on consumer behaviour and digital well-being, and a complete absence of a cohesive ethical framework for smart technology deployment. Although qualitative and quantitative research methodologies serve as the foundation and appropriate tools for social science inquiry, scholars occasionally explore the complex landscape of research by integrating these methodologies into a quantitative-qualitative approach (Saunders, Lewis and Thornhill, 2019).

In this tapestry of research intricacies, this approach emerges as a conduit for triangulating divergent perspectives, enriching the scholarly fabric by harnessing the inherent strengths of both methodologies. In sum, the exploration of methodological underpinnings assumes the role of a scholarly journey—an intellectual voyage through the intricate contours of research design. It crystallises the underlying intent of synthesising rigorous analysis with academic rigour, culminating in an exposition that unveils the intricate interplay between technological evolution, ethical challenges, and the multifaceted dimensions of the smart retail continuum.

5.1.3 Quantitative and Qualitative Methods

Research (Cohen, 1988) underscores the importance of extracting themes, ideas, typologies, and categories from data when using qualitative research methods. The hypotheses that were developed after reading relevant literature were tested at the same time using the deductive quantitative approach, as shown by Acaps (2012). The methodical alignment with the positivist paradigm in this study is in harmony with its quantitative foundation and overall research strategy. This alignment holds significant weight because the quantitative paradigm is inherently associated with positivism, a philosophical stance aimed at comprehending phenomena on a broader scale (Saunders, Lewis and Thornhill, 2009, 2019). In contrast, qualitative research aligns more closely with interpretivism, where researchers pivot towards the collection and analysis of thoughts, expressions, and viewpoints rather than mere factual occurrences (Collis and Hussey, 2014). Qualitative research shares similarities with the inductive technique, which fosters the development of novel hypotheses grounded in investigative endeavours (Collis and Hussey, 2014). Using the inductive method, researchers pinpoint specific phenomena to establish new conceptual frameworks (Bryman and Bell, 2015; Bryman, 2016).

A comparative overview of the fundamental disparities between quantitative and qualitative methodologies, along with their operational mechanisms, is succinctly presented in the table below, adapted from Saunders et al. (2016). This tabular representation serves to encapsulate the principal differences between these research paradigms and illuminate their respective operational methodologies, thereby providing a comprehensive snapshot of their distinctive traits.

Table 13: Comparison of quantitative and qualitative approaches to this study as discussed. Source: Saunders et al., (2016, p. 127)

Areas	**Quantitative**	**Qualitative**	**This study**
Features	Investigates the relation between numerically calculated and statistically evaluated variables	Analyses the meanings and relationships of participants across a range of data collection technologies to establish a new theory	Quantitative
Role of theory in research	Deductive	Inductive	Deductive
Research philosophy	Positivism	Interpretivism	Positivism
Research strategy	Experimental surveys	Theory, analyses of events. storytelling, and ethnography	Experimental Surveys

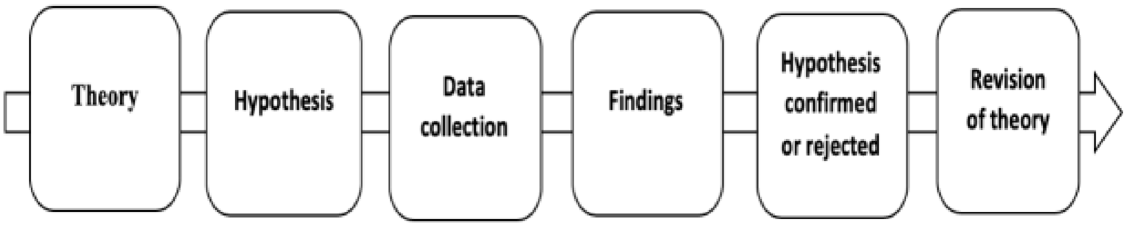
The comprehensive taxonomy proposed by Saunders et al. (2016) clearly divides the methods of quantitative and qualitative research into four subcategories, which can be seen above as a table: defining characteristics, theoretical orientation within the research framework, underlying philosophical orientations, and overarching research strategies.

According to Wallace and Sheldon (2015), the academic view is that quantitative methodology is a powerful way to carefully measure, quantify, and analyse the actions, perspectives, and attitudes of a certain group of participants in relation to the targeted constructs. Agreeing to Trochim (2005), this quantitative approach not only makes it easier to form hypotheses, but it also gives researchers the ability to extrapolate these hypotheses from a small participant pool to a larger and more representative demographic. This extrapolative capability finds its basis in the overarching research strategy of scholarly endeavours, thereby generating insights and revelations substantiated through the adept application of statistical and mathematical instruments, as highlighted by (Ashraful Alam, 2020).

5.1.4 Justification for Implementing Quantitative Methods

Numerous factors underpinned the decision to adopt a quantitative approach in this study as opposed to a qualitative methodology. These factors serve to substantiate and rationalise this choice. Primarily, the adoption of a quantitative approach provided the researcher with the necessary tools to systematically explore the intricate theoretical connections among the central variables at the core of this investigation. These variables encompass perceived privacy concerns, perceived fairness, perceived risk, and trust (as independent variables), purchasing behaviour, e-loyalty, digital well-being (as dependent variables), and smart shopping experience and smart satisfaction (acting as mediating variables). Furthermore, the quantitative approach facilitated a comprehensive examination of the validity and reliability of the research instrument, which is a pivotal component in ensuring the scholarly rigour of this study (Creswell, 2014). By employing this methodological framework, the researcher was able to effectively disentangle the inherent complexities within the variables of interest, thereby enabling rigorous hypothesis testing and precise conclusions concerning the strength, nature, and robustness of the identified relationships. This was relevant both when considering the presence and absence of moderating influences (Bryman, 2016). In contrast, qualitative research typically entails six core constituents, as depicted in the following diagram:

Figure 23::The six main phases of deductive methods adapted from Bryman (2015, p.150)



Moreover, the quantitative method advocates the use of substantial sample sizes, thereby facilitating the extrapolation of empirical findings to broader contexts. This aspect substantiates the rationale behind the selection of this approach (Saunders, Lewis and Thornhill, 2019). In sum, the positivist approach, which employs deductive and quantitative methods, appears to provide a more suitable framework for this study, given the complexity of the subject matter, compared with the interpretivist approach, which employs inductive and qualitative methods.

5.2 Research Design

This study employs a cross-sectional research design to comprehensively investigate the factors that influence consumers' interactions with smart retail technologies. These factors include crucial elements such as perceived privacy concerns, perceived fairness, perceived risk, and trust (serving as independent variables), and purchasing behaviour loyalty and digital well-being (serving as dependent variables), as well as smart shopping experience and smart satisfaction (acting as mediating variables). As emphasised by Saunders et al. (2016), the selection of a research design becomes crucial when the objective is to scrutinise a subset of a population, aiming to derive quantitative or numerical insights into the patterns, perceptions, or beliefs held within that sample. Creswell (2009) categorises research designs into 2 distinct types: (1) cross-sectional design, involving data collection at a single point in time, and (2) longitudinal design, which entails gathering data across multiple time points and evaluating them with a consistent group of respondents over time. For this study, a cross-sectional design was chosen because it has many benefits over a longitudinal design, such as being easier to carry out (Anderson, 1995), having a better sample representation, less dropout, fewer response biases, and better use of time and resources (Malhotra, 2004). Nevertheless, it is essential to acknowledge the inherent merits of longitudinal designs, as duly recognised in the existing literature. The researcher has acknowledged these benefits, and they will be important areas of future research.

To thoroughly examine the hypothesised relationships using structural equation modelling (SEM), the necessity of a sample comprising 200 participants becomes obvious (Tabachnick and Fidell, 2007). Distinguished scholars such as Hair, Black and Babin (2010), Lattin, Carroll and Green (2003), and (Loehlin, 2004) recommend an optimal range of 5 to 10 observations per variable. This recommendation facilitates the application of techniques such as multiple regression, structural equation modelling, and other multivariate data analyses. Given the involvement of approximately 34 pertinent variables in this study, the objective is to attain a substantial and adequate sample size, consisting of over 500 smart or digital-native consumers. This minimum sample size not only ensures a credible level of reliability (Aaker, Kumar and Day, 2001) but also guarantees essential validity for testing purposes (Hoelter, 1983).

5.2.1 Research Context

The digital transformation of retail activities, despite ethical concerns, particularly regarding privacy (Martin and Palmatier, 2020), has become an imperative for retailers seeking to maintain competitiveness in rapidly evolving marketplaces shaped by the proliferation of smart technology. This transformation, coupled with the ubiquitous availability of the internet, empowers consumers to save time and access better deals through convenient online shopping. Consequently, there is a growing demand for elevated smart consumer experiences (Shankar, 2018; Shankar *et al.*, 2021). In response, retailers are making substantial investments in the digital transformation of shopping experiences, transitioning from being interactive and socially engaging to facilitating mere transactions with minimal interaction with retail staff. However, this shift has raised concerns about job security in certain quarters (Du and Xie, 2021).

Research underscores that the digitalisation of retail operations, fuelled by technological advancements, is fostering significant innovation (Lorente-Martínez, Navío-Marco and Rodrigo-Moya, 2020). The pace of advancement has significantly escalated, particularly in the wake of the COVID-19 crisis (Kopalle *et al.*, 2021). Among these transformative technologies, artificial intelligence (AI) stands out, enabling retailers to gain deeper insights into consumer behaviours and preferences, leading to more personalised marketing strategies (Song and Kim, 2022). Studies have indicated that digitalisation profoundly influences the functioning of smart retailers and consumer interactions and relationships (Shankar *et al.*, 2021). The prevalence of AI-driven products and services is increasing in the current market landscape. However, the development and use of AI and smart technologies in general raise ethical concerns, including issues of bias and adoption, contributing to mixed consumer sentiments towards this technology (Du and Xie, 2021; Song and Kim, 2022). In 2017, the AI market was valued at $16.06 billion, with predictions indicating that its value could reach $190.61 billion by 2025 (Du and Xie, 2021). The increasing popularity of smart technology-enabled products and services, such as autonomous vehicles, digital personal assistants (e.g., Amazon's Alexa, Apple's Siri), virtual nurses, robot-advisors, and personalised AI-driven recommendations, underscores a critical juncture. These advancements raise fundamental concerns regarding privacy, trust, and ethical implications (Du and Xie, 2021; Shankar et al., 2021).

5.2.2 Country Specific

In recent years, the retail landscape has undergone a profound transformation driven by rapid advances in smart technologies. This section explores consumer preferences and behaviours in smart retailing with a focus on the United Kingdom. The decision to focus this research on the United Kingdom is informed by a range of demographic, technological, economic, and regulatory factors that uniquely position the country as an exemplary case study for examining smart retailing dynamics.

Unique Justifications for the UK’s Context

The United Kingdom stands out among Western economies because of its diversity of demographics and advanced technological infrastructure. Unlike other Western nations, the UK presents a unique mix of cultural diversity, spanning age groups, genders, socioeconomic strata, and ethnicities, which allows for a granular examination of variations in smart retail preferences and behaviours across distinct population segments (ONS, 2021a, 2021b). For example, compared with Germany, where the population is more homogeneous, the UK offers a broader base for understanding how diverse consumer segments interact with smart retail technologies. In addition, the UK's mature online shopping market in the United Kingdom provides valuable insights into advanced trends. According to the (Office for National Statistics, 2024), in 2023, 87% of UK adults engaged in online shopping in the past year, a figure higher than in countries like France or Italy. This maturity, combined with the UK's robust technological infrastructure and high internet penetration rate (Petrosyan, 2023), makes it an ideal environment for collecting reliable data on consumer behaviours and preferences in smart retailing. The country's technological landscape also includes widespread adoption of mobile payments, AI-driven personalisation tools, and AR shopping applications, further enhancing its suitability as a focal point for this study (Petrosyan, 2023).

Regulatory and Economic Factors

The United Kingdom is distinguished by its well-developed regulatory framework, which significantly impacts consumer trust in online shopping. Laws such as the Consumer Rights Act 2015 and the Data Protection Act 2018 (aligned with GDPR) ensure consumer rights and data privacy, fostering higher trust in e-commerce platforms (European Commission, 2016). These regulations provide a benchmark for understanding how legal frameworks influence smart retail adoption and offer insights that may inform other economies with emerging regulatory standards. For instance, countries like the US, which rely on sector-specific rather than comprehensive regulations, might exhibit different consumer behaviours due to varying levels of trust. Economically, the UK's diverse income distribution allows for an analysis of how economic factors shape smart retail adoption. Affluent consumers may exhibit a preference for advanced features like AI personalisation, while budget-conscious individuals may prioritise affordability and utility. This diversity mirrors broader trends in Western economies, enabling findings from the UK to inform global strategies.

Geographical Diversity

The UK's combination of urban and rural settings adds another layer of complexity to this study. Urban areas, such as London and Manchester, are hubs of innovation, characterized by high adoption rates of smart retail technologies such as cashier-less stores and mobile apps. Conversely, rural areas often face infrastructure challenges, such as limited broadband access, which may hinder their adoption (Ofcom, 2024). Exploring these disparities provides valuable insights into how geographical factors influence smart retail behaviours, which may apply to other countries with similar urban-rural divides.

Comparative Relevance

The UK serves as a microcosm for other Western economies, given its mirror effect in consumer behaviour. For example, trends in online shopping, such as the adoption of AR-enhanced retail experiences, often originate in the United Kingdom and subsequently influence markets in Europe and North America (Petrosyan, 2023). This comparative relevance allows findings from the UK to be extrapolated to other Western contexts, albeit with caution. Variations in cultural norms, regulatory frameworks, and economic conditions across countries necessitate careful interpretation of the results.

Integration with Research Objectives

Focusing on the United Kingdom aligns directly with the study's research objectives, which investigate consumer trust, satisfaction, and loyalty in smart retailing. The UK's advanced technological landscape and regulatory maturity provide an optimal setting for examining how these factors interact to shape consumer behaviour. The insights gained from the UK context will contribute to broader discussions on the role of technology, regulation, and consumer preferences in the evolution of smart retailing globally.

5.2.3 Survey Strategy

Surveys are a cost-effective method for amassing data to facilitate statistical analysis and demographic generalisation (Collis and Hussey, 2014). Rooted in positivism and the logical approach that rigorously examines ideas and hypotheses for validation or refutation

(Bryman, 2016), surveys establish a direct connection with these methodologies. The adoption of the survey methodology is substantiated by various compelling justifications. First, it allows researchers to acquire unbiased information from respondents (Bryman, 2016). Second, it provides an economical means of collecting data from a substantial sample (Collis and Hussey, 2014). Surveys offer a range of data collection avenues, including postal mail, electronic approaches (such as email or web-based self-completion surveys), telephone calls, and interviews (Collis and Hussey, 2014). Although face-to-face interviews are recommended for participants and researchers with ample time (Saunders, Lewis and Thornhill, 2019), they are unsuitable for the present study because of time and financial constraints (Collis and Hussey, 2014). The telephone method is a cost-effective tool for obtaining significant information (Saunders, Lewis and Thornhill, 2019); however, its limitation to self-selected respondents may introduce bias (Collis and Hussey, 2014). Although not the primary method used in this study, the telephone approach was used as a supplementary method. The researcher conducted follow-up phone calls two weeks after distributing the surveys to encourage participation from those who had not yet responded.

The JISC online survey platform supported the researcher's use of an online questionnaire for data collection. When we refer to an "online" questionnaire, we are discussing internal surveys hosted on a website where repositories facilitate potential responses (McDaniel and Gates, 2016). This approach provides researchers with a feasible, swift, and cost-effective way to gather a sample (Collis and Hussey, 2014). Respondents have the flexibility to complete the questionnaire at their convenience (Bryman and Bell, 2016). Online survey tools offer automated features such as text boxes, drop-down options, fonts, and colour choices (Saunders, Lewis and Thornhill, 2019). Additionally, the appearance of the survey can be customised through visual graphics, animation, and an internet connection (McDaniel and Gates, 2016). According to McDaniel and Gates (2016), incorporating a well-designed visual interface and an optimal website layout can enhance the quality of the survey and lead to more thoughtful responses from participants. Furthermore, mobile devices, such as smartphones and tablets, facilitate internet surveys. These devices offer flexible, ongoing, and time- and space-independent data collection techniques (McDaniel and Gates, 2016). Such technologies enable researchers to access respondents whom other survey methods might struggle to reach (McDaniel and Gates, 2016). Online surveys are prevalent in the literature (Bryman and Bell, 2016), and for data collection, the JISC platform was chosen.

Survey execution involves three interconnected stages: sampling, data collection, and instrument development (Collis and Hussey, 2014). The purpose of sampling is to generalise findings from a subset of the population to the entire population (McDaniel and Gates, 2011). "Data collection" encompasses the selection of an appropriate format, be it mailed surveys, online submissions, phone interviews, or in-person interactions (Collis and Hussey, 2014). The development of survey instruments is critical for gathering high-quality information that effectively addresses research questions.

5.2.4 Sampling Strategy and Survey Administration

Hair et al. (2010) emphasised the practical challenges associated with collecting data from an entire population, thus underscoring the importance of employing suitable sampling techniques. In the research context, a population represents the entire set of units, while a sample serves as a representative subset that mirrors the characteristics of the population (Saunders, Lewis and Thornhill, 2019).

Within the scope of this study, the target population consisted of individuals aged 18 years and older who were active web users, with the expectation that they were either already engaged with or likely to engage with smart retailing. No financial incentives were offered, and participation was entirely voluntary. Acknowledging the constraints imposed by limited participant availability, the current research, consistent with numerous empirical studies on technology adoption, utilised a nonprobability convenience sampling method. This approach accommodates situations in which time and financial resources are limited, allowing resourceful use of available assets. A total of approximately 2000 self-administered questionnaires were distributed to potential participants, resulting in the retrieval of 565 completed surveys, which yielded a response rate of 28.25%. Subsequently, incomplete submissions were removed to refine the dataset. The response rate was calculated using the following formula:

$$Response\ Rate = \left(\frac{Number\ of\ completed\ surveys}{Number\ of\ distributed\ surveys}\right) \times 100$$

$$Response\ Rate = \left(\frac{565}{2000}\right) \times 100 = 28.25\%$$

Sampling techniques can be categorised into two main types: probability and nonprobability. Probability sampling is employed when each unit in the population has a measurable chance of being selected. In contrast, nonprobability methods are typically used during the preliminary and pre-testing stages of survey trials (Saunders, Lewis and Thornhill, 2019). The following table provides a succinct overview of the distinctions between probability and nonprobability sampling techniques:

Table 14:Variations between probability and nonprobability sampling methods

Probability (random) sampling	Non-probability (non-random) sampling	This study
The sampling method is generalisable to the population.	Cannot be widespread after the study.	Population results must be generalised.
Enables statistics, experiments, and theories to be used.	There is no interest in population parameters.	Estimate population parameters
Eliminates bias	The sample's adequacy is not understood.	Eliminate bias

Can approximate parameters of demographic samples.	There is no interest in population parameters.	Estimate population parameters
Must have a random selection of units	Cheaper, more comfortable, and quicker to carry out	Ensure the random selection of units

Source: Saunders et al. (2016, p. 118).

Despite the prerequisites for hypothesis testing and making inferences about the population, this study employs a probability sampling approach. In quantitative research, a fundamental objective is to collect data from samples that faithfully represent the broader population. This approach enhances the credibility of statistical analyses and facilitates the derivation of meaningful conclusions that may have broader applicability beyond the immediate sample.

5.2.5 Sample Size

Once an appropriate sampling technique has been established, the next critical consideration is to determine an optimal sample size that effectively represents the underlying population. In this context, Collis and Hussey (2014) emphasise the significance of a sufficiently large sample size that can adequately address fundamental research inquiries. It is imperative that researchers meticulously define a sample size that can capture the intricacies of the target population. However, merely using a substantial sample size does not inherently guarantee increased precision. Conversely, employing a smaller sample size may result in reduced accuracy.

In this study, a conceptual model was examined using structural equation modelling (SEM), a methodology that requires a substantial dataset to yield meaningful results. Adhering to the recommendations of Hair et al. (2010), a minimum sample size of 100 is advised for SEM investigations. Accordingly, the determination of the sample size in this study was guided by empirically established benchmarks for SEM applications, resulting in a sample size of 510 valid responses.

Roscoe (1975) provided a set of guidelines for determining an appropriate sample size, one of which indicated that sample sizes ranging from 30 to 500 are generally suitable for most studies. Notably, for effective subgroup analysis, each category should comprise a minimum of 30 respondents. Given the complexities of multivariate research, such as SEM, the sample size should significantly exceed the number of variables included within the analytical framework, ideally by a factor of ten. For intricate path models, Kline (2011) recommended a minimum sample size of 200. In addition, Comrey and Lee (1992) underscored the variability of acceptable sample sizes, with 50 considered notably inadequate and 1000 being an exemplary sample size. According to Hair et al. (2010), a model with six or more constructs, each with three indicators, would require a sample size of 400 or more. In accordance with this, Schreiber et al. (2006) advocated a guideline of 10 respondents per estimated model parameter, a widely accepted ratio.

To enhance the generalizability of the research findings, a sample size of 400 or more is deemed a fundamental requirement, aligning with the recommendation of Saunders et al. (2009). To achieve this, the survey questionnaire was distributed to a diverse range of individuals aged 18 and above, encompassing approximately 2000 respondents. The rationale behind this approach, as asserted by Saunders et al. (2009), is grounded in the idea that probability-based samples should reach a magnitude that instils confidence in the collected data. Consequently, researchers are faced with a twofold mandate: ensuring a comprehensive analytical scope and maintaining an acceptable margin of error. Therefore, estimating the expected response rate and specifying the percentage of cases anticipated to provide data are crucial in determining the appropriate expansion of the sample size. Following this anticipation, by incorporating the likely response rate and the minimal or adjusted minimum sample size, the actual sample size can be calculated using the following formula:

$$n^a = \frac{n \times 100}{re\%}$$

where n^a is the actual sample size required,

n is the minimum (or adjusted minimum) sample size

$re\%$ is the estimated response rate expressed as a percentage (Saunders, Lewis and Thornhill, 2009).

Given the rationale presented and the use of the structural equation modelling (SEM) method, it becomes evident that the indicated sample size should ideally fall within the range of 100 to 400. However, it is noteworthy that the sample size for this study surpasses the upper limit of this recommended range, as it comprises 510 participants.

5.3 Research Purpose and Type

Respected scholars in the field (Robson, 1993; Yin, 2003; Saunders, Lewis and Thornhill, 2009) have identified three primary research objectives: exploration of new information (exploratory research), clarification of existing phenomena (descriptive research), and explanation of established occurrences (explanatory research). As Robson (1993) points out, the motivation for research may evolve throughout the investigation. Research may serve multiple functions—exploratory, descriptive, or explanatory—depending on the study's specific nature and complexity (Babbie, 2004).

This study investigates the elements and effects of utilising smart technology in the retail industry, focusing on perceived privacy concerns, risk, fairness, and trust and their influence on consumer smart experiences, satisfaction, purchasing behaviour, loyalty, and digital well-being. Therefore, the study is characterised by its exploratory nature, aiming to discover new ideas, while also being descriptive, accurately depicting the current state of affairs. In addition, it is explanatory, seeking to elucidate the complex interactions within the realm of smart retailing. The following sections offer an in-depth analysis of the three research aims.

5.3.1 Exploratory research

Exploratory research is instrumental in constructing comprehensive descriptions of unknown and intricate events or phenomena within academic investigation. Marshall and Rossman (1998, 2014) emphasised its role in exploring uncharted territory, with Yin (2003) defining it as the pursuit of understanding novel phenomena. This method frequently takes centre stage when dealing with ambiguous and multifaceted problems, setting the stage for subsequent investigation phases, such as hypothesis formulation (Neuman, 2007). According to Saunders et al. (2009), exploratory research is a journey that starts with a broad research area and gradually narrows its focus as the investigation unfolds. This method, as described by Robson (1993), is a potent tool for discerning "what is happening" in a given context. It seeks not only to unravel fresh ideas but also to pose critical questions and assess occurrences in a new light.

In the literature review phase, exploratory research aims to provide a profound understanding of the subject under investigation (Kanika, 2015; Trochim, Donnelly and Arora, 2015), which is essential for developing research hypotheses, as emphasised by Churchill (1999). Saunders et al. (2009) outline three essential approaches for conducting exploratory research: a thorough literature study, engaging in meaningful dialogues with subject matter experts or researchers within the field, and executing focused group interviews and case studies. These approaches collectively serve as instrumental means for unravelling the complexities of the research topic, laying the foundation for subsequent investigations.

In the context of this study, which explores the constituents and consequences of employing smart technology in the retail sector and its interaction with consumer perceptions of privacy, fairness, risk, and trust, exploratory research is indispensable. This study provides an initial framework for understanding the intricate dynamics at play within the smart retail landscape, paving the way for the formulation of hypotheses and exploration of critical variables, such as consumer smart experience, smart satisfaction, and their impacts on purchasing behaviour, loyalty, and digital well-being. This exploratory research is a vital first step towards unravelling the multifaceted relationships in the evolving world of smart retail.

5.3.2 Descriptive research

Descriptive research is a fundamental approach aimed at constructing a precise representation of individuals, events, or circumstances (Robson, 1993). This method requires a rigorous preparatory phase, during which the researcher establishes a clear understanding and well-defined scope of the investigation (Dane, 1990). The foundation of descriptive research lies in the formulation of hypotheses derived from insights gathered through exploratory research and a comprehensive literature review (Malhotra, 2004). In its execution, this method utilises systematically structured survey questionnaires, involving a significant number of participants to minimise potential errors and enhance the reliability of findings (Malhotra, 2004). Before initiating the data collection phase, descriptive research necessitates the precise delineation of research questions, the determination of the target population, and the selection of an appropriate analytical methodology. In addition, it emphasises the need to define the essential variables within a given population, covering the dimensions of person, place, and time ("who, what, where, when, and why" aspects) (Zikmund, 2003).

This method also involves exploring antecedent studies and conducting a thorough examination of relevant theories. In the context of this study into the constituents and consequences of the use of smart technology in retail, as well as the influence of perceived privacy concerns, perceived fairness, perceived risk, and trust as mediating variables on customer smart experience and smart satisfaction, leading to downstream effects on purchasing behaviour, loyalty, and digital well-being, the descriptive research approach serves as a solid foundation. This enables us to construct a comprehensive, structured framework that captures the intricate interplay of these variables within the smart retail landscape. This methodological choice is well aligned with the complexity and depth of the subject matter, allowing us to create a robust and detailed portrayal of the phenomena under investigation.

5.3.3 Explanatory research

This study is an explorative investigation into the constituents and consequences of the use of smart technology within the retail sector, with a particular emphasis on the impact of consumers' perceived privacy concerns, fairness, perceived risk, and trust as mediating variables. In addition, this study examines how these mediating variables influence the consumer's smart experience, smart satisfaction, and, ultimately, their purchasing behaviour, loyalty, and digital well-being in the context of smart retail. In the domain of research methodology, it is crucial to differentiate between descriptive and explanatory research. Descriptive research primarily aims to provide a comprehensive account of a particular subject but does not explore the causal relationships between research variables and hypotheses (Zikmund, 2003). Explanatory research takes a step further by leveraging the collected data to develop an understanding of the relationships between variables (Babbie, 2004; Marshall & Rossman, 1998, 2014; M. Saunders et al., 2009; Yin, 2003, 2008). This research approach seeks to explore the causes of the observed phenomena (Neuman, 2007). As Miles and Huberman (1994) note, explanatory research involves the critical task of rendering complex phenomena understandable by demonstrating how their constituent elements interrelate in accordance with certain principles or rules. This endeavour necessitates a well-defined research problem and explicitly stated hypotheses. Explanatory research is particularly valuable when seeking to unravel the intricate web of relationships between variables, which is precisely the objective of this study. It is important to recognise that descriptive research is commonly deployed in fields where extensive prior research has been conducted. However, in the context of this study, explanatory research is the chosen path, as it goes beyond mere description and strives to uncover the underlying causal factors governing the observed relationships among the various elements in the smart retail setting.

5.4 Questionnaire Development

The design of questionnaires is a critical element in research, especially when the goal is to achieve a high response rate and gather accurate and valid responses, which may represent a one-time opportunity (Collis and Hussey, 2014, 2021). Survey design plays a pivotal role in achieving an elevated response rate. Bryman and Bell (2011, 2015) and Bell et al., (2019) have provided valuable insights into enhancing the user-friendliness of online questionnaires. Their suggestions emphasize techniques such as creating an aesthetically pleasing layout, maintaining questionnaire conciseness, offering clear instructions, and including an introductory cover letter. Guided by these principles, the questionnaire was methodically designed to ensure the collection of reliable data for subsequent analysis.

Questionnaire Structure: The questionnaire is structured into nine distinct sections, each serving a specific purpose:

1) Contextual Information
2) Participant Consent
3) Demographic Details
4) Consumer Perceptions of Risk in Smart Retailing
5) Consumer Privacy Concerns
6) Perceived Fairness and Trust
7) Consumer Experience, Satisfaction, Loyalty, Digital Well-being, and Purchasing Behaviour
8) Overall Implications

Question Types: Within the context of questionnaires, two fundamental question types are prevalent: closed and open-ended (Collis and Hussey, 2014, 2021). In positivist research, closed questions are often preferred because of their predefined response categories (Collis and Hussey, 2014). In alignment with this rationale, this study predominantly employed closed questions, a practical choice that streamlined the response process. The survey included a combination of numerical and categorization-based questions, particularly Likert-scale questions. Notably, a seven-point Likert scale was used for assessment queries, providing participants with a range of response choices to effectively convey their perspectives. This calibrated approach to response options enhances the depth and granularity of the collected data.

Rigorous Research: In the pursuit of rigorous research, the careful orchestration of questionnaire design emerges as a fundamental aspect that influences the accuracy of outcomes and the effectiveness of subsequent analysis. By adhering to Bryman's (2015) guidance and embodying the principles outlined by Collis and Hussey (2014), the questionnaire design in this study aims to facilitate participant engagement and secure a well-prepared dataset for comprehensive scrutiny.

5.4.1 Research instrument and measurement scale.

This study employed a comprehensive approach by utilising measurement items and validated scales sourced from the existing literature. Table 2 provides an overview of how the research investigated the components and outcomes of the smart consumer experience within the retail sector. The investigation focused on three distinct purchasing stages: a) the pre-purchase stage, b) the purchase stage, and c) the post-purchase stage, each representing a facet of consumer engagement with smart retailing adapted from Lemon and Verhoef (2016).

Perceived Privacy Concerns (PRIV): Measured using four items adapted from Malhotra, Kim, and Agarwal (2004). **Perceived Fairness (FAIR):** Measured using three items adapted from Martin et al. (2017). **Perceived Risk (PSR):** Measured using three items adapted from Glover and Benbasat (2010). **Trust in smart retailing platforms, products, and services:** Measured using three items adapted from Gefen, Karahanna, and Straub (2003). **Smart Shopping Experience (CE):** Measured using a four-item scale adapted from Roy et al. (2017**). Smart Satisfaction (CS):** Measured using three items adapted from Roy et al. (2017**). Purchasing Behaviour (INT):** Measured using a three-item scale adapted from Roy et al. (2017). **Loyalty towards smart retailing (LOY):** Measured using three items adapted from

Glover and Benbasat (2010). **Consumer digital well-being (WELL):** Measured using three items adapted from El Hedhli, Chebat, and Sirgy (2013).

All items were answered on a 7-point Likert scale (1 = "strongly disagree" and 7 = "strongly agree"). To enhance the rigour of the research, the initial questionnaire underwent critical evaluation and pilot testing with a sample of 35 online shoppers. Pretesting identified and rectified any ambiguities or expressions that could lead to confusion. After incorporating the valuable feedback received from the participants, the final version of the survey was administered to online shoppers.

Data Analysis: To analyse the proposed causal relationships and evaluate the model fit, structural equation modelling (SEM) using SPSS and SmartPLS 4 was employed. This analytical approach allowed for a comprehensive assessment of the hypothesised associations, contributing to the robustness of the research findings.

5.4.2 Measurement for Perceived Privacy Concern (PRIV)

Privacy concerns are crucial within the context of smart retailing research (Liao, Liu and Chen, 2011; Palmatier and Martin, 2019; Martin *et al.*, 2020; Vimalkumar *et al.*, 2021). This is because privacy is a multifaceted concept with various definitions and measurement methods. One seminal definition, proposed by Smith et al. (1996), focuses on the apprehension of practices governing the collection and use of personal information. In contrast, Malhotra, Kim and Agarwal (2004) introduced an alternative conceptualisation, emphasising the subjective perception of fairness in information privacy This conceptualisation highlights the subjective viewpoint regarding the equitable treatment of personal information, which is profoundly relevant to smart retail settings. The emergence of more nuanced definitions, specifically tailored to technological platforms, has been particularly noteworthy as technology has evolved. For instance, Dinev and Hart (2006) discussed the idea of internet privacy concerns, which centres on consumer's perceptual assessments regarding the disclosure of information within the internet domain. This definition gains added relevance in the contemporary epoch of e-commerce and smart retailing, where online transactions and data sharing represent pervasive phenomena. However, various conceptual interpretations and definitions have led to inconsistencies in measuring privacy concerns. This variability can be attributed to factors such as the choice of communication technology, the attributes of shared information, and the research design. Despite this variability, three prominent scales have emerged in scholarly exploration. These instruments encompass the Concern for Information Privacy (CFIP) scale, originating from the work of Smith et al. (1996), the Internet Users' Information Privacy Concerns (IUIPC) scale, which was introduced by Malhotra, Kim and Agarwal (2004), and the DH scale, devised by Dinev and Hart (2006) and abbreviated as such within the academic milieu. Researchers routinely gravitate towards these instruments because of their well-documented reliability and validity (Kim et al., 2023). Researchers often use these instruments because of their reliability and validity. In this study, perceived privacy concerns (PRIV) are classified as an independent variable, as adapted from Malhotra, Kim, and Agarwal (2004). The measurement consists of three items assessed on a 7-point Likert scale, with response options ranging from 1 (strongly disagree) to 7 (strongly agree) as outlined in the *Table 15* provided below.

Table 15:Measurement for Perceived Privacy Concerns

Item	Code	Description	Reference
Perceived Privacy Concerns	PRIV1	When shopping online, I am sensitive to the way that online retailer handles my personal information.	(Malhotra, Kim and Agarwal, 2004)
	PRIV2	When shopping online, It is important to keep my privacy safe from online retailers.	
	PRIV3	When shopping online, personal privacy is very important to me, compared to other ethical factors.	

5.4.3 Measurement for Perceived Fairness (FAIR)

The examination of perceived fairness in smart retailing research through the affordance theory lens provides a nuanced understanding of the complex interplay between technology, consumer concerns, and benefits. Affordance theory, which is deeply rooted in individuals' perceptions and interactions with technology, offers a sophisticated framework for comprehending the pivotal role of perceived fairness in shaping consumer behaviour and decisions (Gibson, 1977, 1979; Norman, 1988, 2016). Within the context of smart retailing, technology is often categorised based on whether it primarily favours smart retailers, focusing on cost savings and efficiency, or caters to consumers by offering convenience and interactivity (Wünderlich, Wangenheim and Bitner, 2013; Roy *et al.*, 2018; Pizzi and Scarpi, 2020). Perceived fairness is consistently characterised in the literature (e.g., Maxham and Netemeyer, 2003; Pizzi and Scarpi, 2020) as the extent to which consumers view their exchanges with another party as equitable and balanced. It involves the perceived balance between what each party contributes and receives within a relationship (Greenberg, 1987), centred around the idea of proportionality, where consumers assess whether what they provide aligns with what they receive (Cropanzano *et al.*, 2001; Pizzi and Scarpi, 2020). In the domain of personal information disclosure, fairness is intimately linked to the comparison between the information consumers provide and the benefits they receive. For instance, consumers evaluate the value of customised services (Wirtz and Lwin, 2009) and access to free or personalised offerings by considering the information shared (Martin and Murphy, 2017). When perceived fairness is high, consumers are more likely to accept certain privacy violations, such as highly targeted advertising, as they perceive the benefits to outweigh the costs. The concept of perceived fairness aligns with the privacy calculus model, which suggests that consumers make decisions regarding personal information disclosure through a cost-benefit analysis within the e-commerce landscape (Dinev and Hart, 2006). This model indicates that consumers weigh the risks and benefits associated with disclosing information and are more inclined to share personal data when the benefits outweigh the perceived risks (Sun et al., 2015; Pizzi and Scarpi, 2020; Trepte, Scharkow and Dienlin, 2020). Notably, the privacy calculus model reveals a privacy paradox in which individuals often deviate from their stated privacy intentions because of the heightened perception of risk associated with disclosing personal information, even when potential benefits exist (Norberg, Horne and Horne, 2007; Pizzi and Scarpi, 2020). When applying these theories to retail technologies, it becomes evident that different technologies can tilt the balance of costs and benefits in favour of either the consumer or the retailer. Technologies perceived as primarily benefiting retailers may lead consumers to perceive lower levels of fairness. As a result, when using such technologies, consumers may express greater concerns about disclosing their personal information because fairness considerations overshadow perceived benefits. This study underscores the dynamic relationship among technology, perceived fairness, risk, consumer privacy concerns, and trust, providing a robust foundation for further exploration and understanding of consumer behaviour in the smart retail setting. The perspective emphasised in this study offers valuable insights for researchers and practitioners in the field, emphasising the intricate interplay between technology, benefits, and the perception of fairness. In this study, the concept of fairness is categorised as "perceived fairness" and serves as an independent variable adapted from Martin, Borah and Palmatier (2017). It was evaluated using four items, rated on a 7-point scale ranging from 1 ("strongly disagree") to 7 ("strongly agree"), as detailed in *Table 16*.

Table 16:Measurement for Perceived Fairness

Item	Code	Description	Reference
Perceived Fairness	FAIR1	I believe that online businesses access my information in a fair way.	(Martin, Borah and Palmatier, 2017)
	FAIR2	I believe that online businesses are honest when using my information.	
	FAIR3	I believe that online businesses manage my information in a reasonable way.	

5.4.4 Measurement for Perceived Risk (PSR)

In the fields of retail studies, the evaluation of perceived risk plays a pivotal role in comprehending consumer behaviour and the adoption of smart retail technologies. Perceived risk is a multifaceted concept, prompting researchers to employ a variety of methodologies for its assessment. This study explores perspectives on measuring perceived risk in the context of smart retail, drawing insights from existing academic literature. Perceived risk essentially concerns the extent of uncertainty and apprehension that consumers face when deciding to adopt technologies or services (Featherman and Pavlou, 2003). In the retail context, it is particularly relevant because embracing innovative technologies often entails unfamiliarity, uncertainty, and concerns about potential adverse outcomes (Martin, Mortimer and Andrews, 2015). Perceived risk typically includes distinct dimensions: performance risk related to concerns about technology reliability and effectiveness; financial risk tied to cost-related concerns; privacy risk involving data security and personal information safeguarding; and psychological risk encompassing fears about complexity and usability (Lim, 2003; Lim *et al.*, 2006). Researchers often employ instruments such as surveys and Likert-type scales to measure these dimensions. For instance, consumers might be asked to express their level of agreement with statements like "I am concerned about the security of my information when using retail technology." In consumer behaviour and retail management, many studies use a simplified approach, treating perceived risk as a unified concept. This approach assesses the overall perceived risk associated with a specific technology, service, or product. For example, Kim, Jin and Swinney (2009) in their study, " The role of etail quality, e-satisfaction and e-trust in online loyalty development process," measured perceived risk as a single construct in the context of online shopping to understand its impact on consumer loyalty in e-commerce. Similarly, Pavlou and Fygenson (2006) explored the adoption of e-commerce technologies, treating perceived risk as a single variable when examining consumers' intentions. Simplifying perceived risk in this manner proves valuable when the research goal is to grasp the general effect of perceived risk in a particular context without delving into its specific dimensions or contributing factors. On the other hand, some studies prefer to examine each dimension of perceived risk individually. For instance, financial risk may be more prominent during purchase decisions, whereas privacy risk might be a significant concern in data collection and personal information use. Glover and Benbasat (2010), in their comprehensive study on perceived risk in e-commerce, introduced a model with three distinct dimensions: risk of functionality inefficiency, risk of information misuse, and risk of failure to gain product benefit. This detailed approach offers a nuanced understanding of perceived risk in e-commerce. Analysing these dimensions individually provides insight into the origins of perceived risks. To provide a comprehensive evaluation, some researchers have adopted an integrated approach that combines aggregated measurements, capturing the entire concept of perceived risk, with distinct assessments of each risk dimension. This method facilitates an analysis that effectively encompasses the various facets of perceived risk. Perceived risk in research is a complex concept that accommodates diverse measurement methods. Researchers may choose to assess the overall perceived risk, its individual dimensions, or a combination of both, depending on their research objectives. As the retail field evolves, researchers should carefully consider how they measure perceived risk to gain a comprehensive insight into consumer behaviour in this dynamic environment. Academic research in this area continues to adapt its measurement approaches to align with the ever-changing landscape of smart retail technologies. In this study, the concept of perceived risk is measured as a single construct operating as an independent variable, adapted from Glover and Benbasat (2010). It is assessed using three items, each rated on a 7-point scale ranging from 1 ("strongly disagree") to 7 ("strongly agree"), as detailed in *Table 17*.

Table 17: Measurement for Perceived Risk

Item	Code	Description	Reference
Perceived Fairness	PSR1	When shopping online, I feel concern that the online retailer may misinform me about their business, products and reputation.	(Glover and Benbasat, 2010)
	PSR2	When shopping online, I feel worried.	
	PSR3	When shopping online, I am concerned that my personal privacy might be misused.	

5.4.5 Measurement for Trust

Consumer trust is the linchpin to nurturing robust relationships between businesses and their consumer base (Corritore, Kracher and Wiedenbeck, 2003; Kim, Seok and Roh, 2023; Wu *et al.*, 2023). This significance is profoundly accentuated in the contemporary digital landscape, were online transactions reign supreme. Trust serves as the bedrock upon which the superstructure of consumer loyalty, recurrent patronage, and favourable word-of-mouth commendations is meticulously constructed (Pavlou, 2003; Pavlou and Gefen, 2004; Hollebeek and Macky, 2019; Yang *et al.*, 2019). These tenets encompass trust in the credibility of smart retailers, the perception that online businesses genuinely prioritise consumer welfare, and the conviction that these enterprises faithfully adhere to their promises, providing invaluable insights into the extent of consumer trust. Quantifying trust-related convictions serves the dual purpose of enabling smart retailers to gauge the alignment of their value proposition with consumer perceptions. When consumers believe that smart retailers authentically prioritise their interests and diligently fulfil their commitments, it serves as an indicator that the messaging and actions of the smart retailer effectively resonate with the target audience (Corritore, Kracher and Wiedenbeck, 2003; Kim, Ferrin and Rao, 2008; Walker, 2016b; Rajavi, Kushwaha and Steenkamp, 2019). The need to measure trust in smart retailing is of paramount importance for several compelling reasons. First, trust serves as the cornerstone of consumer-business relationships, particularly in a landscape characterised by digital transactions and interactions. In the absence of trust, consumers may be wary of engaging with smart retailers, thereby inhibiting their willingness to make purchases or share personal information. Therefore, measuring trust serves as a litmus test for the health of these relationships, allowing businesses to pinpoint areas that require attention and improvement (Kim, Ferrin and Rao, 2008; Walker, 2016).

Second, trust is inexorably linked to consumer loyalty and repeat business, a fact substantiated by a plethora of studies. Empirical evidence consistently underscores that consumers who place their trust in a brand or smart retailers are more likely to become repeat consumers. Furthermore, they are predisposed to disseminate positive word-of-mouth recommendations within their social circles, thereby significantly augmenting a smart retailer’s reputation and customer base (Cyr, 2008; Bilgihan, 2016). Third, trust manifests itself as a multifaceted construct, with its various dimensions bestowing smart retailers with nuanced insights into consumer perceptions. By comprehending whether consumers trust the credibility of a smart retailer, believe that the business authentically cares about their well-being, or possess confidence in the brand’s commitment-keeping abilities, smart retailers can strategically target areas in need of improvement (Chiu, Huang and Yen, 2010; Morey, Forbath and Schoop, 2015; Mahliza, 2020; Gillath *et al.*, 2021). In the digital age, where competition among smart retailers is cutthroat, trust emerges as a formidable competitive advantage. Merely offering products or services is no longer sufficient; smart retailers must also establish trust to stand out in the marketplace. Measuring trust-related beliefs empowers businesses to rigorously evaluate the effectiveness of their trust-building strategies and make well-informed, data-driven decisions aimed at enhancing consumer trust (Gefen, Karahanna and Straub, 2003; Pavlou and Gefen, 2004; Jai, Burns and King, 2013; Kim, Seok and Roh, 2023). The measurement of trust in smart retailing is a strategic imperative for smart retailers exploring the digital landscape. Trust forms the foundation of consumer relationships, loyalty, and business prosperity. A profound understanding of the multi-layered nature of trust will equip smart retailers to finesse their strategies and foster lasting, trust-based connections with their consumers. For this study, trust was evaluated using three items adapted from Gefen, Karahanna and Straub, (2003). These items were assessed on a 7-point scale, ranging from 1 (indicating strong disagreement) to 7 (signifying strong agreement), as shown in Table 18.

Table 18: Measurement for Trust

TRUST	TRUST	Description	Reference
Trust	TRUST 1	I believe that online businesses are trustworthy.	(Gefen, Karahanna and Straub, 2003)
	TRUST 2	I believe that online businesses care about their consumers.	
	TRUST 3	I believe that online businesses keep their promises.	

5.4.6 Measurement for Smart Shopping Experience (CE)

In the contemporary retail landscape, the transformative shift towards digital platforms has sparked a revolution in the shopping experience (Poncin *et al.*, 2017; Shankar *et al.*, 2021; Baabdullah *et al.*, 2022; Banik and Gao, 2023). This paradigm shift encapsulates the concept of a "Smart Shopping Experience," which not only embraces the convenience of online purchasing but also the efficiency, productivity, and overall ease that these platforms offer (Roy *et al.*, 2017; Roy, Balaji and Nguyen, 2020). The significance of measuring this smart shopping experience cannot be overemphasised, as it is pivotal for comprehending the multifaceted impact of smart retailing on consumers' daily lives and purchasing behaviours. Efficiency and productivity stand as the central pillars for consumers seeking convenience in their shopping journeys. The measurement of satisfaction based on these factors enables us to assess how smart retailing optimises the decision-making process, reduces time expenditure, and maximises the acquisition of products. This measurement is especially pertinent in the context of contemporary consumers' fast-paced lifestyles, where time is a valuable commodity.

In their pursuit of expediency, consumers are drawn to platforms that align seamlessly with their need for quick, efficient, and hassle-free experiences (Foroudi *et al.*, 2018; Ameen *et al.*, 2021; Sheth, Jain and Ambika, 2023). Furthermore, the measurement of the smart shopping experience offers a revealing insight into the technological prowess of these platforms. As consumers encounter and explore the various stages of online purchasing, the technological efficiency of the platform plays a pivotal role. This is of paramount significance because it directly influences the overall shopping experience. Measuring the smart shopping experience is essential to shed light on the transformative impact of smart retailing. This not only allows us to better understand consumer behaviour but also aids in the continuous enhancement of digital platforms, ensuring that they remain in sync with the evolving needs and expectations of today's consumers. As such, this measurement serves as a valuable tool in shaping the future of retail, where efficiency and technological excellence are at the forefront of the shopping journey. In this study, the evaluation of the smart shopping experience and efficiency was conducted using four items adapted from Roy et al. (2017). These items were assessed on a 7-point scale, ranging from 1 (strongly disagree) to 7 (strongly agree), as depicted in Table 19.

Table 19: Measurement for Smart Shopping Experience

Items	**Code**	**Description**	**Reference**
Smart Shopping Experience and Efficiency	CE1	My shopping experience is more efficient when I purchase online.	(Roy *et al.*, 2017)
	CE2	My shopping experience is more productive when I purchase online.	
	CE 3	My shopping experience is smoother when I purchase online.	
	CE 4	My shopping experience is easier when I purchase online.	

5.4.7 Measurement for Smart Satisfaction (CS)

In contemporary smart retail settings, the paradigm shift towards digital platforms has indelibly transformed the shopping experience (Shankar *et al.*, 2016, 2021; Shankar, 2019; Hoyer *et al.*, 2020). Central to this transformation is the concept of "Smart Shopping Experience," encompassing not only the convenience associated with online purchasing but also the multifaceted dimensions of efficiency, productivity, and overall ease that these platforms confer upon consumers (Roy *et al.*, 2017, 2018; Roy, Balaji and Nguyen, 2020). It is imperative to underscore the pivotal need for measuring smart satisfaction as a construct in smart retailing research. Smart satisfaction, within the purview of smart retailing, delineates a complex and diverse construct emblematic of the contemporary retail landscape's continual evolution. This construct aptly captures the intricate interplay between innovative technologies and consumer perceptions, delineating their holistic experience within digitally enhanced retail environments. It is imperative to examine the multi-dimensional facets that collectively reinforce the significance of smart satisfaction within the ambit of smart retailing research (Roy *et al.*, 2017).

Smart satisfaction is inexorably tied to the consumer-centric integration of technology within the retail framework. These smart technologies are painstakingly designed and adopted with the primary intent of augmenting the customer experience. Hence, smart satisfaction serves as a barometer to assess how effectively these technologies cater to the dynamic needs and expectations of the modern consumer (Oliver, 2014; Roy *et al.*, 2017; Byun, Hong and William James, 2023). This construct investigates deeper than mere usability, encompassing the broader notions of consumer empowerment, engagement, and holistic contentment. Furthermore, smart satisfaction aligns seamlessly with expectation-confirmation theory, which is a fundamental underpinning of consumer behaviour and technology acceptance research (Roy *et al.*, 2017). Within the context of smart retailing, it scrutinises the extent to which consumers' initial expectations regarding technology adoption are met or even exceeded during their actual interactions with these smart retail technologies. The resonance between expectations and real-world experiences is a focal point of examination within the ambit of smart satisfaction. Perceived shopping value represents another salient dimension of smart satisfaction (Roy et al., 2017; Adapa et al., 2019). It is intricately interwoven with the utility, ease of use, relative advantage, and overall enjoyment that consumers derive from smart retail technologies. Furthermore, this construct transcends individual elements by investigating how these technologies influence overarching consumer behaviour, brand loyalty, and consumers' propensity to continue using these technological innovations. Efficiency and convenience, which are pivotal drivers of consumer adoption in the smart retailing landscape, are also encapsulated within the compass of smart satisfaction (Bhatnagar, Misra and Rao, 2000; Jiang, Yang and Jun, 2013; Duarte, Costa e Silva and Ferreira, 2018). This dimension scrutinises the extent to which these technologies streamline the shopping experience, effectively reduce transaction costs, and significantly curtail the temporal investments demanded by consumers. The fulfilment of these efficiency- and convenience-driven expectations is a critical underpinning of smart satisfaction.

Smart satisfaction further extends its purview to examine the continuum of technological adoption, encompassing initial intention, ongoing utilisation, and post-purchase satisfaction. This holistic perspective underscores the intricate relationship dynamics between consumers and technology and expounds on the implications of post-purchase satisfaction for future technology adoption decisions (Jacobsen, 2018; Pizzutti et al., 2022). Within the paradigm of smart retailing, smart satisfaction exerts a profound influence on consumer loyalty. This study unearths the mechanisms by which consumer perceptions and satisfaction with smart technology influence loyalty to retailers. The transformation of satisfied consumers into brand advocates who perpetually engage with the brand affirms the construct's far-reaching implications within the retail domain. Ultimately, smart satisfaction epitomises a fount of invaluable insights. For retailers, it serves as a guiding compass, offering actionable feedback derived from consumer experiences to recalibrate their smart retailing strategies, aligning them more closely with consumer needs and expectations. For researchers, it unlocks a treasure trove of opportunities for exploring the ever-evolving dynamics of smart retailing, providing fertile ground for continued innovation and enrichment of the retail sector's tapestry. Smart satisfaction has emerged as a multifaceted and intricately woven construct within smart retailing research (Roy *et al.*, 2017; Roy and Naidoo, 2021). It serves as a compass not only for retailers aiming to deliver superlative shopping experiences through smart technologies but also for researchers seeking to unravel the intricate tapestry of smart retailing dynamics. As the domain of smart retailing continues its relentless evolution, the construct of smart satisfaction will retain its preeminent position, steering the trajectory of retail innovation and the consumer-centric paradigm. In this study, smart satisfaction was measured using three items, of which three captured hedonic motivation, adapted from Roy et al. (2017). Items were assessed on a 7-point scale ranging from 1 = strongly disagree to 7 = strongly agree, as shown in Table 20.

Table 20: Measurement for Smart Satisfaction

Item	**Code**	**Description**	**Reference**
Smart Satisfaction	CS 1	Shopping online is fun.	(Roy et al., 2017)
	CS 2	Shopping online is enjoyable.	
	CS 3	Shopping online is entertaining.	

5.4.8 Measurement for E-Loyalty

Understanding and measuring consumer loyalty in the context of smart retailing is paramount for smart retailers to build and maintain lasting relationships with their consumers. Loyalty is a multidimensional concept that goes beyond mere transactional interactions and reflects the depth of the emotional connection between a customer and a brand (Glover and Benbasat, 2010). The factors mentioned—sense of belonging, emotional connection, and strong emotions—are crucial indicators of customer loyalty. The sense of belonging to a favourite online retailer signifies a consumer's perception of being part of a larger community or ecosystem. This sense of belonging fosters a feeling of inclusivity in which consumers see themselves as integral parts of a retailer's success story. Similarly, experiencing an emotional connection indicates that the retailer has succeeded in creating emotional resonance with the consumer. This emotional bond transcends the utilitarian aspect of transactions, making the consumer more likely to eventually stay committed to the brand. In this study, loyalty was measured using a 3-item scale adapted from Glover and Benbasat (2010). Items were assessed on a 7-point scale ranging from 1 = strongly disagree to 7 = strongly agree, as shown in *Table 21*.

Table 21: Measurement for Loyalty

Items	**Code**	**Description**	**Reference**
Loyalty	LOY1	I have a sense of belonging to my favourite online retailer.	(Glover and Benbasat, 2010; Fang, 2019)
	LOY2	I experience an emotional connection with my favourite online retailer.	
	LOY3	I have strong emotions towards my favourite online retailer.	

5.4.9 Measurement for Purchasing Behaviour (INT)

Understanding consumer purchasing intention and behaviour is vital for online businesses to gauge the likelihood of consumers making future purchases (Chen, 2008; Allal-Chérif, Simón-Moya and Ballester, 2021). It offers valuable insights into consumer loyalty, satisfaction, and the overall effectiveness of smart retailing platforms. Expressing intentions to use online shopping more frequently, being willing to use online shopping in the near future and planning to continue using online shopping provide a strong basis for measuring (re)purchasing intention. The intention to use online shopping more frequently in the future signals a shift in consumer consumption behaviour. This change in behaviour can be influenced by various factors, including convenience, improved experiences, and changing preferences. Measuring this intention helps businesses anticipate shifts in demand and tailor their strategies to accommodate evolving consumer preferences. In this study, (re)purchasing intention was measured using three items adapted from Pavlou (2003) and Roy et al. (2017). Items were assessed on a 7-point scale ranging from 1 = strongly disagree to 7 = strongly agree, as shown in *Table 22*.

Table 22:Measurement for Purchasing Behaviour

Items	Code	Description	Reference
(Re)Purchasing Intention	INT1	I intend to use online shopping more frequently in the future.	(Pavlou, 2003; Roy et al., 2017)
	INT2	I am willing to use online shopping in the near future.	
	INT3	I will continue to use online shopping in the future.	

5.4.10 Managing Common Bias

The data used for this analysis were collected at a point in time, with respondents providing their input on both predictor and criterion variables. This type of data may be prone to a bias called method bias (CMB). CMB refers to the variation that is not directly related to the underlying concepts being measured. Rather, it stems from the manner in which the measurements are conducted (Podsakoff *et al.*, 2003). From an equation modelling (SEM) perspective, CMB is seen as an artefact resulting from the measurement system used in an SEM study rather than being influenced by the actual causal relationships in the model being examined. In science, it is widely recognised that CMB poses challenges because it can affect the accuracy of measurements. However, strategies have been proposed by Podsakoff et al. (2003) to mitigate or monitor instances of CMB. To address the influence of the CMB, several measures were implemented. First, a clear distinction was made between the measuring predictor and criterion variables. To achieve isolation, a conscious effort was made to separate the indicator and criterion variables and to provide instructions. In this way, respondents could review the instructions before answering questions, reducing the chances that their responses would influence subsequent responses. In addition, we explicitly stated in the cover letter that there were no incorrect answers and that their responses would remain anonymous. We took care in designing the questionnaire to minimise any confusion regarding the scale items and question wording.

For data analysis, we used a method called covariance-based structural equation modelling (CB SEM). To address collinearity issues, we conducted a test. According to Kock (2015), this method is more effective than confirmatory factor analysis for detecting collinearity-related method bias (CMB). We checked each variance inflation factor (VIF) resulting from this assessment. If any VIF exceeds 3.3, it indicates CMB contamination within the model. On the other hand, VIFs below this threshold would indicate that no CMB was present in the model (Podsakoff et al., 2003; Podsakoff et al., 1986). The results of the evaluation of the CMB areas for this study are presented in Chapter 6.

5.4.11 Participant Selection Process

The participant selection process adhered to a systematic methodology designed to align with the study's research objectives and the positivist paradigm. The target population comprised individuals aged 18 years and older who were active internet users engaged in related technologies. This focus ensured the inclusion of respondents who had firsthand experience of constructs such as trust, perceived privacy concerns, and e-loyalty, which are core elements of the study.

To achieve this, a nonprobability convenience sampling technique was employed due to time constraints, resource constraints, and the practicalities of accessing a sufficiently large sample. Convenience sampling allowed for swift and efficient data collection while ensuring the inclusion of participants with relevant experiences. Specifically, over 2000 self-administered questionnaires were distributed via the JISC online survey platform, supplemented by distribution through additional online platforms, including email and WhatsApp. This multichannel distribution strategy maximises participation and ensures a diverse demographic reach. The final dataset comprised 510 valid responses after eliminating incomplete surveys. The sample size exceeded the recommended thresholds for structural equation modelling (SEM), ensuring sufficient statistical power and robustness (Comrey and Lee, 1992; Hair, Black and Babin, 2010b).

Efforts were made to minimise bias and enhance representativeness. The multi-platform approach ensured a wider reach, targeting diverse demographic segments reflective of the UK population, including variations in age, gender, socioeconomic status, ethnicity and geographic location. By leveraging platforms like WhatsApp and email, the study expanded beyond traditional survey methods to reach participants who might not have been engaged through social media alone and influence post-purchase outcomes. This approach ensures that the dynamic interactions between consumers and smart technologies are critically examined, offering valuable insights for both academic research and practical applications in smart retailing.

5.4.12 Limitations and Potential Biases

Whilst the approach effectively yielded a robust sample size and facilitated timely data collection, several limitations and potential biases must be acknowledged to ensure transparency and academic rigour:

Reliance on Convenience Sampling: The use of a practical nonprobability convenience sampling technique introduces limitations regarding generalizability. Participants were self-selected, which may lead to an over-representation of individuals more engaged with smart retail technologies and under-representation of those less digitally active or hesitant. This creates a potential bias towards favourable perceptions of smart retailing and limits the ability to generalise findings to a wider population.

Geographical Bias: The online distribution of the survey likely skewed participation in urban areas with higher internet penetration and technological infrastructure. Rural participants with limited access to smart retail technologies are underrepresented. This geographical bias may restrict the applicability of the findings to regions with differing levels of digital connectivity and engagement.

Response Bias: The online survey format introduces potential response bias because participants may provide socially desirable answers or exaggerate their engagement with smart retailing. Moreover, the lack of financial incentives may have discouraged responses from certain demographic groups, such as individuals from lower-income backgrounds, further affecting sample diversity.

Cross-Sectional Design: This study employed a cross-sectional design, capturing consumer behaviours and attitudes at a single point in time. While this approach provides a snapshot of current trends, it fails to account for changes over time, particularly in a dynamic field like smart retailing, where technological advancements and external factors may significantly influence consumer behaviour.

Limited Integration of Qualitative Insights: The study's reliance on a quantitative approach facilitated rigorous testing of hypotheses but precluded a deeper exploration of contextual factors influencing consumer behaviours. The absence of qualitative data limited the ability to capture nuanced insights into the underlying motivations and barriers that affect trust, satisfaction, and loyalty in smart retail environments.

5.5 Pilot Study

A pilot study assumes a critical role in the trajectory of research, serving as an indispensable preliminary endeavour that precedes the main study. This preliminary exploration serves to unveil and rectify any latent flaws within the research design, instrumentation, and measurement scales before embarking on the principal study (Saunders, Lewis and Thornhill, 2009, 2019). The foremost objective of a pilot study, as outlined in *Table 23*, is to ensure a mutual understanding between the survey's contents and the respondents. This, in turn, establishes a commendable level of content validity, in accordance with (Churchill, 1999). As Ismail, Kinchin and Edwards (2017) emphasised, it is imperative to unearth and address any potential errors or ambiguities nestled within the questionnaires before starting the actual data collection process.

As outlined in *Table 23*, it is evident that conducting a pilot test is an indispensable step before deploying a data collection questionnaire. The purpose of this pilot test was to enhance the questionnaire and allow the researcher to gauge the quality and reliability of the questions, aligning with the perspectives of Saunders et al. (2019). In this context, validity pertains to the process by which experts provide guidance on the statistical validity and appropriateness of the questionnaire, whereas reliability concerns the consistency of responses to the questions (Saunders, Lewis and Thornhill, 2009, 2019). The significance of a pilot study in the scope of smart retailing research cannot be overstated. Given the dynamic and evolving nature of smart retailing (Poncin *et al.*, 2017; Pantano and Dennis, 2019; Chang and Chen, 2021), it is paramount to ensure that the research tools employed are finely tuned to the specific context of the study. In this context, the pilot study functions as a diagnostic tool, helping researchers identify and mitigate any potential issues related to data collection instruments, question clarity, and overall survey structure. It serves as a quality assurance step, allowing researchers to fine-tune their research approach to ensure robust and reliable data collection during the principal study.

In addition, in the landscape of smart retailing, timely detection and rectification of errors and ambiguities in questionnaires are vital. With the rapid integration of technologies and ever-evolving consumer behaviours in smart retail environments, outdated or imprecise survey instruments can lead to misleading or inconclusive results. Hence, a pilot study is a critical step in refining survey instruments to reflect the contemporary realities of smart retailing. It is an essential component of methodological rigour that ensures that the main study is built on a solid foundation and that its results reflect the intricate dynamics within the smart retail landscape. Consequently, the pilot study plays a crucial role in enhancing the overall quality, reliability, and validity of the research findings in the context of smart retailing.

Table 23:The purpose of the pilot test

Objective	Relevance to This Study
Examining Questionnaire Language and wording	Relevant and Applicable
Evaluating Questionnaire Sequence	Directly Applicable
Assessing Questionnaire Structure	Highly Relevant
Developing Respondent Familiarity	Pertinent to the Study's Goals
Testing and Educating Survey Enumerators	Directly Applicable
Estimating Response Rate	Significantly Relevant
Predicting Questionnaire Completion Time	Closely Tied to the Study
Testing of Analysis Procedure	Directly Applicable

The pilot study for this research was conducted from May 17, 2022, to May 30, 2022, with an online survey administered to a cohort of UK-based consumers. Before the pilot, the online survey underwent pre-testing with feedback from five individuals to ensure clarity and format. After revisions, an informal pre-test group of 35 individuals contributed 30 validated surveys, representing respondents from various locations across the UK. Although three surveys were incomplete, they provided constructive feedback, and two surveys did not reach the researchers. Participants were instructed to apply the questionnaire's inquiries to their experiences in the smart retailing ecosystem, including product or service acquisition and seeking product information. Unlike previous studies that focused on online shopping persistence intentions with specific platforms or providers, this study prompted participants to consider all their online shopping activities. They were specifically asked to evaluate question clarity, ambiguity, question coherence, survey layout, and any challenges encountered in completing the survey within the given timeframe. Ambiguously developed items were reconsidered and potentially rephrased based on participant feedback collected through face-to-face interactions and email correspondence.

Demographic data, including birth year, gender, education, ethnicity, and engagement with smart retailing, were collected at the beginning of the survey during the pilot study. This demographic information served the dual purpose of understanding respondents' online shopping context and identifying potential differences in online shopping behaviours based on demographic characteristics. The survey instruments are provided in English. Feedback from the 30 participants in the pilot study revealed insights into the survey's length, language, layout, and time allocation. The participants represented a diverse group of online consumers, spanning different generational categories, including students, professionals, and individuals of various age groups. Most respondents belonged to Generation Y (born between 1980 and 1996), with one Baby Boomer (born before 1964) and 12 from Generation X (born between 1965 and 1979). Generation Z (born between 1997 and 2003) was not represented, as outlined in *Table 24*.

Table 24: outline of sampling strategy for pilot data in this study

Sampling Strategy Component	**Description**
Target Population	Consumers in the United Kingdom
Sampling Method	Convenience Sampling
Sample Size	30 participants
Data Collection Period	May 17, 2022, to May 30, 2022
Pre-Test Phase	Feedback from 5 individuals
Informal Pre-Test Group	35 individuals, yielding 30 validated surveys
Language of Survey	English
Incomplete Surveys	Three incomplete surveys with constructive feedback
Surveys Not Received	Two surveys not received by researchers
Demographic Information	Collected at the beginning of the survey, including birth year, gender, education, ethnicity, and engagement with smart retailing
Generational Distribution	Generation Y (n=17), Baby Boomers (n=1), Generation X (n=12), Generation Z (n=0)
Feedback Collection	Through face-to-face interactions and email correspondence

An exploratory analysis was conducted, and the results were found to be satisfactory. Most Cronbach's alpha values exceeded or met the widely accepted threshold of 0.7, confirming the study's internal consistency and reliability. The detailed results of the reliability analysis are provided in *Table 25*. The Cronbach's alpha values provided for each construct offer insights into the internal consistency and reliability of the measurement items within each construct (Hair *et al.*, 2013). These values are crucial for determining the trustworthiness of the data gathered through these items.

Perceived Privacy Concern, Fairness, Perceived Risk, and Trust: These constructs all exhibit high Cronbach's alpha values, ranging from 0.862 to 0.913. This indicates that the items within these constructs are strongly related and consistently measure the intended constructs. Researchers can have confidence in the reliability of these constructs in assessing participants' perceptions.

Smart Shopping Experience: The Smart Shopping Experience construct demonstrates the highest Cronbach's alpha of 0.955. This exceptionally high value underscores the internal consistency and reliability of the four items used to measure this construct. This indicates that these items effectively capture the multifaceted aspects of the smart shopping experience.

Purchasing Behaviour: Similarly, purchasing behaviour shows a very high Cronbach's alpha of 0.953. This indicates that the three items assessing purchasing behaviour are closely related and provide a reliable measure of this construct.

E-Loyalty, with Cronbach's alpha of 0.838, maintains a good level of internal consistency. While not as high as some other constructs, it indicates that these items reliably measure electronic loyalty. Researchers can have confidence in the accuracy of the measurements.

Smart Satisfaction: Smart satisfaction has a Cronbach's alpha of 0.794, which, while acceptable, is slightly lower than that of some other constructs. This indicates that the three items used for measuring smart satisfaction have good but not excellent internal consistency. Researchers may consider further refinement of these items to improve reliability.

Digital Well-being: Digital well-being displays the lowest Cronbach's alpha of 0.688. While still acceptable, it indicates that there is room for improvement in the reliability of this construct. Researchers should revisit the measurement items to enhance internal consistency.

In summary, Cronbach's alpha values provide a valuable assessment of the reliability of the constructs in this study. Researchers can be confident in the measures of perceived privacy concern, perceived fairness, perceived risk, trust, smart shopping experience, purchasing behaviour, and e-loyalty. Smart satisfaction is reliable but has some room for improvement, and digital well-being may benefit from refining its measurement items to enhance internal consistency. High internal consistency is vital to ensure that the data collected accurately reflect the underlying constructs and allow for meaningful and reliable analyses. Building upon the success of the pilot study, the final survey configuration considered factors such as time investment, response categories, implementation costs, and the expected proportion of unresponsive participants, aligning with the insights of Tull and Hawkins (1993).

Table 25:Reliability Statistics for Pilot Data

Construct	Cronbach's alpha	Number of items
Perceived Privacy Concern	.863	3
Perceived Fairness	.913	3
Perceived Risk	.901	3
TRUST	.862	3
Smart Shopping Experience	.955	4
Smart Satisfaction	.794	3
Purchasing Behaviour	.953	3
E-Loyalty	.838	3
Digital Well-being	.688	3

5.5.1 Data Analysis

This study-initiated data collection with a rigorous data cleaning process aimed at safeguarding the integrity of results by identifying and handling anomalies and outliers. SPSS was employed for data encoding, enhancing the analysis's reliability through the systematic detection of abnormal observations. Subsequently, structural equation modelling (SEM) was employed to rigorously scrutinise and substantiate the conceptual model. The decision to use SmartPLS 4 for managing the study's structural pathways is of significant methodological importance. SmartPLS 4, which is well known for its proficiency in handling complex structural analyses, was chosen to meticulously calibrate the intricate relationships between variables within the research framework. This method reflects a thoughtful decision-making process and a commitment to thoroughly exploring the complex connections within the conceptual framework.

The adoption of SmartPLS 4 in this study signifies a deeper methodological approach than traditional SEM techniques. It acknowledges the software's inherent advantages, particularly its ability to model intricate relationships within a relatively small dataset. The user-friendly interface and latent variable modelling capabilities of SmartPLS 4 emphasise the importance of conducting a comprehensive analysis of the underlying constructs. Nevertheless, it is crucial to critically assess the potential limitations associated with the adoption of SmartPLS 4. Despite its advantages, its relative novelty may pose limitations concerning existing literature and established best practices. In addition, understanding the software's complex algorithms is essential for extracting meaningful insights. In summary, this study's data refinement, encoding, and rigorous model validation processes demonstrate the meticulousness inherent in empirical research. The study's commitment to methodological expertise is underscored by the thoughtful use of SmartPLS 4, which encourages scholarly discussions on both its benefits and possible limitations as an advanced analytical tool.

5.5.2 Structural Equation Modelling (SEM)

Various research fields use the Structural Equation Modelling (SEM) approach, which is a flexible multivariate analysis method. These include education (María *et al.*, 2014), marketing (Guenther *et al.*, 2023), psychology (Priester, 2010), Engineering (Takyi-Annan and Zhang, 2023), and Agriculture (Lee *et al.*, 2022). Notably, Gefen, Rigdon and Straub (2011) strongly advocate its use in scientific inquiries, particularly focusing on behavioural intention, with special relevance in the field of IS research. Gefen, Straub and Boudreau (2000) demonstrate that the SEM method is useful for studies that want to find out how independent and dependent variables are related by using relevant literature or theoretical frameworks. In this context, two distinct measurement approaches are discernible within SEM: formative and reflective. Formative measurements consist of indicators that stem from latent variables and are non-interchangeable (Byrne, 2010a). Conversely, reflective measurements feature highly correlated and interchangeable latent variables, necessitating rigorous scrutiny of their reliability and validity (Byrne, 2010b; Sarstedt *et al.*, 2014). Given that our measurements rely on Likert-point data drawn from established theories and relevant literature, adhering to the rules of reflective measurement scales is paramount (Hair Jr *et al.*, 2021; Sarstedt, Ringle and Hair, 2021). The SEM approach presents multiple avenues of implementation, with partial least squares structural equation modelling (PLS-SEM), covariance-based SEM (CB-SEM), and component-based SEM being the most common. PLS-SEM possesses the advantage of demanding fewer samples while focusing on explaining variance in dependent constructs (Hair *et al.*, 2013). In contrast, CB-SEM permits the direct testing of measurement and structural invariance, allowing for the confirmation or rejection of theories. Nevertheless, CB-SEM is stringent in its data assumptions, requiring a normal distribution and large sample sizes. PLS-SEM, on the other hand, exhibits more flexibility in data assumptions, particularly in scenarios with limited participant numbers (Wong, 2019). Component-based SEM is typically operationalized through Generalised Structured Component Analysis (GSCA). For the current study, PLS-SEM was chosen as the preferred method. The rationale behind this choice lies in the practical constraints, as obtaining a quota sample can be cost-prohibitive and limiting. Thus, the focus is on obtaining highly representative data while meeting the minimum sample size requirement (n = 510).

5.5.3 Partial Least Square Equation Modelling (PLS-SEM)

Partial least squares structural equation modelling (PLS-SEM) is a variance-based SEM approach developed in the mid-1960s by Herman Wold, an econometrician and statistician (Wold, 2004). In comparison to covariance-based SEM (CB-SEM), PLS-SEM offers greater flexibility for exploratory modelling. There are compelling reasons for selecting PLS-SEM as the primary approach for this study.

First, PLS-SEM figures out latent variables by putting together exact weighted linear combinations of observed variables. This means that the scores for these latent variables can be used to make predictions (Wong, 2019). Second, PLS-SEM does not estimate all parameters simultaneously; instead, it separates them during calculations. Investigating the significance between parameters facilitates the advancement of knowledge regarding both the research model and measurements (Rodríguez-Entrena et al., 2018). Third, PLS-SEM requires a relatively smaller sample size than other SEM approaches (Wold, 2004) Notably, PLS-SEM has established itself as the primary technique applied in information systems (IS) research (Gefen et al., 2011), making it the most suitable choice for the thesis's objectives.

Despite the advantages of the PLS-SEM approach, it is not without potential issues, including (1) the risk of biased estimation and (2) the potential to generate many mean square errors in estimates of component loadings and path coefficients (Wong, 2019). However, these concerns can be mitigated by scrutinising the model's outer loadings, average variance extracted (AVE), composite reliability, and square root. According to Hair et al. (2013), the software packages available for PLS-SEM analysis include SmartPLS, PLS-PC, and PLS-Graph. For this study, SmartPLS was chosen as the software package because of its reputation for providing reliable results in academic studies with relatively complex models and small sample sizes (Chin, 1998). Moreover, SmartPLS has proven effective in management-related research with a focus on prediction (Chin, 1998; Ringle, Sarstedt and Straub, 2012; Hair Jr *et al.*, 2021; Sarstedt, Ringle and Hair, 2021).

Table 26 :Comparison Between Covariance-based and Component-Based SEM

Features	Covariance-based	Partial Least Square	Square Component-based
Objective/ purpose	Build causal models	Predictive causal system	Build Causal relationships
Measurement	Reflective measure	Reflective and formative	Reflective and formative
Distributional assumption	Multivariate normality (Parametric)	Cross Validated, component-based estimation	Predictor specification (nonparametric)
Parameter estimates	Consistency at large: at least 10 times the number of items in complex constructs.	Small to moderate complexity (e.g., less than 100 variables)	Consistency at large: at least 10 times the number of items in complex constructs.
Model evaluation	Goodness of fit, overall model fit, R^2 , AGFI	R^2, Q^2 , f^2 composite reliability, AVE, outer loadings and square root	R^2, significant t-values
Best suited for:	Confirmatory research and theory testing	Predictive exploratory research and theory testing	Exploratory research and theory building

Source (Jen, 2021)

5.5.4 Assessment of Measurement Model

PLS-SEM comprises two fundamental components: the measurement model and the structural model, which serve as integral parts of the analysis framework (Hair JR *et al.*, 2010; Hair *et al.*, 2013). Both sub-modes require comprehensive statistical scrutiny before hypothesis testing. Given that this study uses reflective measurement scales, the assessment of the measurement model begins with an examination of the relationships between the constructs and their respective measures. This encompasses the scrutiny of outer model loadings, as proposed by Wong (2019), and the evaluation of the reliability of the measures, in line with Ali et al. (2018). Moreover, ensuring the precise measurement of the constructs necessitates a rigorous evaluation of construct validity (Hair, Black and Babin, 2010b; Hair JR et al., 2010; Hair et al., 2013). Validity, a critical facet of measurement model assessment, refers to the degree to which a construct accurately reflects its intended meaning (Hair Jr *et al.*, 2021). On the other hand, the measure's reliability underscores the internal consistency of the measurements. Thorough assessment of the measurement model is pivotal for model validation and determining whether the items adequately represent the underlying constructs (Sarstedt et al., 2021). In this study, we examined the outer loadings of each item and computed the average variance extracted (AVE) and heterotrait-monotrait ratio of correlations (HTMT) to evaluate convergent and discriminant validity. To evaluate the internal consistency reliability, we employed composite reliability (CR) and rho_A, as recommended by (Dijkstra & Henseler, 2015). Through statistical evidence, AVE supports convergent assessment, which checks how well a latent variable explains the differences between its parts. According to Wong (2019), it is crucial to examine indicator loadings before gauging convergent validity. Each indicator should exhibit a loading higher than 0.4, with values closer to 0.7 indicating satisfactory discriminant and convergent validity (Hulland, 1999; Hair *et al.*, 2013). This study adheres to the benchmark set forth by Bagozzi and Yi (1988), which calls for AVE values to be 0.5. An AVE value of 0.50 signifies that the latent variable accounts for at least 50% of the variance among its items, thus establishing convergent validity.

Discriminant validity assessment, on the other hand, is employed to ensure that a reflective construct exhibits robust distinctions from other constructs (Hair et al., 2012). Traditionally, this is achieved by employing Fornell and Larcker (1981) criterion, which compares the AVE, representing the shared variance within constructs, with the squared correlation. Nonetheless, Hair et al. (2021) proposed the use of HTMT for reflective constructs to achieve a more precise discriminant validity assessment, as indicated by (Henseler et al., 2016). Notably, a high HTMT value close to 1 indicates invalid discriminant validity, whereas a value approaching 0.90 indicates insufficient discriminant validity. Wong (2019) further advised that the tolerance of HTMT in models with predictive purposes should not exceed 0.85.

The level of internal consistency reliability shows how well the measurements work for what they're supposed to do, making sure that the measurements accurately reflect the things that are being studied (Hair *et al.*, 2019). In this context, our evaluation of internal consistency reliability adheres to Wong’s (2019) recommendations, employing both Cronbach’s alpha and composite reliability. Notably, the higher the composite reliability value, the greater the reliability. As per prevailing standards, values ranging between 0.60 and 0.70 are deemed acceptable; those falling between 0.70 and 0.90 indicate satisfactory reliability; and values of 0.95 or higher signify a high degree of internal consistency and reliability. In addition to composite reliability, Dijkstra and Henseler (2015) introduced the concept of rho_A as a modern approach for assessing internal consistency and reliability. Statistically, the rho_A value should be 0.70 or greater. However, values exceeding 1 indicate invalid internal consistency and reliability. The key components to be assessed under the measurement model are summarised in *Table 26* and *Table 27*.

Table 27:Measurement Model Assessment Indices

Measurement Model Assessment	Recommended Thresholds
AVE	≥ 0.5
HTMT	<0.85
CR	≥0.6 and 0.7, acceptable ≥0.95, good
Rho_A	≥0.7

Source (Jen, 2021)

5.5.5 Assessment of Structural Model

According to Hair et al. (2012), the assessment of the structural model is crucial for determining the model's capacity to predict the outcome variable. Standard criteria are used to judge this ability to predict, which is an important part of the evaluation process (Hair Jr *et al.*, 2021). These include the coefficient of determination (R^2), predictive relevance (Q^2), examination of collinearity, and the model's effect size (f^2). A concise summary of the requisite values for evaluating the structural model is outlined in *Table 26* - *Table 28*. Collinearity, a concept focusing on interrelationships among predictor constructs, is critically examined to ensure the absence of bias in regression results and identify potential candidates for elimination (Wong, 2019). In Partial Least Squares Structural Equation Modelling (PLS-SEM), this concern is addressed through the Variance Inflation Factor (VIF). As advocated by Hair et al. (2021), VIF values should ideally hover around 3 or lower, with values exceeding 5 indicative of multicollinearity issues. Models afflicted by multicollinearity challenges may necessitate the development of higher-order models grounded in theory (Wong, 2019). Following the investigation of multicollinearity, the assessment of R^2 takes centre stage. The coefficient of determination is a measure of a model's explanatory power, often determined through the examination of the R^2 value (Jen, 2021; Shmueli et al., 2019).

Moreover, the R^2 value is synonymous with in-sample predictive power (Roldán and Sánchez-Franco, 2012). With a range between 0 and 1, values closer to 1 signify a higher degree of predictive power. Recommendations by Hair et al. (2013) suggest that R^2 values of 0.75 indicate substantial predictive power, 0.50 denote moderate, and values below 0.25 reflect weak predictive power. However, exceptionally high R^2 values (R^2 > 0.90) may indicate overfitting, implying that the model might not generalize well to different samples. As a result, R^2 values between 0.10 and 0.25 are deemed acceptable. The dimension of effect size is encapsulated by the f^2 value, which offers a ranking of the predictor constructs' relevance to the outcome variable. As a general guideline, f^2 values smaller than 0.02 represent small effects, values exceeding 0.15 are considered medium, and values surpassing 0.35 suggest large effect sizes. Predictive relevance, quantified through the Q^2 metric, amalgamates both out-of-sample prediction and in-sample explanatory power (Sarstedt *et al.*, 2014). The Q^2 value serves as an overarching indicator of the model's predictive accuracy (Geisser, 1974; Jen, 2021). While R^2 focuses predominantly on in-sample data, Q^2 amalgamates both out-of-sample and in-sample aspects. Calculation of Q^2 is contingent on a blindfolding procedure, involving the systematic removal of original data points to make prognostications. As per Hair et al. (2021), it's imperative that Q^2 values exceed zero, with values greater than 0, 0.25, and 0.50 signifying small, medium, and large predictive relevance, respectively.

Table 28:Structural Model Assessment Indices

Structural Model Assessment	Recommended Threshold
VIF	≤ 3
$\boldsymbol{R\ 2}$	>0.72, satisfaction >0.56, commitment
$\boldsymbol{f\ 2}$	Between 0.10 and 0.25, acceptable <0.02, small ≥0.15, medium ≥0.35, large
$\boldsymbol{Q2}$	0, small ≥0.25, medium ≥0.50, large

Source (Jen, 2021)

5.5.6 Data Coding

Data coding is a critical step in research, where textual survey responses are converted into numerical data, allowing for effective analysis of participant feedback (Hair et al., 2010, 2013). Data coding was methodically executed to ensure a smooth transition from text to numeric values. Microsoft Excel was employed as a valuable tool to facilitate the conversion process. It enabled the systematic transformation of textual data into numerical formats. Furthermore, the researcher took the strategic step of assigning labels to dummy variables, enhancing the interpretability of subsequent analyses. Once the data had undergone this comprehensive translation, they were imported into the Statistical Package for Social Sciences (SPSS), a widely recognised tool known for its robust analytical capabilities. This collaborative effort between Excel and SPSS resulted in the transformation of raw data into a format suitable for the in-depth exploration of underlying patterns and relationships. SmartPLS 4 played a pivotal role in the subsequent analysis. This approach, which is renowned for its proficiency in structural equation modelling and latent variable analysis, added depth and rigour to the analytical process of the study. Using SmartPLS 4, the researcher showcased a commitment to exploring complex relationships within the data from multiple dimensions. However, it is essential to consider a comparative perspective within the context of data coding and analysis. While the use of Microsoft Excel and SPSS is commendable, it is crucial to juxtapose these choices with potential alternatives. Other platforms may offer nuanced functionalities that could lead to improved data interpretation. In addition, the transition from Excel to SPSS raises questions about potential discrepancies and data integrity, emphasising the need for diligent validation procedures. In summary, the journey from text to numeric representations, along with the adept use of Excel, SPSS, and SmartPLS 4, demonstrates the methodological acumen that forms the foundation of empirical research. While the choice of these tools is praiseworthy, it invites scholars to engage in a comparative dialogue about alternative options and their implications for analytical robustness.

5.5.7 Reliability and Validity

This study undertook a comprehensive assessment of both convergent and discriminant validity, a critical endeavour in establishing the relationship between survey items and their corresponding constructs. Convergent validity, a crucial component of this effort, pertains to the tendency of items to align around a specific construct (Hair JR *et al.*, 2010). Its validity hinges on three vital dimensions: factor loading, average extracted variance (AVE), and composite reliability. Convergent validity, as a concept, revolves around the persistent investigation of the alignment of indicators with their respective constructs. Factor loading plays a central role in quantifying the strength of the correlation between an indicator and its underlying construct. In addition, AVE provides insights into the degree to which indicators converge around their associated constructs, indicating the percentage of variance that these indicators capture. Composite reliability complements this validation by gauging the consistency of the items within a construct. Discriminant validity, another dimension of this study, emerges when considering two distinct aspects: AVE values and the squared correlation coefficient between pairs of constructs. We address this dimension effectively by comparing the average variances associated with each pair of constructs against the established threshold for discriminant validity. As per Hair et al. (2014), the threshold dictates that each construct's average variance should exceed the square of the correlation estimates between the two constructs. In the context of validity and reliability evaluations, it is valuable to incorporate a comparative standpoint. While exploring these domains, it is advisable to compare and contrast these methodologies with potential alternative approaches. Different validation and reliability indices offer diverse perspectives, potentially yielding fresh insights into construct coherence and indicator reliability. In summary, the thorough examination of convergent and discriminant validity, coupled with the diligent assessment of reliability using Cronbach's alpha, underscores the methodological rigour inherent in this study. These techniques are firmly established and prevalent in academic research. Nevertheless, it is essential to acknowledge their respective merits and possible limitations, as they contribute to the ongoing scholarly discourse concerning research methodology.

5.5.8 Covariance-Based Structural Equation Modelling (CB-SEM)

Structural Equation Modelling (SEM) has become a prominent analytical method for investigating various phenomena in the social sciences (Hair, Black and Babin, 2010b; Hair JR et al., 2010). Within the spectrum of SEM techniques, covariance-based structural equation modelling (CB-SEM) plays a crucial role in uncovering complex relationships among multiple variables (Hair *et al.*, 2013). CB-SEM allows for the examination of intricate connections between both endogenous and exogenous factors, providing a comprehensive view of these relationships. The choice to employ CB-SEM through SmartPLS 4 reflects the researcher's careful consideration and alignment with the study's objectives. This selection is well-suited for conducting multiple regression analyses and agrees with the research goal of scrutinising the interplay between dependent and independent variables (Anderson and Gerbing, 1988). However, when it comes to SEM and CB-SEM, it is valuable to engage in a comparative analysis. Comparing CB-SEM with other potential methodologies, such as partial least squares structural equation modelling (PLS-SEM), can offer fresh perspectives on the research constructs. Each method has unique strengths and limitations, and exploring these can yield valuable insights. To summarise, the strategic adoption of SEM, particularly CB-SEM through SmartPLS 4, exemplifies the methodological precision inherent in this study. While this choice aligns with the research's trajectory, it also encourages a comparative discussion of alternative approaches. This prompts scholars to investigate the intricacies and implications of diverse analytical pathways.

5.5.9 Assessment of Model Fit

Within the scope of covariance-based structural equation modelling (CB-SEM), evaluating model fit is a fundamental aspect of empirical studies. Scholars concur that conducting at least four essential fitness tests is imperative to gauge the appropriateness of the SEM model (Hair *et al.*, 2013). The core of this evaluative process revolves around pivotal fit indices, notably the chi-square statistic, goodness of fit (GFI), adjusted GFI, comparative fit index (CFI), and root mean square error approximation (RMSEA). The normed fit index (NFI) and the Tucker-Lewis index (TLI) are universally recognised as vital gauges of model adequacy (Hair *et al.*, 2013). This study explores exhaustive scrutiny of the model's suitability within the CB-SEM framework. It encompasses a meticulous examination of six model fit indices explicitly tailored for CB-SEM. This analytical rigour underscores a proactive commitment to thoroughly assessing the model's alignment with empirical data. For a detailed account of these indices and their respective recommended thresholds, as outlined in *Table 29*.

Table 29: Assessment of Model Fit: Source: Hair et al., (2014)

Goodness-of-fit types	**Acceptable levels of goodness-of-fit**
Absolute fit measures	
Goodness-of-fit index (GFI)	Greater than or equal to 0.90
Root mean square error of approximation (RMSEA)	Acceptable fit less than or equal to 0.08, good fit less than or equal to 0.05, the marginal fit between 0.09 and 0.1
Incremental fit measures	
Tucker –Lewis index (TLI)	Greater than or equal to 0.90
Comparative fit index (CFI)	Greater than or equal to 0.90
Adjusted goodness-of-fit index (AGFI)	Greater than or equal to 0.80
Incremental fit index (IFI)	Greater than or equal to 0.90
Parsimonious fit measures	
Normed chi-square (CMIN/DF)	CMIN/DF value is greater than or equal to 1.0 and less than or equal to 5.0.

However, in the pursuit of evaluating model fit, a comparative standpoint warrants consideration. While the chosen indices reflect the researchers' judgement, a more comprehensive evaluation can be attained by encompassing additional fit indices such as the standardised root mean square residual (SRMR) and the on-normalised fit index (NNFI). Incorporating these indices would enrich the overall evaluation of the model's fit. In sum, appraising the model's fit in the context of CB-SEM is the cornerstone of the methodological rigour inherent in this study. The use of diverse fit indices not only signifies a dedication to methodological precision but also encourages scholars to explore alternative indices for further investigation. By integrating both selected and potential indices, this study embraces a holistic approach to model fit evaluation, providing a well-rounded perspective on this intricate terrain.

5.5.10 Hypothesis Testing

Structural equation modelling (SEM) is a widely employed tool and method used by researchers to investigate and evaluate hypotheses. It is noteworthy that SEM comprises two distinct components: covariance-based SEM (CB-SEM) and partial least squares SEM (PLS-SEM). PLS-SEM is a modelling approach that emphasises the optimisation of explained variance within latent constructs (Hair et al., 2013). A notable distinction between PLS-SEM and CB-SEM lies in their respective objectives. PLS-SEM focuses on replicating the covariance matrix while placing less emphasis on highlighting dissimilarities (Hair et al., 2013). The primary objective of this study was to employ CB-SEM as the methodology for assessing the proposed hypotheses. The process of validating these hypotheses is dependent on the convergence of estimates, critical ratios (t values), and critical values (p values) to substantiate the evaluation procedure. To thoroughly evaluate the proposed model, we employ the SmartPLS 4 platform. However, there is also an opportunity for a scholarly discussion that considers the perspectives of both confirmatory factor analysis (CFA)-based structural equation modelling (SEM) and partial least squares (PLS) SEM. Both paradigms possess distinct advantages. Partial least squares structural equation modelling (PLS-SEM) is a statistical technique that emphasises the maximisation of variance, whereas covariance-based structural equation modelling (CB-SEM) aims to replicate covariance patterns. This engenders a discourse regarding the merits of these entities and the contexts in which they are most appropriate. The use of SEM as a means of hypothesis testing serves to underscore the methodology employed in this study. The differentiation between CB-SEM and partial least squares structural equation modelling contributes to the scholarly rigour of the study, placing particular emphasis on CB-SEM in accordance with the research goals. However, when comparing these SEM paradigms, it prompts reflection on the methodology employed. This study situates itself within the broader academic discourse.

5.5.11 Participant Feedback

Feedback from the 30 participants in the pilot study provided valuable insights into critical aspects of the survey, including its length, language, layout, and time allocation, directly contributing to improvements in the main survey. Participants, representing a diverse group of online consumers—including students, professionals, and individuals across various generational categories—offered detailed feedback through face-to-face interactions and email correspondence. Their feedback was instrumental in refining the survey to enhance its clarity, usability, and alignment with the research objectives.

Key Contributions to Survey Improvements:

Question Clarity and Language Refinement: Participants highlighted ambiguities in the wording of some survey items. For instance, technical terms such as "smart retail technologies" and "digital well-being" were identified as potentially confusing. Based on this feedback, these terms were either simplified or accompanied by brief explanations to ensure that the participants fully understood the questions, thereby reducing the risk of misinterpretation.

Adjustment of Survey Length and Time Allocation: Feedback revealed that the initial survey was perceived as overly lengthy, leading to participant fatigue and a potential decline in response quality. Redundant or non-essential questions were removed, and the survey was streamlined to focus on the core constructs of trust, privacy concerns, satisfaction, and e-loyalty. This adjustment reduced the estimated completion time, ensuring that the survey was engaging and manageable for respondents.

Improved Layout and Logical Flow: Participants noted that the original survey structure disrupted the logical flow of questions. For example, items addressing post-purchase behaviours appeared earlier than those focusing on pre-purchase factors. The survey layout was restructured to follow a chronological sequence aligned with the consumer journey (pre-purchase, purchase, post-purchase), providing a more intuitive and cohesive experience for respondents.

Revised Measurement Scales: Inconsistencies in the response scales were identified, particularly in terms of balance and granularity. For example, some Likert-type scales lack neutral options or evenly distributed response categories. These scales were revised to ensure uniformity and adherence to best practices in survey design, thereby improving the reliability and validity of the collected data.

Enhanced Usability and Accessibility: Participants flagged technical issues with the online survey platform, such as difficulties navigating between sections and unclear instructions for multi-part questions. In response, the survey interface was enhanced with clear instructions, simplified navigation, and the inclusion of progress indicators to improve usability and reduce drop-off rates.

Tailoring to Cultural and Contextual Relevance: Participants provided feedback on the cultural and contextual relevance of certain examples and scenarios presented in the survey. Adjustments were made to align these elements with the retail environment in the UK to ensure greater relevance and relatability for the target audience.

Demographic and Screening Questions: The pilot study underscored the importance of screening respondents for eligibility and collecting demographic data to ensure representativeness. Screening questions were added to confirm that the participants were active users of smart retail technologies, thereby enhancing the reliability of the sample. The pilot study facilitated an iterative feedback loop in which insights from the participants were used to dynamically refine the survey instruments. This process ensured that the final survey was not only clear and user-friendly, and aligned more closely with participants' real-world experiences within the smart retailing ecosystem. By integrating participant feedback, the main survey achieved greater precision, reliability, and validity in capturing data relevant to the study objectives.

Impact on the Main Survey: The feedback from the pilot study was pivotal in addressing potential weaknesses in the survey design and ensuring accurate measurement of the constructs under investigation. The improvements made as a result of this feedback enhanced participant engagement, reduced the likelihood of misinterpretation and increased the overall quality and reliability of the data collected, thus strengthening the foundation for the study's empirical analysis.

5.5.12 Pilot Limitation

Despite the comprehensive nature of the pilot study, it is crucial to acknowledge certain limitations encountered during its execution. One limitation pertains to the absence of representation from Generation Z among the participants. While efforts were made to include a diverse group, the lack of Generation Z respondents could impact the generalizability of the findings, particularly given the focus on smart retailing. Additionally, while Cronbach's alpha values indicate good internal consistency for most constructs, the slightly lower value for the digital well-being construct indicates room for improvement. I approach the findings with an awareness of these limitations and consider them in the broader context of the study.

5.6 Ethical Consideration

Ethical considerations serve as the foundation upon which the code of ethics is constructed, a notion emphasised by Collis and Hussey (2014). Human subject research is a domain in which ethical imperatives exert substantial influence. Researchers in this ethical domain bear the delicate responsibility of addressing issues such as harm prevention, voluntary engagement, confidentiality preservation, and privacy safeguards (Collis and Hussey, 2014). This study has unwaveringly adhered to these ethical principles.

Before embarking on data collection, the study rigorously upheld ethical standards. Essential ethical clearances were diligently obtained, laying the foundation for a research journey marked by integrity. Participants were comprehensively briefed on the study's objectives and their pivotal role, aligning with the fundamental principle of informed and voluntary participation. Importantly, the voluntary nature of participation was underscored, granting participants the autonomy to withdraw at any point. This underscores the commitment to respecting participants' autonomy. The meticulous effort to safeguard participants' anonymity and confidentiality underscores the conscientiousness embedded within this ethical framework, which aligns with the guidelines set by the Brunel University Ethics Committee. It is notable that compliance with this committee's stipulations necessitates the submission of a document bearing both student and supervisor signatures to the Academic Programme Administration. The ethical journey further intersects with the procedural guidelines outlined in Brunel Research Ethics Online (BREO), which delineate the protocols for ethical approval diligently observed in this study.

A participant information sheet was judiciously provided to the participants, outlining the study objectives. Importantly, the study's ethical commitment extended beyond documentation, including briefing calls and extensive email communication to ensure participants' full comprehension. As the study transitioned into the survey phase, ethical protocols were rigorously upheld. Both verbal and written consents were meticulously obtained, embodying the study's commitment to ensuring consent from the participants. In parallel, field notes were carefully documented to maintain transparency in the research process. Moreover, policy documentation was diligently reviewed, reflecting the ethical diligence inherent in this study. However, within the field of ethical considerations, a comparative perspective is essential.

The study's ethical adherence can be juxtaposed with alternative ethical frameworks, potentially enriching the discourse on ethical research practices. In sum, the ethical path explored by this study attests to a resolute commitment to ethical principles. This ethical fabric underscores the researcher's respect for participants, dedication to transparency, and thorough adherence to ethical guidelines. Nevertheless, a comparative viewpoint could unveil diverse ethical nuances inherent in various research paradigms.

Chapter 6: Data Analysis

This chapter offers a comprehensive overview of the analysis and findings of this research, gleaned through the varied analytical methodologies discussed in the preceding chapter. Within this framework, an in-depth analysis of the results is presented to illuminate a deeper understanding of the digital or smart consumer experience within smart retail settings, alongside the consequences stemming from the use of smart technology-themed products and services on consumer behaviour. A total of 510 respondents were included in this study, their distribution spanning diverse demographic categories encompassing gender, age, educational attainment, and generational cohorts delineated by year of birth. Employing SPSS 26.0 (statistical analysis software) and SmartPLS 4, the dataset was scrutinised to unveil its insights. The initial phase of the analysis focused on preliminary screening and data management. This involved checking for any missing data or common measurement errors and evaluating aspects such as normality, homoscedasticity, and multicollinearity. Subsequently, descriptive statistics pertaining to the various constructs within the model were presented, employing formats such as frequency distributions, percentages, and graphical representations. The next step encompassed a thorough evaluation and discussion on the validity and reliability of the measurement scales. Following this, an exploratory and confirmatory factor analysis (EFA and CFA) was conducted, thus enriching the theoretical framework. In succession, a meticulous assessment involving structural equation modelling (SEM) was executed to either confirm or refute the hypothesised relationships. This rigorous analysis explored the intricate interplay between smart technology-themed products and their influence on consumer behaviour, as well as the assimilation of the digital consumer experience in smart retail settings. In conclusion, the robustness of the findings was fortified by conducting thorough validation checks, thus ensuring the reliability of the result.

6.1 DATA MANAGEMENT

To test the relationships (hypotheses) introduced in the study model in Figure 1, an online-based questionnaire was developed to collect quantitative data from the United Kingdom (UK). The data collection process transpired from May 2022 to February 2023, a timeframe that coincided with the implementation of comprehensive restrictions mandated by the UK government. These measures were a response to the pervasive prevalence of the COVID-19 virus. Within this context, the judicious selection of an online-based questionnaire as the instrument for data acquisition emerged as a fitting strategy. This choice was particularly relevant given the prevailing constraints such as travel limitations, widespread lockdowns, and the imperative of observing social distancing protocols within the country. These measures were strategically deployed to mitigate the transmission of the COVID-19 pandemic. The Jisc online survey platform was employed as the medium for formulating and administering the web-based questionnaire.

The primary aim of the study was explained to the respondents right from the onset of the questionnaire, accompanied by a categorical assurance of the confidentiality that would enshroud their responses. The recruitment of participants for this study hinged on the strategic utilisation of both snowball and convenience sampling techniques. To ensure the inclusion of individuals who possessed familiarity with smart retailing products and services in the UK, a preliminary screening question was thoughtfully incorporated at the inception of the questionnaire. This methodological step was meticulously undertaken to ensure the appropriateness of the study participant pool. This study employed a diverse array of multivariate analysis techniques, utilising a total of 28 items to gauge the nuances of the 9 constructs intrinsic to the theoretical model. Moreover, adherence to established guidelines, as recommended by Hair, Black and Babin, (2010), was rigorously observed. This encompassed the requirement of acquiring 10 responses for each individual item, in tandem with a stipulated minimum sample size of 360 respondents.

The online questionnaire was disseminated through a strategic dissemination approach in alignment with contemporary practises. This encompassed the sharing of the survey link across prominent social media platforms such as Facebook, LinkedIn, WhatsApp, and Telegram. Furthermore, the survey link was distributed via email channels, primarily targeting participants from Brunel University to over 1600 potential participants. This outreach effort yielded a total of 565 questionnaires returned by respondents. However, a comprehensive examination of the returned questionnaires revealed that 55 of the returned questionnaires were incomplete due to missing information. Consequently, these questionnaires were deemed unsuitable for inclusion and were subsequently excluded from the data analysis. This discerning approach culminated in a refined pool of 510 questionnaires that exhibited the requisite completeness and validity necessary for thorough data analysis.

6.1.1 Data Preparation

Accurate and effective data preparation is an essential step in any survey, as it can significantly impact, positively or negatively, the quality and accuracy of the data analysis produced. Pérez et al. (2015) assert that the data preparation phase can be structured in a variety of ways to facilitate efficient and effective data analysis to ensure that the data is complete, consistent, and error-free. Prior to data entry, the first phase of data preparation necessitates editing of the questionnaire before any data entry is made. Even though the survey was administered online with systematic rules that prevented participants who were not qualified for the study and to minimise unanswered questions, the collected data were double-checked for completeness. This step was crucial to ensuring that all necessary data was captured and minimising any missing or incomplete responses. Following the editing of the questionnaire, coding and data entry were performed using the computer-based programme Statistical Package for Social Sciences (SPSS). All variables and related items were coded to facilitate quicker grouping and analysis of the gathered data for the study. The questionnaire coding enabled seamless transfer of data from the online database to Excel and SPSS statistical software. The coding process is also essential for ensuring that data is accurately and consistently labelled, making it simpler to interpret and analyse. This stage of data preparation further identifies any potential data entry errors, such as misinterpretation, which can affect the accuracy of the final data analysis. In a broad sense, data preparation is a crucial step in any survey as it ensures that the collected data is complete, accurate, and easily analysed. By following a structured approach to data preparation, researchers can produce high-quality results that provide valuable insights into the studied topic.

6.1.2 Missing Data

In research, handling missing data is a common challenge that can significantly impact the outcomes of data analysis, often complicating the task of drawing precise conclusions. (Hu and Bentler (1999) hold the view that this challenge becomes more complex when using structural equation modelling (SEM) because it requires complete data to accurately calculate fit measures such as the chi-square, goodness-of-fit index, and modification indices. Schumacker and Lomax (2004), in agreement, recommend managing missing data effectively when conducting research to ensure the validity and reliability of the analysis and results. It is a widely held view that, regarding the issue of missing data, the study needs to determine the nature and pattern of the missing values to evaluate how the absence of this data may affect the accuracy and applicability of the research findings. Many scholars hold the view that if the missing values are randomly distributed, it is reasonable to assume that the missing data are missing at random, meaning that they are missing by chance and not due to an underlying pattern. In such cases, the data may be safely disregarded. However, if the missing data are not randomly distributed, it can lead to biassed results and reduce the generalizability of the findings. Schumacker and Lomax (2004) hold the view that up to 5% of the missing data is acceptable. Drawing upon prior discussions on the significance of missing data, this study utilised the SPSS missing value analysis approach employing the Expectation-Maximisation (EM) methodology. The findings indicate that no missing data was detected at either the item or construct level. Therefore, there was no necessity to analyse the patterns or implement any solution to address the issue of missing data. These findings indicate that the questionnaire was comprehensible and relevant to the subsidiary's specific situation.

6.1.3 Test of Normality

In quantitative studies, assessing normality is a fundamental step in the analysis of both univariate and multivariate experimental datasets. Hair et al. (2013) held the view that the test for normality of the dataset holds a pivotal significance and serves as a fundamental tool for assessing the distribution characteristics of research variables. Shapiro-Wilk and Kolmogorov-Smirnov tests were used to evaluate the distribution of variables in the research datasets for this study, as recommended in extant literature (Hair *et al.*, 2013). The results of these assessment are presented in *Table 30* and *Table 31* below. The findings strongly show that all variables successfully passed both the Kolmogorov Smirnov and Shapiro Wilk assessments. This result can be attributed to aspects, including the sample size utilised in the research, which involved 510 participants. It's worth noting that these evaluations are more dependable, for sample sizes of over 200 individuals (Hair *et al.*, 2013). Hence, it's crucial to grasp that these test outcomes do not indicate a deviation, from the data distribution (Hair *et al.*, 2007).

Table 30: Tests of Normality - (Kolmogorov and Shapiro test)

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Perceived Privacy Concerns	.140	510	<.001	.903	510	<.001
Perceived Fairness	.103	510	<.001	.973	510	<.001
Perceived Risk	.093	510	<.001	.967	510	<.001
Trust	.124	510	<.001	.979	510	<.001
Smart Shopping Experience	.094	510	<.001	.964	510	<.001
Smart Satisfaction	.104	510	<.001	.977	510	<.001
Purchasing Behaviour	.145	510	<.001	.927	510	<.001
E-Loyalty	.079	510	<.001	.975	510	<.001
Digital Well-being	.138	510	<.001	.972	510	<.001

a. Lilliefors Significance Correction

Table 31 presents insights regarding the distribution properties of the variables in the dataset based on skewness and kurtosis values. The variable "perceived privacy concern" exhibits a slight imbalance, as indicated by its skewness value of approximately 0.956. Moreover, its kurtosis value of 0.768 signifies that its distribution exhibits platykurtosis. The variable representing "perceived fairness" exhibits a negative skew of approximately 0.178, indicating a marginal leftward imbalance. Furthermore, the kurtosis value of 0.361 indicates an alternative distribution. The variable representing "perceived risk" exhibits a skewness of 0.521 and a kurtosis value in proximity to zero, indicating that its distribution closely approximates that of a normal distribution. The trust variable displays a marginally negative skewness of approximately 0.134 and a kurtosis value of 0.494, collectively indicating that its distribution is marginally leptokurtic. The variable "smart shopping experience" exhibits a negative skewness of approximately 0.468 and a kurtosis near zero, indicating that its distribution is approximately normal. The variable representing "smart satisfaction" exhibits a negative skewness of approximately 0.200 and a kurtosis of 0.651, indicating that its distribution is marginally leptokurtic. In conclusion, the kurtosis and skewness values of 1.421 and 0.856, respectively, for the variable "intentions," indicate that this variable has heavier tails in its leptokurtic distribution. The distribution of "E Loyalty" exhibits a skewness value of approximately 0.119 and a kurtosis of 0.594, indicating a platykurtic shape to some degree. Conversely, the variable associated with "digital well-being" exhibits a marginally leptokurtic distribution, as evidenced by its kurtosis value of 0.454 and a small negative skew of approximately 0.368. In sum, measurements of skewness and kurtosis offer valuable insights into the configuration and properties of data distributions. Skewness measures facilitate researchers in comprehending the distribution of variables; negative skewness signifies a skew, whereas positive skewness signifies an opposite skew. Kurtosis values exceeding 3 signify distributions characterised by heavier tails, whereas values below 3 denote platykurtic distributions characterised by lighter tails. From a practical standpoint, the ability to determine whether a dataset exhibits leptokurtosis or not provides statisticians and data analysts with insights into the data's characteristics and variability. Frequently, leptokurtic distributions indicate the presence of outliers or more extreme values in the data, which can be crucial when developing hypotheses or decisions.

Table 31: Tests of Normality - (Skewness and Kurtosis test)

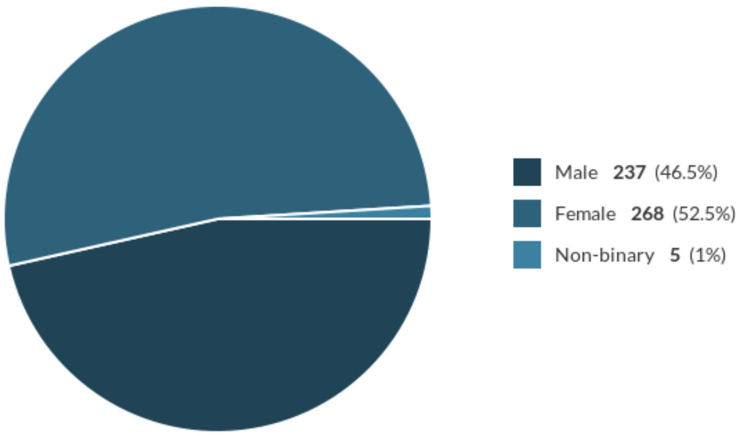
Tests of Normality - (Skewness and Kurtosis test)

	Skewness	Kurtosis
Perceived Privacy Concerns	- .956	.768
Perceived Fairness	-.178	-.361
Perceived Risk	-.521	-.011
Trust	-.134	.494
Smart Shopping Experience	-.468	.010
Smart Satisfaction	-.200	.651
Purchasing Behaviour	-.856	1.421
E-Loyalty	.119	-.594
Digital Well-being	-.368	.454

6.1.4 Sample Profile

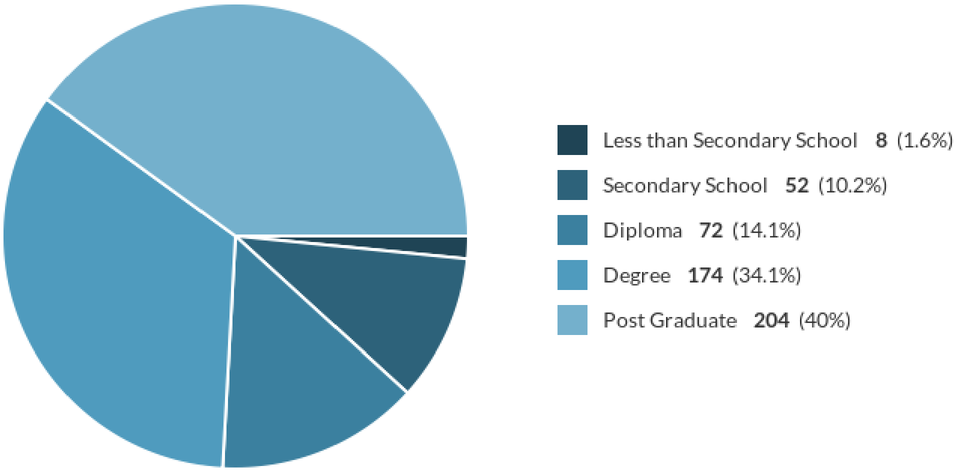
This section presents and discusses an analysis of the statistical categories from both descriptive and inferential perspectives. Scholars (Hair et al., 2010) use descriptive statistics, such as frequencies, percentages, and means, to characterise and summarise sample data. In contrast, (Hair et al., 2007, 2010) recommended exploring the relationships between variables using inferential statistics, including correlations. This study investigates perceived privacy concerns, perceived fairness, and perceived risk in relation to consumer trust. It then examines how consumer trust influences their smart shopping experience, as well as how this experience impacts smart satisfaction and purchase behaviour. In addition, this study explores how smart satisfaction affects purchasing habits, e-loyalty, and digital well-being. This thesis scrutinises all these aspects within the context of active online consumers involved in smart technology-embedded retail environments via the prism of affordance theory. The sample data consists of individuals aged 18 years or older who have engaged in online shopping or used smart retail technologies. To ensure the convenience and accuracy of the data sample in representing the entire population, participants from diverse generational cohorts, educational backgrounds, and genders were considered. A thorough analysis of the sample profile data revealed substantial representation across various demographics, including gender, age, education level, and ethnicity. We conducted a comprehensive self-administered survey with 510 participants, primarily UK-based consumers, to gain a profound understanding of active online consumers' perceptions of affordance related to smart technology-integrated retailing and online shopping. *Figure 24* shows the distribution of survey participants, comprising 52.5% females, 46.5% males, and 1% non-binary.

Figure 24: Gender of respondents



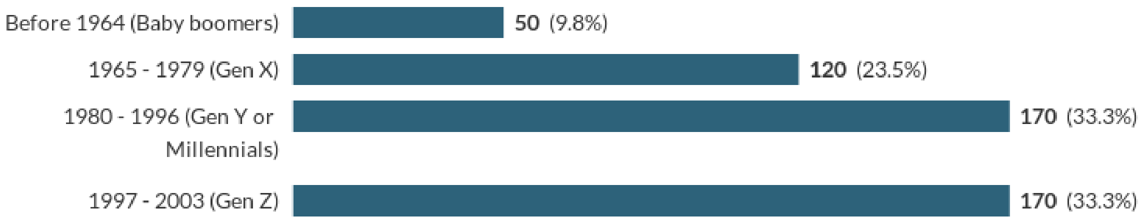
Furthermore, most of the research participants, accounting for 74.1%, held university degrees, with 40% holding postgraduate degrees and 34.1% possessing undergraduate degrees. In addition, 14.1% of the participants held diplomas, whereas 10.2% had secondary school-level education. A minor fraction comprising 1.6% of the research participants reported either no formal education or dropping out before completing secondary school, as shown in *Figure 25*.

Figure 25 : Level of Education



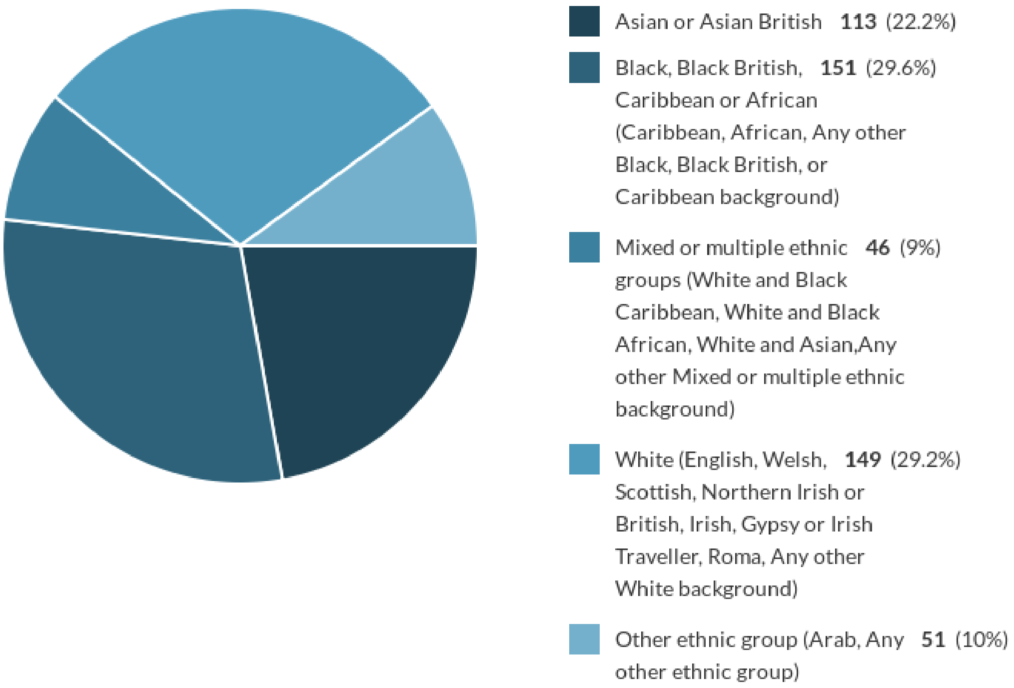
The sample size for the study was deemed appropriate based on Saunders, Lewis, and Thornhill (2009) to provide reliable data and insights into the subject matter. By focusing on UK-based online consumers, the study captured the perception of a population that is highly engaged in smart technology-embedded retailing and online shopping, as the UK is one of the most technologically advanced nations in the world. In terms of generational cohorts, 33.3% of the research participants were from Generation Z born between 1997 and 2003. Similarly, Generation Y or Millennials born between 1980 and 1996 comprised 33.3%, while Generation X born between 1965 and 1979 accounted for 23.5%. Baby boomers and the prior generations represented 9.8% of the sample in *Figure 26*.

Figure 26: Respondents year of birth



As further shown in Figure 27, ethnicity of the sample distribution consists of Asian or Asian British, representing 22.2%, Black, Black British, Caribbean or African (Caribbean, African, Any other Black, Black British, or Caribbean background) 29.6%, Mixed or multiple ethnic groups (White and Black Caribbean, White and Black African, White and Asian, Any other Mixed or multiple ethnic background) 9%, followed by White (English, Welsh, Scottish, Northern Irish or British, Irish, Gypsy or Irish Traveller, Roma, Any other White background) who represent 29.4% and 9.9% represented Other ethnic group (Arab, Any other ethnic group).

Figure 27: Ethnicity of respondents



The survey encompassed a broad spectrum of digital ethics topics, including perceived privacy concerns, perceived fairness, and key behavioural factors such as perceived risk, trust, smart shopping experience, satisfaction, purchasing behaviour, e-loyalty, and digital well-being in the context of smart retailing (Lu and Yi, 2023; Lu, He and Ke, 2023). To enhance representativeness and ensure a comprehensive understanding of the target population, participants were intentionally selected from diverse generational cohorts, educational backgrounds, genders, and ethnic groups (see *Table 32*).

The high percentage of respondents holding postgraduate degrees (40%) can be attributed to the purposive sampling strategy employed in this study. Given the study's focus on advanced smart retailing technologies and digital affordances, it was imperative to include respondents with higher levels of education who are more likely to engage deeply with and critically assess these technologies (McLean and Wilson, 2019). Research indicates that individuals with postgraduate education often possess greater exposure to technological innovations and are better equipped to evaluate complex digital systems, making them ideal candidates for a study of this nature (Gefen et al., 2003). Moreover, the inclusion of highly educated respondents ensures that the insights gained are reflective of informed consumers who are key drivers of smart retail adoption. However, this study acknowledges that this demographic skew towards postgraduate qualifications may limit the generalisability of the findings to less-educated populations. To mitigate this limitation, the study also included a significant proportion of respondents with lower educational levels, ensuring diversity across other demographic variables such as age, gender, and ethnicity (Kumar and Kashyap, 2018; Kumar, Ramachandran and Kumar, 2021). In addition to education level, the purposive sampling strategy ensured representation across generational cohorts (Baby Boomers, Gen X, Millennials, and Gen Z) and ethnic groups. This approach was designed to capture a broad range of consumer experiences with smart retail technologies, enhancing the depth and relevance of the insights (McLean, Osei-Frimpong and Barhorst, 2021).

Table 32: Demographic variables

		Count	Percentage (%)
What is your year of birth?	Before 1964 (Baby boomers)	50	9.8%
	1965 - 1979 (Gen X)	120	23.5%
	1980 - 1996 (Gen Y or Millennials)	170	33.3%
	1997 - 2003 (Gen Z)	170	33.3%
What is your gender?	Male	237	46.5%
	Female	268	52.5%
	Non-binary	5	1.0%
What is your Highest Educational Level?	Less than Secondary School	8	1.6%
	Secondary School	52	10.2%
	Diploma	72	14.1%
	Degree	174	34.1%
	Postgraduate	204	40%
What is your Ethnicity?	Asian or Asian British	113	22.2%
	Black, Black British, Caribbean or African (Caribbean, African, Any other Black, Black British, or Caribbean background)	151	29.6%
	Mixed or multiple ethnic groups (White and Black Caribbean, White and Black African, White and Asian, Any other Mixed or multiple ethnic backgrounds)	46	9%
	White (English, Welsh, Scottish, Northern Irish or British, Irish, Gypsy or Irish Traveller, Roma, Any other White background	149	29.2%
	Other ethnic group (Arab, Any other ethnic group)	51	10%

Source; SPSS Output, 2023.

6.1.4 Sample Profile

The data reveal that 40% of the survey participants hold postgraduate degrees, a significantly high proportion that warrants further analysis. This demographic characteristic may result from various factors related to participant recruitment, context, and the nature of the survey topic. The factors include the following:

Participant Recruitment Channels: The survey was disseminated through multiple channels, including the JISC platform, Brunel University networks, WhatsApp, email, and LinkedIn. A substantial proportion of participants were recruited from Brunel University, where postgraduate education is prevalent. University-affiliated networks inherently attract individuals with higher education levels, including current students, alumni, and staff, many of whom hold postgraduate qualifications. The professional nature of platforms like LinkedIn may also have contributed to the high percentage of postgraduate participants, as users of this platform are often professionals or academics with advanced qualifications.

Self-Selection Bias: The voluntary nature of survey participation introduces self-selection bias, where individuals with a strong interest in smart retailing technologies or academic research may be more inclined to participate. Such individuals are more likely to possess higher educational qualifications, contributing to the over-representation of postgraduate respondents.

Geographical Context and National Trends: The study's UK focus is also relevant. The UK has a high proportion of individuals with tertiary education, especially in urban areas where internet use and technology adoption are more widespread. National statistics show that 16% of the UK adult population holds a postgraduate degree, which, while smaller than the survey percentage, reflects a broader trend of educational attainment in the country (Office for National Statistics, 2023).

Survey Content and Relevance: The focus on smart retailing technologies, a relatively niche and sophisticated topic, may have disproportionately appealed to individuals with advanced educational backgrounds. Postgraduates and professionals with an interest in technology, retail, or consumer behaviour were likely drawn to the survey, further skewing the sample composition.

Brunel University's Role in Recruitment: A significant proportion of participants were recruited through Brunel University networks, where postgraduate students and alumni are prominent. This reliance on university-affiliated networks inevitably shaped the demographic profile of the sample.

6.1.5 Descriptive Statistics

Descriptive statistics encompass three essential indicators: frequency distribution, central tendency calculation, and distribution measurements. In this analytical phase, all statistical measures were applied. To ensure uniformity in measurement across the survey items, a descriptive statistic was employed. Each measurement item was evaluated on a 7-point Likert scale, where a score of 7 represented strong agreement and 1 indicated strong disagreement. As detailed in the *Table 33*, the descriptive statistics of various dimensions within the context of consumer behaviour toward smart retailing were explored. The dataset comprises responses from 510 participants. The mean, standard deviation, and standard error were computed for each dimension, providing insights into the central tendency, variability, and precision of the collected data.

Starting with the construct "perceived privacy concerns," the survey respondents demonstrated an average score of 5.62, indicating a moderate level of apprehension regarding privacy issues within the smart retailing landscape. The relatively low standard deviation of 1.25 indicates a degree of consistency in the responses, signifying a shared level of concern. This interpretation is supported by a narrow standard error of 0.05536. Shifting the focus to "perceived fairness," the mean score was 3.69, reflecting a moderately positive perception of fairness within smart retail contexts. With a standard deviation of approximately 1.37, there is some variability in responses, indicating diverse opinions on fairness. Nevertheless, the standard error of 0.06057 underscores the reliability of this finding. Examining the dimension of "perceived risk," respondents reported an average score of 4.70, signifying a moderate level of perceived risk associated with smart retailing. The standard deviation of 1.37 indicates variation in responses, indicating diversity in the extent of perceived risk. The standard error of 0.06052 emphasises the stability of this result. In the context of the "trust" construct, participants expressed a mean score of 4.21, reflecting a moderate level of trust in smart retailing platforms, services, or products. The relatively low standard deviation of 1.05 indicates a consistent level of trust among respondents, thereby reaffirming uniformity. The standard error of approximately 1.05141 further substantiates this observation. Turning to "Smart Shopping Experience," the mean score is 4.97, denoting a moderately positive perception of the overall shopping experience in smart retailing. With a standard deviation of approximately 1.28, there is some variability in responses, signifying that while the general sentiment is favourable, opinions differ. The standard error of approximately 1.28199 is consistent with this observation. Focusing on "Smart Satisfaction," respondents reported an average score of 4.65, signifying a moderately high level of satisfaction within smart retailing. The low standard deviation of 0.92 implies that the responses were relatively consistent. The standard error of approximately 0.04082 reaffirms the stability of this finding. Concerning "purchase behaviour," the mean score is approximately 5.59, indicating a positive inclination towards future purchases within the smart retailing landscape. With a standard deviation of approximately 1.06, there is a degree of variation in the responses. Nevertheless, the standard error of 0.04674 underscores the reliability of this result.

In terms of "e-loyalty," the mean score was 3.61, indicating a moderate level of e-loyalty among participants. A standard deviation of approximately 1.51 indicates diversity in responses, signifying varying levels of e-loyalty sentiment. The standard error of 0.06683 accentuates this diversity. Finally, the dimension "Digital Wellbeing" portrays an average score of 4.32, implying a moderately positive perception of digital well-being within the smart retail context. The standard deviation, approximately 1.21, indicates some variability in responses, indicating that while the general sentiment is positive, there are differing degrees of agreement. The standard error of approximately 0.05351 is consistent with this observation.

In summary, these descriptive statistics provide a comprehensive understanding of participants' perspectives on various dimensions of consumer behaviour in smart retailing. The consistent application of mean, standard deviation, and standard error measures facilitates a nuanced interpretation of the data, elucidating both common trends and divergent viewpoints among respondents. These findings are significant within the study's objectives and have implications for the broader field of consumer studies and smart retailing strategies.

Table 33:Descriptive Statistics

Descriptive Statistics

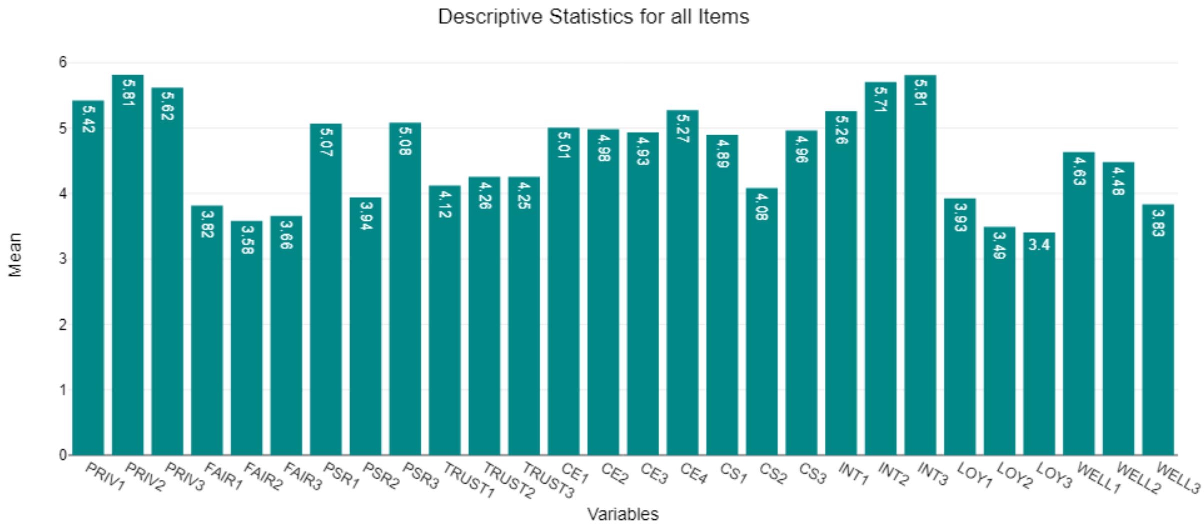
	N	Minimum	Maximum	Mean		Std. Deviation
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic
Perceived Privacy Concerns	510	1.00	7.00	5.6183	.05536	1.25030
Perceived Fairness	510	1.00	7.00	3.6850	.06057	1.36796
Perceived Risk	510	1.00	7.00	4.6967	.06052	1.36663
Trust	510	1.00	7.00	4.2118	.04656	1.05141
Smart Shopping Experience	510	1.00	7.00	4.9739	.05677	1.28199
Smart Satisfaction	510	1.33	7.00	4.6471	.04082	.92176
Purchasing Behaviour	510	1.00	7.00	5.5915	.04674	1.05544
E-Loyalty	510	1.00	7.00	3.6065	.06683	1.50930
Digital Well-being	510	1.00	7.00	4.3150	.05351	1.20850
Valid N (listwise)	510					

Furthermore, descriptive statistics were systematically employed to comprehensively assess all items in the dataset. *Table 60* in appendix while, summarises key statistical metrics, including the standard deviation (SD), mean, and variance, for each item and *Figure 28* presents the mean for all items. Examination of these descriptive statistics revealed intriguing patterns that warrant in-depth exploration. It is significant that the computed means (M) for all items consistently exceeded the critical threshold of 2. This observation holds significant relevance within the context of this study, signifying the prevalence of noteworthy trends in participants' responses. This uniformity in mean values across items serves as an initial indicator of the robustness of the data and the commonalities in participant perspectives. This indicates a coherent alignment in the evaluation of these constructs.

Moreover, a compelling observation arises from the analysis of standard deviations (SD). Several items exhibited low SD values, indicating tight clustering of data points around the respective means. This clustering implies that a substantial proportion of respondents voiced similar sentiments, signifying a remarkable convergence of viewpoints among participants. This alignment affirms the consistency of their perceptions and evaluations.

In the context of reliability, an in-depth assessment was conducted to fortify the credibility of the findings. Each item exceeded the conventional benchmark of 0.7 for Cronbach's alpha (α), indicating a commendable level of internal consistency, as prescribed by established guidelines (Hair *et al.*, 2007). A notable number of items even surpassed the 0.8 threshold, underscoring a high level of reliability, while others exceeded 0.9, a testament to their exceptional reliability. This rigorous evaluation of reliability accentuates the stability and consistency of the measurement instruments employed, significantly enhancing the overall trustworthiness of the study findings. The cumulative impact of these statistical values underscores an internal consistency ranging from satisfactory to exceptionally high. This harmonious convergence of respondent perspectives, coupled with stable construct measurement, substantially bolsters the validity of the study findings. As the research progresses, the analytical focus will shift towards exploratory factor analysis. This next phase seeks to unveil the latent dimensions or constructs underlying the measured variables, thus providing a deeper and more nuanced understanding of the phenomena under investigation. By exploring the interrelationships among these variables, this analytical approach aims to align them with the theoretical framework guiding this research, further enriching our understanding of the complex web of factors at play.

Figure 28: Mean for all items.



6.1.6 Outliers and Treatments

Outliers are data points that deviate significantly from the typical range of values (Hair JR *et al.*, 2010; Hair *et al.*, 2013). They can be either extremely high or low and can disrupt the assumption of data normality (Hair *et al.*, 2013). Outliers are typically categorised as univariate and multivariate outliers. Univariate outliers represent cases in which a single variable exhibits extreme values that deviate from the expected population values (Grubbs, 1969). In contrast, multivariate outliers involve cases with unusual combinations of scores on at least two variables (Varmuza and Filzmoser, 2016). To identify and address outliers in the dataset, both multivariate and univariate methods were employed. The Mahalanobis distance (D^2) was used to detect multivariate outliers. D^2 is a common measure for identifying multivariate outliers and involves calculating the distance between a distribution and a data point. If a case has a D^2 value greater than the critical value, which is determined from a chi-square distribution table (Dattalo, 2013), it is considered a multivariate outlier. In this analysis, no multivariate outliers were detected. Subsequently, univariate outliers were assessed by examining the Z-scores. To prepare for this analysis, all data values were standardised. Univariate outliers were identified based on standard Z-scores, typically within the range of +3.29 to -3.29 (Field, 2017). *Table 34* provides an overview of the standard scores for each construct in the dataset.

Table 34:Construct's Standard Scores

	Z Scores		
Construct	**N**	**Minimum**	**Maximum**
Perceived Privacy Concerns	510	5.6183	1.00
Perceived Fairness	510	3.6850	1.00
Perceived Risk	510	4.6967	1.00
Trust	510	4.2118	1.00
Smart Shopping Experience	510	4.9739	1.00
Smart Satisfaction	510	4.6471	1.33
Purchasing Behaviour	510	5.5915	1.00
E-Loyalty	510	3.6065	1.00
Digital Wellbeing	510	4.3150	1.00

These Z-scores illustrate the standardisation of values for each construct, and several constructs have extreme values that deviate significantly from the mean. In this analysis, a robust partial least squares (PLS) approach was employed to mitigate the impact of outliers (Schamberger *et al.*, 2020). Robust PLS, introduced by Dijkstra and Henseler (2015), is particularly useful for analysing data that contains outliers. It is considered a reliable method for addressing the influence of outliers and ensuring the robustness of statistical analysis. This approach was chosen to maintain data integrity and avoid potential information loss resulting from the removal of outliers, which is not always a recommended practice. The evaluation of Pearson correlation estimates is crucial in this context. Pearson correlation is renowned for its susceptibility to outliers, as even a single outlier can significantly distort the correlation estimate (Yuan and Bentler, 1998; Schamberger *et al.*, 2020). It is important to note that, apart from Pearson, Spearman's and Kendall's correlation measures can also be used (Gideon, 2007). Nevertheless, for this study, the Pearson correlation is employed to derive the correlation estimate. Some estimators, like the minimum covariance determinant (MCD) and minimum volume ellipsoid (MVE), can help improve the final estimate's accuracy and lessen the effect of outliers (Schamberger *et al.*, 2020). These estimators establish a representative subsample that remains unaffected by outliers. Notably, these methods were integrated into the chosen software, SmartPLS, and applied in the final assessment. Given the potential influence of outliers on the data, this thesis has thoughtfully adopted a bootstrapping method to conduct partial least squares structural equation modelling (PLS-SEM). Bootstrapping has been introduced as a valuable technique for datasets containing outliers in PLS-SEM (Salibian-Barrera, 2005; Jen, 2021).

6.1.7 Multicollinearity Assessment

In the context of structural equation modelling (SEM), it is imperative to assess multicollinearity among latent variables before conducting the analysis. Multicollinearity arises when there are strong correlations between independent variables, potentially leading to difficulties in isolating their individual effects on the dependent variable (Hair *et al.*, 2019). Table presents the results of variance inflation factor (VIF) analysis for each construct to evaluate the presence of multicollinearity.

Table 35:VIF values for each construct in the analysis

Construct	**VIF Value**
CE1 (Smart Experience 1)	2.391
CE2 (Smart Experience 2)	2.727
CE3 (Smart Experience 3)	3.061
CE4 (Smart Experience 4)	2.366
CS1 (Smart Satisfaction 1)	1.997
CS2 (Smart Satisfaction 2)	1.307
CS3 (Smart Satisfaction 3)	2.077
FAIR1 (Perceived Fairness 1)	2.789
FAIR2 (Perceived Fairness 2)	3.346
FAIR3 (Perceived Fairness 3)	3.079

INT1 (Purchasing Behaviour 1)	1.790
INT2 (Purchasing Behaviour 2)	3.324
INT3 (Purchasing Behaviour 3)	2.798
LOY1 (E- Loyalty 1)	2.478
LOY2 (E- Loyalty 2)	4.709
LOY3 (E- Loyalty 3)	3.683
PRIV1 (Perceived Privacy concerns 1)	2.084
PRIV2 (Perceived Privacy concerns 2)	2.432
PRIV3 (Perceived Privacy concerns 3)	2.203
PSR1 (Perceived Risk 1)	1.684
PSR2 (Perceived Risk 2)	1.613
PSR3 (Perceived Risk 3)	1.668
TRUST1 (Trust 1)	1.731
TRUST2 (Trust 2)	1.871
TRUST3 (Trust 3)	1.764
WELL1 (Well-being 1)	1.563
WELL2 (Well-being 2)	1.819
WELL3 (Well-being 3)	1.533

The VIF values provide insight into the level of multicollinearity for each construct. A VIF threshold of 5 is typically used as an indicator of multicollinearity (Hair *et al.*, 2013). Notably, none of the constructs examined in this analysis exhibit VIF values exceeding this critical threshold. Therefore, the results indicate that multicollinearity is not a significant problem in this study. It is worth noting that the construct LOY2 (Loyalty) has a relatively higher VIF of 4.709. Although this value is below the critical threshold, further scrutiny of LOY2 may be necessary to comprehend the source of this multicollinearity and its potential implications for the analysis. However, it is important to reiterate that none of the constructs, including LOY2, exhibit VIF values exceeding 5, signifying that multicollinearity does not pose a substantial challenge in this study. In sum, the VIF analysis indicates that the latent variables under investigation in this study do not exhibit significant multicollinearity. This study can proceed with confidence in analysis, recognising that the relationships between constructs are not unduly influenced by multicollinearity.

6.1.8 Common method bias: errors in variable

Given the inherent risk of common method bias (CMB) in studies reliant on self-reported data from a single source, we implemented rigorous measures to mitigate this potential problem (Podsakoff *et al.*, 2003). Methodological precautions, including clear and specific question design, avoidance of ambiguous language, incorporation of multiple questions for each concept, respondent anonymity, and reduction of evaluation apprehension, were meticulously integrated into the study design. To validate the effectiveness of this study's CMB mitigation strategies, two key statistical analyses were performed. First, the Harman single-factor test assessed whether a single factor could account for the majority of variance (Podsakoff et al., 2003). The results demonstrated that the items could be categorised into 10 factors, with the highest covariance explained by a single factor at only 13.74%. This implies that CMB is not a significant concern in this study.

Second, following the approach of Liang et al. (2007), a common method factor was introduced in the partial least squares (PLS) model. We calculated the variances substantively accounted for by the principal constructs and the common method factor for each indicator. Subsequently, we examine the average variance explained by substantive constructs and the common method factor. Table 2 presents values of 0.748 and 0.008 for the substantive constructs and the common method factor, respectively. The ratio of substantive variance to method variance is approximately 93.5:1, indicating that the indicators' substantive variances significantly outweigh their method variances. Moreover, all substantive factor loadings are significant, whereas the most common method factor loadings are insignificant. These results, aligned with the findings of Liang et al. (2007), affirm that CMB is not a substantial concern in our study. The thorough design of this study, coupled with robust statistical analyses, substantiates the effectiveness of our efforts to mitigate common method bias. The findings underscore the reliability of the data collected, with the substantive variances of indicators far surpassing the method variances. Researchers can confidently interpret the study results and be assured that common method bias has been addressed and minimised in our research design.

The VIF values for each indicator, along with the variance attributed to the principal construct and common method factor, are presented in the table below.

Indicator	VIF	Variance Principal Construct	Variance Common Method Factor
CE1	2.391	0.583	0.417
CE2	2.727	0.632	0.368
CE3	3.061	0.672	0.328
CE4	2.366	0.423	0.577
CS1	1.997	0.501	0.499
CS2	1.307	0.766	0.234
CS3	2.077	0.606	0.394
FAIR1	2.789	0.358	0.642
FAIR2	3.346	0.299	0.701
FAIR3	3.079	0.325	0.675
INT1	1.790	0.558	0.442
INT2	3.324	0.301	0.699
INT3	2.798	0.357	0.643
LOY1	2.478	0.404	0.596
LOY2	4.709	0.213	0.787
LOY3	3.683	0.271	0.729
PRIV1	2.084	0.479	0.521
PRIV2	2.432	0.411	0.589
PRIV3	2.203	0.454	0.546
PSR1	1.684	0.594	0.406
PSR2	1.613	0.620	0.380
PSR3	1.668	0.599	0.401
TRUST1	1.731	0.578	0.422
TRUST2	1.871	0.535	0.465
TRUST3	1.764	0.566	0.434
WELL1	1.563	0.640	0.360
WELL2	1.819	0.549	0.451
WELL3	1.533	0.652	0.348

Note: Variance calculations follow the formula $Variance = \frac{1}{VIF}$

6.2 Reliability Assessment

The constructs examined in this study include the evaluation of perceived privacy concerns, perceived fairness, perceived risk, trust, smart shopping experience, smart satisfaction, purchasing behaviour, e-loyalty and digital well-being.

The assessment of all these constructs was conducted using multiple-item, fully anchored, seven-point, and Likert scales. The concept of reliability is of utmost importance because it involves examining the consistency of individual measurement items across multiple instances that are derived from a single source of information (Straub, 1986). Therefore, the primary focus of the initial scientific investigation is to determine the reliability of the research instrument. Before starting the data analysis process, a thorough assessment was conducted to evaluate the reliability and validity of all research instruments. In the present context, Cronbach's α and corrected item-to-total correlations are statistical measures that serve as benchmarks, facilitating the identification of potential item modifications or eliminations (Nunnally and Bernstein, 1994). Cronbach's α is a widely recognised measure used to assess the reliability of each construct, which is an essential requirement for conducting further analytical procedures. The initial items of the scale were selected with great care from pre-existing measures that have been validated in the field of information systems. These items were then adjusted to align with the specific context of smart retailing.

In accordance with the recommendations of Nunnally (1978), a minimum of three items per construct were incorporated whenever possible, thereby establishing a strong foundation for reliability. According to Nunnally and Bernstein (1994), a benchmark of 0.3 was set as the acceptable threshold for corrected item-to-total correlations. In cases where items displayed negative correlations, they were promptly excluded from further consideration. The assessment of internal consistency was conducted using Cronbach's α, a statistical measure that evaluates the correlations between items within a scale and across the entire scale. A threshold of 0.8 is widely recognised as acceptable, according to Fornell and Larcker (1981). However, Hair et al. (2006) indicated that values exceeding 0.7 and even 0.6, as proposed by Nunnally (1978), are considered satisfactory. The adequacy of the reliability coefficients, including composite reliability or Cronbach's α, for each measure was assessed using the parameters proposed by Hair et al. (2006), Nunnally (1978), and Fornell and Larcker (1981). The reliability assessment involved examining the responses obtained from a group of online consumers in the United Kingdom who participated in a survey on smart retailing, or online shopping. The survey comprised 28 items that were used to measure internal consistency and correlations between items. Likert scales were used in all cases. The Cronbach's α scores for the variables showed a significant increase, with values ranging from 0.928 to 0.961, which clearly exceeded the accepted minimum threshold of 0.7 (Hair et al., 2006). In addition, it is worth noting that all item-to-total correlation values exceeded the established benchmark of 0.3, as indicated by Nunnally and Bernstein (1994). The values listed in *Table 36* outlines the Cronbach's α scores that exceed the threshold of 0.7 (Hair et al., 2006; Bagozzi and Yi, 1988), indicating strong reliability coefficients for each variable. The comprehensive evaluation conducted demonstrates a significant level of reliability across the variables, which is crucial for the subsequent stages of analysis. Within the field of social science research, which is known for its efforts to quantify abstract concepts such as intention, behaviour, satisfaction, and enjoyment and trust, accurately measuring these variables continues to be an ongoing difficulty. Currently, the principle of validity assumes a prominent role as it pertains to the ability of a test to faithfully represent established knowledge (Bannister and Mair, 1968).

As discussed in previous chapter, face validity refers to the participants perceptions regarding the congruence between the questions asked and the objectives of the study. During the initial phase of the pilot study, participants expressed agreement that the questions effectively captured the intended purpose of the study. Furthermore, the establishment of content validity necessitated a meticulous evaluation of constructs by engaging with esteemed scholars in the field, who confirmed that the items in the questionnaire accurately reflected the scope of the study, as noted in previous chapter.

Table 36: The domain and items of the construct in the extant literature, factor loadings, descriptive statistics and reliabilities.

Coding	Constructs and item measurement	Factor Loading	Mean	Std. Deviation	Cronbach's alpha	
PRIV	**PERCEIVED PRIVACY CONCERNS**				**0.861**	
PRIV1	My shopping experience is more efficient when I purchase online.	0.855	5.4235	1.45564		
PRIV2	My shopping experience is more productive when I purchase online.	0.886	5.8137	1.30685		(Malhotra, Kim and Agarwal, 2004)
PRIV3	My shopping experience is smoother when I purchase online.	0.725	5.6176	1.47170		
FAIR	**PERCEIVED FAIRNESS**				**0.909**	
FAIR1	When shopping online, I feel concern that the online retailer may misinform me about their business, products and reputation.	0.819	3.8176	1.52519		
FAIR2	When shopping online, I feel worried.	0.876	3.5804	1.47820		(Martin, Borah and Palmatier, 2017)
FAIR3	When shopping online, I am concerned that my personal privacy might be misused.	0.936	3.6569	1.45728		
PSR	**PERCEIVED RISK**				**0.787**	
PSR1	When shopping online, I feel concern that the online retailer may misinform me about their	0.767	5.0667	1.53270		(Glover and Benbasat, 2010)

	business, products and reputation.					
PSR2	When shopping online, I feel worried.	0.704	3.9412	1.70417		
PSR3	When shopping online, I am concerned that my personal privacy might be misused.	0.762	5.0824	1.65404		
TRUST	**TRUST**				**0.812**	
TRUST 1	I believe that online businesses are trustworthy.	0.787	4.1235	1.26555		
TRUST 2	I believe that online businesses care about their consumers.	0.768	4.2569	1.26254		(Gefen et al., 2003)
TRUST 3	I believe that online businesses keep their promises.	0.750	4.2549	1.17008		
CE	**SMART SHOPPING EXPERIENCE**				**0.899**	
CE1	My shopping experience is more efficient when I purchase online.	0.813	5.0078	1.47005		
CE2	My shopping experience is more productive when I purchase online.	0.829	4.9804	1.42653		(Roy *et al.*, 2017)
CE3	My shopping experience is smoother when I purchase online.	0.830	4.9333	1.37886		

CE4	My shopping experience is easier when I purchase online.	0.851	5.2725	1.34231		
CS	**SMART SATISFACTION**				**0.771**	
CS1	The product received through online shopping is closed to my expectation.	0.737	4.8941	1.07323		
CS2	The product received through online shopping exceed my expectations.	0.616	4.0824	1.20293		(Roy *et al.*, 2017)
CS3	I am satisfied with the product purchased through online shopping.	0.849	4.9647	1.07239		
INT	**PURCHASING BEHAVIOUR**				**0.863**	
INT1	I intend to use online shopping more frequently in the future.	0.762	5.2588	1.29214		
INT2	I am willing to use online shopping in the near future .	0.839	5.7059	1.14033		(Roy *et al.*, 2017)
INT3	I will continue to use online shopping in the future.	0.874	5.8098	1.14778		
LOY	**E-LOYALTY**				**0.910**	
LOY1	I have a sense of belonging to my favourite online retailer.	1.083	3.9255	1.66742		
LOY2	I experience an emotional connection with my favourite online retailer.	0.826	3.4922	1.61857		(Glover and Benbasat, 2010)

LOY3	I have strong emotions towards my favourite online retailer.	0.696	3.4020	1.63496		
WELL	**WELL-BEING**				**0.776**	
WELL1	Online shopping platforms have benefited my overall digital skills.	0.674	4.6333	1.43246		
WELL2	Online shopping helps me improve the quality of life.	0.787	4.4784	1.42063		(El Hedhli et al., 2013)
WELL3	Online shopping helps me improve my social well-being.	0.737	3.8333	1.51277		

6.3 Individual Construct Analysis Reliability Assessment

In the present analysis, a comprehensive examination of a collection of constructs, including their item measurements, factor loadings, means, standard deviations, and Cronbach's alphas, is undertaken within the context of a quantitative research study. This study investigates diverse facets of online shopping behaviour, including perceived privacy concerns, perceived fairness, perceived risk, trust, smart shopping experience, smart satisfaction, purchasing behaviour, e-loyalty, and well-being. These constructs are denoted by their abbreviated labels, and a systematic exploration of each is undertaken with a focus on evaluating their reliability, item measurements, and factor loadings. In the following sections, the dependability of each item is discussed.

6.3.1 Perceived Privacy Concerns Reliability Assessment

The construct PRIV demonstrates a high level of internal consistency with a Cronbach's alpha of 0.861, surpassing the advised threshold of 0.7 as stipulated by (Hussey et al., (2023), indicating that the items within this construct are closely related and measure a common underlying concept. Factor loadings for PRIV1 and PRIV2 are substantial, indicating that these items strongly contribute to the measurement of perceived privacy concerns. However, PRIV3 exhibits a lower factor loading, which may indicate that it is a weaker indicator of the construct. The means and standard deviations for these items indicate that respondents tended to have moderate to high levels of perceived privacy concerns when shopping online, with PRIV2 having the highest mean (see *Table 37*).

Table 37: Reliability assessment for perceived privacy concerns

Construct	***Cronbach's Alpha***	***Item***	***Factor Loading***	***Mean***	***Std. Deviation***
PERCEIVED PRIVACY CONCERNS	0.861	PRIV1	0.855	5.4235	1.45564
		PRIV2	0.886	5.8137	1.30685
		PRIV3	0.725	5.6176	1.47170

6.3.2 Perceived Fairness Reliability Assessment

Cronbach's alpha for the perceived fairness construct (FAIR) is exceptionally high at 0.909, surpassing the advised threshold of 0.7 as stipulated by Hussey et al. (2023), indicating very high internal consistency reliability. This construct appears to be a robust measure of perceived fairness. Factor loadings for FAIR1, FAIR2, and FAIR3 are all quite high, with values of 0.819, 0.876, and 0.936, respectively, indicating their strong contribution to the construct. The means for these items are all close to each other, with standard deviations indicating moderate levels of concern about fairness when shopping online (see table 35).

Table 38: Reliability assessment for perceived fairness.

Item	***Factor Loading***	***Mean***	***Std. Deviation***
FAIR1	0.819	3.8176	1.52519
FAIR2	0.876	3.5804	1.47820
FAIR3	0.936	3.6569	1.45728
Cronbach's Alpha	**0.909**		

6.3.3 Perceived Risk Reliability Assessment

Cronbach’s alpha for the perceived risk construct (PSR) is 0.787, meeting the advised threshold of 0.7 as stipulated by Hussey et al. (2023), indicating acceptable internal consistency. The factor loadings are moderate, with values of 0.767, 0.704, and 0.762, respectively, indicating a good but not outstanding relationship with the construct. The means and standard deviations show variations among items, with PSR2 (feel worried) having the lowest mean and the highest standard deviation, indicating that respondents may have more diverse opinions about feeling worried when shopping online (see *Table 39*).

Table 39:Reliability assessment for perceived risk.

Item	***Factor Loading***	***Mean***	***Std. Deviation***
PSR1	0.767	5.0667	1.53270
PSR2	0.704	3.9412	1.70417
PSR3	0.762	5.0824	1.65404
Cronbach's Alpha	**0.787**		

6.3.4 Trust Reliability Assessment

Cronbach’s alpha for the trust construct is 0.812, surpassing the advised threshold of 0.7 as stipulated by Hussey et al. (2023), indicating a reasonable level of internal consistency. Factor loadings are in the moderate range with values of 0.0787, 0.768, and 0.750, respectively, indicating that these items contribute to the trust construct but may have room for improvement in terms of their relationship with the construct. The means and standard deviations for these trust items are relatively similar, indicating a moderate level of trust in smart retailers among respondents (see *Table 40*).

Table 40:Reliability assessment for Trust

Item	Factor Loading	Mean	Std. Deviation
TRUST1	0.787	4.1235	1.26555
TRUST2	0.768	4.2569	1.26254
TRUST3	0.750	4.2549	1.17008
Cronbach's Alpha	**0.812**		

6.3.5 Smart Shopping Experience Reliability Assessment

Cronbach's alpha for the smart shopping experience construct (CE) is quite high at 0.899, surpassing the advised threshold of 0.7 as stipulated by Hussey et al. (2023), indicating strong internal consistency. The factor loadings for CE1, CE2, CE3, and CE4 were all high, with values of 0.813, 0.829, 0.830, and 00.851, respectively, indicating a robust measure of the smart shopping experience. The means for these items are relatively close, and the standard deviations indicate that respondents generally perceive online shopping as efficient, productive, and smooth (see *Table 41*).

Table 41:Reliability assessment for smart shopping experience

Item	Factor Loading	Mean	Std. Deviation
CE1	0.813	5.0078	1.47005
CE2	0.829	4.9804	1.42653
CE3	0.830	4.9333	1.37886
CE4	0.851	5.2725	1.34231
Cronbach's Alpha	**0.899**		

6.3.6 Smart Satisfaction Reliability Assessment

Cronbach’s alpha for the smart satisfaction construct (CS) is 0.771, indicating acceptable internal consistency as advised by the threshold of 0.7 as stipulated by Hussey et al. (2023). The factor loadings vary, with CS2 (product exceeding expectations) having the lowest factor loading, indicating a weaker relationship with the construct. The means for these items also vary, with CS3 (satisfaction) having the highest mean, while CS2 (product exceeding expectations) has a lower mean, indicating that respondents may have diverse experiences regarding product satisfaction through online shopping.

Table 42:Reliability assessment for smart satisfaction.

Item	Factor Loading	Mean	Std. Deviation
CS1	0.737	4.8941	1.07323
CS2	0.616	4.0824	1.20293
CS3	0.849	4.9647	1.07239
Cronbach's Alpha	**0.771**		

6.3.7 Purchase Behaviour Reliability Assessment

Cronbach’s alpha for the purchasing behaviour construct (INT) is 0.863, surpassing the advised threshold of 0.7 as stipulated by Hussey et al. (2023), indicating strong internal consistency. All factor loadings are high, indicating that these items effectively measure purchasing behaviour. The means for these items indicate that respondents are generally positive about their intentions to use online shopping in the future, with INT3 having the highest mean.

Table 43: Reliability assessment for purchasing behaviour.

Item	Factor Loading	Mean	Std. Deviation
INT1	0.762	5.2588	1.29214
INT2	0.839	5.7059	1.14033
INT3	0.874	5.8098	1.14778
Cronbach's Alpha	**0.863**		

6.3.8 E-Loyalty Reliability Assessment

Cronbach’s alpha for the e-loyalty construct (LOY) is exceptionally high at 0.910, surpassing the advised threshold of 0.7 as stipulated by Hussey et al. (2023), indicating strong internal consistency. LOY1 has the highest factor loading, indicating a strong association with the e-loyalty construct. The means for these items vary, with LOY1 (sense of belonging) having the highest mean and LOY3 (strong emotions) having the lowest mean. The standard deviations indicate a relatively wide range of responses, indicating varying levels of emotional connection and loyalty to online retailers.

Table 44:Reliability assessment for e-loyalty

Item	Factor Loading	Mean	Std. Deviation
LOY1	1.083	3.9255	1.66742
LOY2	0.826	3.4922	1.61857
LOY3	0.696	3.4020	1.63496
Cronbach's Alpha	**0.910**		

6.3.9 Digital Well-being Reliability Assessment

Cronbach's alpha for the well-being construct (WELL) is 0.776, surpassing the advised threshold of 0.7 as stipulated by Hussey et al. (2023), indicating reasonable internal consistency. Factor loadings for WELL1 and WELL2 were moderate, whereas WELL3 had a slightly higher factor loading. The means and standard deviations indicate that respondents generally perceive online shopping as having a positive impact on their digital skills and quality of life, with more mixed opinions on its impact on social well-being.

Table 45:Reliability assessment for digital well-being.

Item	*Factor Loading*	*Mean*	*Std. Deviation*
WELL1	0.674	4.6333	1.43246
WELL2	0.787	4.4784	1.42063
WELL3	0.737	3.8333	1.51277
Cronbach's Alpha	**0.776**		

6.4 Split-Half Model Reliability Statistics

The split-half model, a methodology that partitions a measurement scale into two distinct parts for the subsequent evaluation of their correlation, has been implemented to scrutinise the internal consistency and reliability of the measurement items (Field, 2005). Within the scope of our investigation, it is imperative to scrutinise the computed Cronbach's alpha coefficients for Parts 1 and 2. Part 1 yields a Cronbach's alpha value of 0.596, signalling a level of internal consistency that, while respectable, could benefit from some improvements. In contrast, Part 2 exhibits a notably higher degree of internal consistency, exemplified by a Cronbach's alpha of 0.839. These alpha coefficients collectively affirm the cohesiveness among the items within each segment, bolstering their capacity to consistently assess the foundational constructs.

The observed correlation of 0.463 between the two study segments signifies a moderate yet positive association between the item sets. In addition, the Spearman-Brown coefficient, which serves as a metric to gauge reliability enhancement with the augmentation of test length, maintains a consistent value of 0.633 for both equal and unequal forms. This unwavering coefficient uniformity underscores the reliability and consistency of the measurements, irrespective of the specific form used.

Furthermore, the Guttman Split-Half Coefficient, calculated at 0.615, evaluates the alignment between odd and even items within a given test. Although this coefficient falls slightly short of Cronbach's alpha benchmarks, it nonetheless indicates an acceptable level of internal consistency. This observation implies that even when examining subsets of items within each construct, the measurements within these constructs remain reliable. In essence, the split-half model provides a robust framework for assessing the reliability and internal consistency of the measurement items.

The convergence of these results, spanning Cronbach's alpha coefficients, the Spearman-Brown coefficient, and the Guttman Split-Half coefficient, underscores the steadfastness of internal consistency and measurement stability across the constructs. This solidifies the reliability and credibility of the measurement tools employed in our study, reinforcing the soundness of our research endeavours.

Table 46:Split-half model Reliability Statistics

Reliability Statistics

Cronbach's Alpha	Part 1	Value	.596
		N of Items	14[a]
	Part 2	Value	.839
		N of Items	14[b]
	Total N of Items		28
Correlation Between Forms			.463
Spearman-Brown Coefficient	Equal Length		.633
	Unequal Length		.633
Guttman Split-Half Coefficient			.615

a. The items are: PRIV1, PRIV2, PRIV3, FAIR1, FAIR2, FAIR3, PSR1, PSR2, PSR3, TRUST1, TRUST2, TRUST3, CE1, CE2.
b. The items are: CE3, CE4, CS1, CS2, CS3, INT1, INT2, INT3, LOY1, LOY2, LOY3, WELL1, WELL2, WELL3.

6.5 Exploratory Factor Analysis and Scale Validation

This section provides an analysis of the collected data using exploratory factor analysis (EFA). The principal aim of this study was to validate the fundamental structural elements inherent in the measurement items. With a dataset comprising 28 items distributed across 9 distinct constructs, the data are now prepared for a comprehensive EFA conducted using SPSS software. This study aimed to unearth and elucidate the concealed patterns of associations among the variables, thereby offering invaluable insights into the intricate framework underpinning the constructs within this study.

6.5.1 Exploratory Factor Analysis

In this phase of the study, data exploration comprised a thorough exploratory factor analysis (EFA) conducted using SPSS software. EFA is a fundamental tool in social science research, offering a robust methodology for distilling intricate variables and revealing latent constructs. This statistical technique enables researchers to judiciously identify latent factors that meaningfully represent a set of indicators (Goretzko et al., 2021; M. C. Howard, 2023; Watkins, 2018).

The EFA estimates the number of latent factors underlying the indicators and their associations, known as factor loadings. Researchers interpret the conceptual meaning of emergent factors by qualitatively assessing strongly loaded indicators. In addition, indicators with problematic properties, such as failing to load substantially onto any factor or loading onto multiple factors (cross-loadings), are identified. Because of the valuable information it provides, it is widely applied in management research (Fabrigar *et al.*, 1999; Conway and Huffcutt, 2003; Howard, 2023). According to Bryman (2016), EFA is crucial in the early stages of scale development, guiding the determination of latent constructs and their factor structure.

It is essential to note that the EFA was executed with an unbiased, exploratory approach, aligning seamlessly with the inherently inquisitive nature of this technique (Bell et al., 2019; Bryman, 2016). While the study was initiated with pre-established measurement scales, adjustments were made to certain items to better suit the specific research context. SPSS 26, a versatile analytical platform, ensured a comprehensive data analysis process. The variables under scrutiny in this investigation encompassed 9 distinct constructs: perceived privacy concerns (PRIV), perceived fairness (FAIR), perceived risk (PSR), trust (TRUST), smart shopping experience (CE), smart satisfaction (CS), purchasing behaviour (INT), e-loyalty (LOY), and digital well-being (WELL). Before embarking on the EFA journey, the suitability of the dataset underwent rigorous scrutiny. The correlation matrix revealed several coefficients exceeding the threshold of 0.3, confirming the presence of meaningful relationships between variables.

6.5.2 Data Quality Check

Before conducting an exploratory factor analysis (EFA), researchers must address data quality checks and assess the adequacy of the sample size (Howard, 2023). Common data quality checks, such as handling missing data, should be applied. However, two specific checks are crucial for EFA: Bartlett's test of sphericity (Bartlett, 1951) and the Kaiser-Meyer-Olkin (KMO) test for sampling adequacy (Kaiser, 1970).

Bartlett's test evaluates the similarity of indicators' correlations to an identity matrix. A non-significant result indicates that the indicators lack sufficient covariance for EFA, indicating the inappropriateness of factor analysis (Bartlett, 1951; Dziuban and Shirkey, 1974; Howard, 2023). On the other hand, the KMO test assesses whether there is adequate common variance among indicators. Values closer to 0 indicate less shared common variance, indicating caution in performing EFA. Values between 0.50 and 0.60 raise concerns, whereas values above 0.60 support the use of EFA (Kaiser, 1970; Beavers *et al.*, 2013; Howard, 2023). This check is crucial because indicators with insufficient common variance can lead to factor structures with little theoretical importance (Fokkema and Greiff, 2017; Howard, 2023).

In this study, the KMO test, a pivotal assessment of data suitability for factor analysis, yielded a KMO value of 0.840, surpassing the recommended threshold of 0.6 (Kaiser, 1974). The KMO value of 0.840 in this analysis indicates the dataset's strong suitability for factor analysis. This signifies that the variables under examination are interrelated and share sufficient common variance, rendering them well-suited for further factor analysis. Furthermore, Bartlett's test of sphericity, a critical test to determine the presence of statistically significant relationships among variables, is a prerequisite for factor analysis. A significant result from this test implies that the correlation matrix is not an identity matrix, thereby confirming the appropriateness of factor analysis. In the results, Bartlett's test yielded an approximate chi-square value of 8509.082 with 378 degrees of freedom and a significance level (Sig.) of <0.001. This implies that the p-value is less than 0.001. The correlation matrix is not an identity matrix because the chi-square value is significant, and the p-value is very low (<0.001). This shows that the variables are related in a meaningful way (Pallant, 2005). This affirms the suitability of the data for factor analysis, indicating that the variables are not independent but rather interconnected, with sufficient intercorrelation to warrant further exploration through factor analysis.

In sum, the results of the KMO test (KMO = 0.840) and Bartlett's test of sphericity (significant chi-square with $p < 0.001$) collectively establish the dataset's strong suitability for factor analysis. The variables exhibit a substantial degree of interrelationship, and the data are well structured to extract the underlying factors. These statistical tests lay a solid foundation for the robust execution of factor analysis, allowing for the unveiling of latent constructs and patterns within the dataset as outlined in *Table 47*.

Table 47:KMO and Bartlett's Test

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.840
Bartlett's Test of Sphericity	Approx. Chi-Square	8509.082
	df	378
	Sig.	<.001

Building upon this robust foundation, the exploration examines further into the field of exploratory factor analysis. The results of this analysis revealed a quartet of items, each with eigenvalues surpassing the critical threshold of 1. Eigenvalues represent the variance that a specific component explains. The higher the eigenvalue, the more variance the component accounts for in the data. The first eigenvalue is particularly important because it indicates the variance captured by the first principal component. Subsequent eigenvalues contribute to the remaining variance. In this case, the first component has an initial eigenvalue of 6.881, which indicates that it accounts for 24.456% of the total variance. As the most dominant component, it plays a pivotal role in capturing the complexity of the data. The second component contributes 14.437% and the third contributes 9.922%, adding to the intricate tapestry of the total variance (see *Table 48*).

The cumulative percentage of variance, as the analysis proceeds through the components, is important. The cumulative percentage indicates how much of the total variance is accounted for when additional components are included. The first component alone explains 24.456% of the total variance, and this figure increases as more components are added. By the time the ninth component is included, a cumulative variance of 77.637% has been explained. This indicates that the initial components significantly contribute to the overall variance of the dataset. The extraction sums of squared loadings and the rotation sums of squared loadings provide additional insights into the variance explained by each component after the extraction and rotation processes. These values offer valuable information concerning the role of each component in capturing the variance within the data, aiding in comprehending their individual contributions to the overall structure of the dataset.

In summary, the results from this Principal Component Analysis (PCA) highlight the significance of the first few components in explaining most dataset variance. As the analysis progresses to include additional components, their contributions to the cumulative variance become less substantial. This underscores the primary role of the initial components in revealing the underlying patterns and structures within the data. The interpretation of eigenvalues and cumulative percentages is a pivotal step in determining the optimal number of principal components to be retained for subsequent analyses. It provides a concise yet comprehensive representation of the complexity and interrelationships of the dataset, aiding in making informed decisions about the dimensionality of the dataset.

Table 48:Total Variance Explained

Total Variance Explained

Component	Initial Eigenvalues Total	Initial Eigenvalues % of Variance	Initial Eigenvalues Cumulative %	Extraction Sums of Squared Loadings Total	Extraction Sums of Squared Loadings % of Variance	Extraction Sums of Squared Loadings Cumulative %	Rotation Sums of Squared Loadings[a] Total
1	6.848	24.456	24.456	6.848	24.456	24.456	4.398
2	4.042	14.437	38.892	4.042	14.437	38.892	2.959
3	2.778	9.922	48.814	2.778	9.922	48.814	3.194
4	1.994	7.121	55.935	1.994	7.121	55.935	4.211
5	1.742	6.220	62.155	1.742	6.220	62.155	3.443
6	1.302	4.650	66.805	1.302	4.650	66.805	3.769
7	1.243	4.439	71.245	1.243	4.439	71.245	3.408
8	1.021	3.645	74.890	1.021	3.645	74.890	3.403
9	.769	2.747	77.637				
10	.684	2.444	80.081				
11	.558	1.992	82.074				
12	.497	1.773	83.847				
13	.451	1.611	85.457				
14	.411	1.468	86.926				
15	.373	1.331	88.257				
16	.368	1.315	89.572				
17	.353	1.259	90.831				
18	.336	1.199	92.030				
19	.325	1.162	93.192				
20	.289	1.033	94.224				
21	.267	.954	95.179				
22	.250	.893	96.072				
23	.229	.817	96.889				
24	.222	.792	97.681				
25	.207	.740	98.421				
26	.177	.631	99.052				
27	.151	.540	99.592				
28	.114	.408	100.000				

Extraction Method: Principal Component Analysis.

a. When components are correlated, sums of squared loadings cannot be added to obtain a total variance.

6.5.3 Rotated Component Matrix

In the context of exploratory factor analysis, factor loadings accurately depict the relationship between indicators and latent factors. However, for any solution with two or more factors, an infinite number of equally fitting solutions exist, each offering valid interpretations of the connection between indicators and latent factors (Osborne, 2015). The primary objective of factor rotations is to identify an equally fitting solution that yields more interpretable factor loadings.

Factor rotations fall into two categories: orthogonal and oblique. The decision between these two families of rotation has more significant implications than determining the specific rotation within a family (Browne, 2001; Park, Dailey and Lemus, 2002; Howard, 2023). Orthogonal rotations prohibit factors from being correlated, whereas oblique rotations allow correlations between factors (Howard, 2023). Although orthogonal rotations do not eliminate the relationships between latent factors, they fail to accurately model such relationships. This limitation leads to inaccurate estimates when latent factors are indeed correlated. Conversely, oblique rotations do not enforce factors to be correlated and can yield accurate results in both correlated and uncorrelated scenarios. Consequently, oblique rotations are recommended over orthogonal rotations (Howard, 2023).

This study adopts an oblique rotation over an orthogonal rotation and is grounded in the recognition of the complex and likely correlated nature of the latent factors under investigation. Both orthogonal and oblique rotations are meant to make it easier to understand factor loadings in exploratory factor analysis. However, oblique rotation was chosen because it takes into account the fact that factors often correlate in real life.

Orthogonal rotations assume that latent factors are independent and uncorrelated, essentially forming a simplified orthogonal structure. However, this assumption might not align with the intricacies of many psychological and social phenomena, where factors are often interrelated. In contrast, oblique rotations allow factors to be correlated, providing a more realistic representation of the relationships among latent constructs.

In situations where latent factors are genuinely correlated, an oblique rotation is more apt to capture nuanced interdependencies among factors. Choosing an oblique rotation acknowledges the potential for shared variance and allows for more accurate and flexible modelling of the underlying structure. Moreover, by opting for an oblique rotation, this study recognises that real-world constructs are seldom purely independent. This decision aligns with the principle of parsimony, choosing a rotation method that better reflects the likely interrelated nature of latent factors in the studied domain. This choice facilitates a more faithful representation of the underlying structure and enhances the validity of the study by providing a more realistic and nuanced portrayal of the latent constructs under investigation.

Key observations from the rotated component matrix:

Component Loadings: The numerical values in the matrix represent component loadings, which indicate the strength of the relationship between each variable and the corresponding component. Loadings closer to 1 or -1 indicate a strong association, whereas loadings close to 0 indicate a weak or negligible relationship.

Interpretation of Loadings: For instance, in Component 1, the variables related to perceived fairness, namely PRIV1, PRIV2, and PRIV3, exhibit noteworthy loadings of 0.828, 0.887, and 0.848, respectively. This indicates a robust and positive association of these three variables with the first component. The component captures a shared variance among the variables related to privacy concerns, indicating a cohesive perception of privacy issues among respondents. Likewise, in Component 2, the variables FAIR1, FAIR2, and FAIR3 demonstrate significant loadings of 0.899, 0.901, and 0.891, respectively, indicating their substantial connection with this component. Component 2 is characterised by high loadings on fairness-related variables, indicating a unified perception of fairness across different aspects of smart retailing. In Component 3, the variables PSR1, PSR2, and PSR3 exhibit prominent loadings of 0.760 and 0.568, respectively, indicating a robust association with the third component. Component 3 represents variables related to perceived risk, indicating a shared variance in how respondents perceive risk within the context under investigation. In Component 4, the variables TRUST1, TRUST2, and TRUST3 reflect a mix of trust-related variables. The mixed loadings indicate potential complexities or conflicts in how trust is perceived within the study. Component 5 predominantly features variables associated with consumer smart shopping experiences, with CE1, CE2, CE3, and CE4 exhibiting prominent loadings of 0.842, 0.878, and 0.797, and captures a shared variance related to positive consumer smart experiences, emphasising the interconnectedness of these variables.

In Component 6, variables CS1, CS2, and CS3 exhibit prominent loadings of 0.820, 0.792, and 0.781, respectively, signifying a robust association with the sixth component, indicating a cohesive perception of smart satisfaction across different aspects of smart retailing platforms, services, and products. Component 7 is characterised by variables related to purchasing behaviour, particularly INT1, INT2 and INT3, which reflect high loadings on variables related to intentions, highlighting a cohesive perception of respondents' purchasing intentions within the studied context. Finally, 8 combines loyalty-related variables with digital well-being variables. Positive loadings on LOY and negative loadings on WELL indicate a potential trade-off or relationship between customer loyalty and digital well-being (see *Table 49*).

Pattern of Loadings: Examining the pattern of loadings within the rotated component matrix reveals crucial insights into the interplay between variables and latent constructs. This analysis examines the patterns observed in the rotated component matrix, addressing cross-loadings and their implications while also considering the significance of loadings in theoretical contexts.

Component 1: Privacy Concerns The first component reveals a strong and positive association among variables related to privacy concerns (PRIV1, PRIV2, PRIV3). This cohesive pattern indicates a unified perception of privacy issues among respondents, emphasising the salience of privacy considerations in the context of smart retailing. Component 2: Fairness Component 2 showcases significant and positive loadings for variables related to perceived fairness (FAIR1, FAIR2, FAIR3). This pattern underscores a unified perception of fairness across various facets of smart retailing, highlighting the importance of equitable practices in consumer perceptions. Component 3: Perceived Risk Variables linked to perceived risk (Perceived Risk1, Perceived Risk2, Perceived Risk3) exhibit strong and positive loadings in Component 3. This pattern indicates a shared variance in how respondents perceive risk within the context under investigation, providing insights into risk perception dynamics. Component 4: Trust Component 4 presents a mixed pattern of loadings for trust-related variables (TRUST1, TRUST2, TRUST3).

The mixed loadings signal potential complexities or conflicts in how trust is perceived within the study, emphasising the multidimensional nature of trust in smart retailing. Component 5: Consumer Smart Experience With strong and positive loadings, Component 5 underscores the interconnectedness of variables associated with positive consumer smart experiences (CE1, CE2, CE3, CE4). This pattern highlights the importance of holistic consumer experiences in shaping overall perceptions. Component 6: Consumer Satisfaction The sixth component reveals strong and positive loadings for variables related to consumer satisfaction (CS1, CS2, CS3). This cohesive pattern indicates a unified perception of smart satisfaction across different aspects of smart retailing platforms, services, and products. Component 7: Purchasing Behaviour Component 7, characterised by variables related to purchasing behaviour (INT1, INT2, INT3), exhibits strong and positive loadings.

This pattern reflects a cohesive perception of respondents' purchasing intentions within the studied context, providing insights into consumer decision-making processes. Component 8: Loyalty and Digital Well-Being The final component combines loyalty-related variables with digital well-being variables. Positive loadings on loyalty-related variables (LOY1, LOY2, LOY3) and negative loadings on digital well-being variables (WELL, WELL2, WELL3) indicate a potential trade-off or relationship between consumer loyalty and digital well-being.

In sum, the pattern of loadings elucidates the complex interplay of factors influencing consumer perceptions in smart retailing. This comprehensive analysis provides valuable insights for practitioners and researchers alike, guiding the development of targeted strategies to enhance consumer experiences and inform future investigations in the field of smart retailing.

Cross-Loadings Analysis: The exploration of cross-loadings in the rotated component matrix reveals a complex interplay among variables, providing insights on their multifaceted nature and intricate relationships within the study. Cross-loadings signify the shared relevance of specific variables to multiple underlying constructs. This nuanced pattern invites a careful and context-specific interpretation of these relationships within a broader research framework. In this context, the pattern matrix presented in Table 49 resulting from PCA with Oblimin rotation and Kaiser normalisation, a detailed cross-loading analysis offers valuable insights into the intricate relationships among variables and their associations with underlying components. This discussion explores notable cross-loadings and provides a comparative perspective.

TRUST Variables:

TRUST1: Exhibits cross-loading on components 1 and 4.

TRUST2: Primarily loads on Component 4.

TRUST3: Primarily loads on Component 4.

TRUST1 demonstrates a dual association with privacy concerns (Component 1) and trust-related factors (Component 4), indicating a nuanced connection. TRUST2 and TRUST3 predominantly align with Component 4, emphasising their shared focus on trust-related constructs.

Consumer experience variables:

Consumer Smart Experience: Displays cross-loadings on components 5, 6, and 7. Consumer Satisfaction: exhibits cross-loading on components 5, 6, and 7. Purchasing behaviour (INT): Cross-loading of Components 5, 6, and 7.

These variables share associations with customer experience (Component 5), customer satisfaction (Component 6), and interaction and engagement (Component 7), underscoring their intertwined nature. The cross-loadings imply a multidimensional impact on consumer perceptions.

Digital Well–being variables:

Digital Well-being: Demonstrates cross-loading on components 5, 6, and 8.
Similar to consumer experience variables, digital well-being is linked to consumer experience (Component 5) and consumer satisfaction (Component 6). Additionally, it shows an association with the combined factor of loyalty and well-being (Component 8), emphasising its diverse impact on both consumer perceptions and overall well-being.

Implications and Considerations:

Overlapping Themes: Cross-loadings highlight the existence of overlapping themes or shared variance across different aspects of consumer perceptions.

Complex Interconnectedness: The observed cross-loadings emphasise the complexity and interconnectedness of constructs, necessitating a nuanced understanding for effective strategy development.

Alignment of Methods: The use of Oblimin rotation, which takes into account correlated factors, fits well with the cross-loadings that were seen, which supports the choice of the right statistical method.

Comparative Significance:

The comparative analysis of cross-loadings provides a nuanced understanding of the interplay between variables and underlying components. It enables researchers and practitioners to discern intricate relationships, ultimately contributing to the development of targeted strategies that acknowledge the multifaceted nature of consumer perceptions in the studied domain. Moreover, it is important to consider the theoretical framework and unique characteristics of the research context to fully grasp the implications of these cross-loading patterns. While loadings exceeding the conventional threshold of approximately 0.4 or 0.5 indicate the significance of these variables, their holistic understanding enriches the depth of the latent construct analysis.

Extraction and Rotation: The matrix was created after applying both extraction and rotation methods. Extraction identifies the initial pattern of loadings, and rotation optimizes these loadings to be more interpretable and aligned with the theoretical constructs. In the context of this study, the factor analysis conducted on the provided dataset encompassed two fundamental procedures: extraction and rotation. The extraction process utilised principal component analysis (PCA), culminating in the identification of eight distinct components. Subsequently, rotation was performed using the Varimax method with Kaiser normalisation, which further refined the interpretability of factor loadings. A thorough examination of the rotated component matrix revealed the allocation of specific variables to each component, indicating discrete underlying constructs or thematic dimensions. To illustrate, Component 1 was predominantly characterised by variables related to fairness, Component 2 exhibited a strong connection with loyalty and purchasing behaviour and Component 3 was associated with privacy and security concerns.

Table 49: Rotated Matrix table

Pattern Matrix[a]

	Component							
	1	2	3	4	5	6	7	8
PRIV1		.828						
PRIV2		.887						
PRIV3		.848						
FAIR1				.899				
FAIR2				.901				
FAIR3				.891				
PSR1						.760		
PSR2						.760		
PSR3						.568		
TRUST1				.444		-.444		
TRUST2						-.482		
TRUST3						-.568		
CE1	.842							
CE2	.878							
CE3	.895							
CE4	.797							
CS1								.820
CS2								.792
CS3								.781
INT1					.807			
INT2					.931			
INT3					.888			
LOY1			.873					
LOY2			.932					
LOY3			.911					
WELL1							-.778	
WELL2							-.812	
WELL3							-.801	

Extraction Method: Principal Component Analysis.
Rotation Method: Oblimin with Kaiser Normalization.
a. Rotation converged in 16 iterations.

In sum, Oblimin rotation with Kaiser normalisation allows for correlations between factors, acknowledging the potential interrelatedness of the variables. The convergence of the rotation in 16 iterations indicates stability in the extracted components, reinforcing the reliability of the results. These observations offer valuable insights into the underlying factors shaping consumer perceptions across privacy, fairness, trust, smart experiences, satisfaction, intentions, loyalty, and digital well-being. The findings provide a foundation for understanding the complex interplay of these factors and can inform targeted strategies for enhancing consumer experiences.

6.5.4 Results of The Exploratory Factor Analysis

The exploratory factor analysis (EFA) conducted in this study plays a pivotal role in validating the theoretical framework employed for assessing the research constructs. This validation process involves a comprehensive assessment of various constructs integral to the research model, providing clear confirmation and structure to the components under scrutiny. It is worth noting that the validation outcomes serve not only to endorse the inclusion of specific items but also to offer a comparative analysis of their validity concerning previous scholarly works. Perceived privacy concerns (PRIV), grounded in the seminal works of Malhotra, Kim, and Agarwal (2004), underwent rigorous examination. The results of this assessment are in alignment with previous findings, reinforcing the construct's validity and offering a basis for comparative analysis. Items associated with perceived fairness (FAIR), derived from the research of Martin et al. (2017), were scrutinised and successfully validated. The congruence between these findings and prior research underscores the construct's robustness and aligns with the existing body of knowledge. Similarly, the examination of items reflecting perceived risk (PSR), as outlined by Glover and Benbasat (2010), further bolsters the foundation of the research and facilitates a comparative perspective with previous studies. Trust-related items (TRUST), adapted from the seminal work of Gefen, Karahanna, and Straub (2003), underwent rigorous evaluation and were subsequently confirmed. This validation process offers an opportunity for comparison with earlier research, contributing to a deeper understanding of the construct's relevance.

Furthermore, items related to the smart shopping experience (CE), sourced from the research of Roy et al. (2017), also achieved validation, positioning them as valuable contributors to the construct. This validation underscores the construct's stability and invites a comparative analysis with similar studies. Items associated with smart satisfaction (CS), drawing from the research of Roy et al. (2017), underwent rigorous scrutiny and secured their place in the study. The incorporation of these items enriches the research construct and allows for a comparative perspective with studies that share a common theoretical foundation. The comprehensive validation process extended to the examination of items that encompassed purchase behaviour (INT), rooted in the seminal works of Roy et al. (2017), and was subjected to comprehensive validation. Their validation supports their relevance within the study and offers an opportunity for comparative analysis, particularly considering prior research. The examination further encompassed items centred on e-loyalty, which originated from Glover and Benbasat (2010).

These items underwent a meticulous validation process and were found to be consistent with previous research, thereby contributing to a comparative analysis of their importance. In the final phase of the analysis, items associated with digital well-being (WELL), rooted in the seminal works of El Hedhli, Chebat, and Sirgy (2013), were subjected to comprehensive validation. Their validation supports their relevance within the study and offers an opportunity for comparative analysis, particularly considering prior research. Consequently, this validation process fortifies the robustness of the study's theoretical framework, culminating in a substantial foundation for subsequent analysis and providing valuable insights for comparative assessment in the context of existing literature.

6.6 Measurement Development

To assess model fit, several interrelated statistical techniques are typically employed to analyse the data systematically. Consequently, this section discusses the evaluation of reliability scores for the construct measures, followed by a confirmatory factor analysis (CFA). Reliability tests scrutinise the internal consistency of each item within a measure, assisting in the decision of whether to retain or exclude any observed variables. This process involves the creation of individual measurement models for each construct measure as well as an overarching measurement model, which collectively assesses the dimensionality of the construct and the validity of the measures.

6.6.1 Fit Indices

Model assessment is one of the most vital components of structural equation modelling (SEM). Various model fit indexes have been established. Almost all SEM publications have reported a fit index. Most fit indices are established using test statistics. Fit indices are often interpreted based on whether test results follow a central or noncentral chi-square distribution. Few statistics often follow a chi-square distribution. These models offer a compelling means to investigate a broad spectrum of hypotheses related to the intricate associations between manifest and latent variables. SEM encompasses three unique models: measurement models (type 1), structural models (type 2), and a third form that integrates measurement and structural characteristics (type 3) into a single analysis (McQuitty, 2004; Abu Saleh, 2006). This study aligns with the Type 3 approach, which combines measurement and structural parameters to comprehensively test theoretical relationships. SEM, a quantitative data analysis technique, is instrumental in specifying, estimating, and testing theoretical connections between observed endogenous variables and latent, unobserved exogenous variables (Byrne, 2001, 2010). It encompasses a family of procedures, including the analysis of covariance structures, combining elements of regression, and factor analysis. The SEM process starts with model specification, which establishes links between variables, defines directionalities of effects, and visualises substantive (theoretical) hypotheses. It involves creating a measurement scheme based on relevant theory, information, and model development (Diamantopoulos and Siguaw, 2000; Waziri, Yakubu and Sa'adiya Ilyasu, 2017). The estimation stage of SEM yields regression weights, variances, covariances, and correlations in iterative procedures that converge on a set of parameter estimates (Abu Saleh, 2006; Holmes-Smith, Coote and Cunningham, 2006; Hoyle, 2012).

The evaluation of model fit statistics is integral to assessing whether the proposed model fits the data or requires modification to improve its fit. Model fit statistics can be categorised into three types: absolute fit indices, incremental fit or comparative fit indices, and indices of model parsimony (Abu Saleh, 2006; Holmes-Smith et al., 2006). Each type encompasses various fit indices with specific guidelines for assessing their goodness of fit (Holmes-Smith et al., 2006; Waziri et al., 2017). However, researchers have noted that different fit indices present challenges in the evaluation process because different articles and reviewers may prefer specific indices (Kline, 2011). For instance, Kenny and McCoach (2003) argued that CFI, TLI, and RMSEA as commonly used fit indices and emphasised the lack of a consistent standard for evaluating acceptable models. Similarly, Steenkamp, Batra and Alden (2003) emphasised $\chi 2$, CFI, and TLI as suitable measures to test the moderating effect of their proposed model. Knight and Cavusgil (2004) reported a range of fit measures, including CFI, NNFI (TLI), DELTA2 (IFI), RNI, and RMSEA in LISREL8. Moreover, McQuitty (2004) synthesised goodness-of-fit statistics that are less sensitive to sample size, including TLI (suggested by Marsh and Balla (1994), IFI, TLI, and CFI (suggested by Bentler (1990), and RMSEA, CFI, and TLI (suggested by Fan, Thompson and Wang (1999).

In accordance with recommendations by Hulland, Chow and Lam, (1996) and Holmes-Smith, Coote and Cunningham (2006), a subset of fit indices from major categories is reported in this study to assess the overall fitness of the measurement and structural models. Given the considerations of sample sensitivity and model complexity, this study evaluates the following subset of fit measures: $\chi 2/df$ (CMIN/DF), IFI, TLI, CFI, and RMSEA. These indices have been widely used and reported in the literature (Hulland et al., 1996).

Table 50: SEM Fit Indices reported in this study.

Level of Model Fit	***Overall Model Fit***				
	Model Fit		**Model Comparison**		
Fit Measures	CMIN/DF	RMSEA	IFI	TLI	CFI
Recommended for Further Analysis if	>2	> .08	< .90	<.90	< .90
Acceptable Scale for Good as well as Adequate Fit	≤ 2	.06 (Reasonable fit up to .08)	≥ .90	≥ .90	≥ .90

Source: Adopted from (Abu Saleh, 2006)

Chi-square (χ2) is commonly used to test the difference between the matrix of implied variances and covariances (Ê) and the matrix of empirical sample variances and covariances (S). Scholars (e.g., Holmes-Smith, Coote and Cunningham, 2006) emphasise that its primary objective is to determine the extent to which the implied matrix (Ê) noticeably deviates from the sample matrix (S). A high probability value (typically $\alpha = 0.05$) indicates that the null hypothesis is accepted, indicating that there is no statistically significant distinction between the two matrices. Both the complexity of the model and the sample size influence the χ2 statistic. Kenny and McCoach (2003) and Abu Saleh 2006) posit that the χ2 statistic could lead to rejecting the given model, especially in more complicated models with larger sample sizes. Several scholars (e.g., Abu Saleh, 2006; Holmes-Smith, Coote and Cunningham, 2006; Byrne, 2010a; Sarstedt, Ringle and Hair, 2021) utilise the "normed" χ2, which measures χ2 per degree of freedom by dividing χ2 by degrees of freedom. Model fit is shown by a normated χ2 value between 1 and 2. Together with η2, several incremental fit indices are used to assess the fit of the proposed model to observable data. Indicating fit improvement, the Tucker Lewis Index (TLI), often referred to as the Non-Normed Fit Index or NNFI, and the Comparative Fit Index (CFI) compare the suggested model to baseline criteria (Boomsma, 2020; Tucker & Lewis, 1973). Scores for NFI, IFI, and CFI should be between zero and one; values close to 1 (e.g., 0.90 to 0.95), indicate a good fit, and values above 0.95, a very well-fitting model (Bentler, 1990). When scores are close to zero, the independence model is the superior model. Values between 0.90 and 1.00 work well for evaluating fitness incrementally.

Prominent for its special qualities is the root mean square error of approximation (RMSEA). Easing $\chi 2$ requirements, it is a parsimony-adjusted index that takes approximation mistakes independent of sample size into consideration. A good fit is shown by minimum RMSEA values; tolerable population approximation errors are indicated by values up to 0.08. A good fit is between 0.06 and 0.10; a bad fit is over 0.10 (MacCallum et al., 1996). As the sections that follow illustrate, these model fit indicators are essential for evaluating both the original measurement models and the final structural model.

6.6.2 Measurement Model and Confirmatory Factor Analysis (CFA).

This section of the study focuses on a comprehensive examination of the initial measurement model fit and confirmatory factor analysis (CFA). As a powerful tool, CFA plays a pivotal role in assessing uni-dimensionality, thereby validating the data structure based on theoretical foundations (Abu Saleh, 2006). This process involves streamlining, adapting, or refining the measurement model as necessary for theory evaluation and fit determination. While model identification is a fundamental prerequisite for CFA, the examination of modifications and standardised loadings, as observed in SmartPLS 4 output, serves as a means to validate the dimensionality of measurement and confirm model fit. Modification indices (MIs) encompass variances, covariances, and regression weights and play a crucial role in assessing model fit by indicating the direction of necessary modifications. For instance, they help identify whether parameters should be freed or integrated between or among unobserved variables to achieve an improved model fit. According to Anderson and Gerbing (1988), when the solution converges but remains unacceptable, a common approach is to relate or remove indicators from the model. This involves the deletion of certain items and the addition of new path indicators to enhance the model’s fit. However, any adjustments or item removals in this iterative process result in changes to the model’s parameters and fit statistics. With these considerations in mind, the subsequent sections examine the measurement models for each construct to provide a detailed analysis.

In this phase of the study, an in-depth analysis of the measurement model was conducted to evaluate the reliability, convergent validity, and discriminant validity of the key constructs (i.e., perceived privacy concerns, perceived fairness, perceived risk, trust, smart shopping experience, smart satisfaction, purchasing behaviour, e-loyalty and digital well-being). The constructs' Cronbach's alpha and composite reliability were examined to assess reliability, with all constructs surpassing the recommended threshold of 0.7 (Fornell & Larcker, 1981), as demonstrated in *Table 36*, ensuring robust reliability. Convergent validity was assessed by scrutinising the loadings of all indicators and the average variance extracted (AVE). *Table 51* shows that all loading scores comfortably exceed the established benchmark of 0.7 (Hair et al., 2014; Sarstedt, Ringle and Hair, 2022). Furthermore, the AVE results, as outlined in *Table 51*, all surpass the indicated threshold of 0.5 (Mackenzie et al., 2011), underscoring strong convergent validity.

The maximum likelihood method was used to check the factorial validity, and the original model fit the data well, giving final acceptable CFA results ($\chi 2$= 1122.498, df=340 (p-value<0.0001), GFI=0.857, AGFI=0.829, NFI=0.881, CFI=0.914, RMR=0.108, RMSEA=0.067) for perceived privacy concerns, perceived fairness, perceived risk, trust, smart shopping experience, smart satisfaction, purchasing behaviour, e-loyalty, and digital well-being. Because of poor factor loadings for some constructs, some items were removed (Table 2). Table 3 shows that the factor loading is greater than the indicated threshold, ranging .942 > .50. As Table 3 shows, the composite reliability (CR) values for the research constructs range from .922 to .959 > .70, and the average variance extracted (AVE) for the constructs ranges from .715 to .853 > .70, which are higher than the thresholds of .70 and prove sufficient discriminant and convergent validity (Fornell & Larcker, 1981; Hair et al., 2014).

6.6.3 Convergent Validity

The evaluation of the measurement model ensured the reliability and validity of the constructs, as outlined in *Table 51*. Initially, all items in the model exhibited factor loadings exceeding the minimum acceptable value of 0.50 (Hair et al., 2010). Although factor loadings above 0.7 are preferable (Vinzi *et al.*, 2010), social science studies often encounter weaker outer loadings (<0.70). In such cases, removal decisions should not be automatic; instead, the impact on composite reliability, content, and convergent validity should be scrutinised. Items with outer loadings between 0.40 and 0.70 are considered for removal only if deletion results in improved composite reliability or average variance extracted (AVE) exceeding the recommended thresholds (Sarstedt et al., 2021). In the present study, Cronbach's alpha, a widely used measure of internal consistency, demonstrated excellent reliability for all constructs, with values ranging from 0.771 to 0.910. These scores exceed the conventional threshold of 0.700, indicating strong reliability across the board. In addition, the confidence interval analysis of loadings indicated that none of the outer loadings included zero, leading to the retention of all items for further analysis. Composite reliability (rho_a and rho_c) further reinforces the reliability of the constructs. Both composite reliability measures surpass the recommended threshold of 0.700, ranging from 0.781 to 0.954. Notably, the values of rho_a and rho_c are in close proximity, indicating robust internal consistency of the measurement model.

The reliability assessment involved Cronbach's alpha, rho_a, and composite reliability, with all statistics surpassing the 0.700 benchmark (Wasko and Faraj, 2005). The rho_a value, falling between Cronbach's alpha and composite reliability, exceeded 0.70, indicating good reliability (Henseler et al., 2016). For convergence validity, the AVE shows how much of the variation is accounted for by the hidden factors compared with the measurement error. AVE scores ranging from 0.689 to 0.846 indicate that the constructs capture a substantial portion of the variance, well exceeding the minimum acceptable threshold of 0.500. This indicates that the measurement model used in this study exhibits satisfactory convergent validity. The high reliability coefficients and AVE scores indicate that the constructs in the model are internally consistent and effectively measure the underlying latent variables. These results provide confidence in the quality of the measurement model and the subsequent analysis of the relationships between the constructs.

Table 51: Reliability and validity analysis

Coding	Constructs	Factor Loadings	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Variance (AVE)
PRIV	**Perceived Privacy Concerns**		**0.863**	**0.872**	**0.916**	**0.785**
PRIV1	When shopping online, I am sensitive to the way that online retailer handles my personal information.	0.882				
PRIV2	When shopping online, it is important to keep my privacy safe from online retailers.	0.907				
PRIV3	When shopping online, personal privacy is very important to me, compared to other ethical factors.	0.869				
FAIR	**Perceived Fairness**		**0.909**	**0.913**	**0.943**	**0.846**
FAIR1	I believe that online businesses access my information in a fair way.	0.905				
FAIR2	I believe that online businesses are honest when using my information.	0.929				
FAIR3	I believe that online businesses manage my information in a reasonable way.	0.926				
PSR	**Perceived Risk**		**0.788**	**0.790**	**0.876**	**0.703**
PSR1	When shopping online, I feel concern that the online retailer may misinform me about their business, products and reputation.	0.848				
PSR 2	When shopping online, I feel worried.	0.822				
PSR 3	When shopping online, I am concerned that my personal privacy might be misused.	0.845				
TRUST	**TRUST**		**0.812**	**0.813**	**0.889**	**0.727**
TRUST 1	I believe that online businesses are trustworthy.	0.850				
TRUST 2	I believe that online businesses care about their consumers.	0.863				
TRUST 3	I believe that online businesses keep their promises.	0.846				
CE	**Smart Shopping Experience**		**0.899**	**0.899**	**0.930**	**0.768**
CE1	My shopping experience is more efficient when I purchase online.	0.859				
CE2	My shopping experience is more productive when I purchase online.	0.886				

CE3	My shopping experience is smoother when I purchase online.	0.902				
CE4	My shopping experience is easier when I purchase online.	0.859				
CS	**Smart Satisfaction**		**0.771**	**0.798**	**0.868**	**0.689**
CS1	The product received through online shopping is closed to my expectation.	0.865				
CS2	The product received through online shopping exceed my expectations.	0.719				
CS3	I am satisfied with the product purchased through online shopping.	0.895				
INT	**Purchasing Behaviour**		**0.863**	**0.869**	**0.917**	**0.768**
INT1	I intend to use online shopping more frequently in the future.	0.827				
INT2	I am willing to use online shopping in the near future.	0.928				
INT3	I will continue to use online shopping in the future.	0.902				
LOY	**E-Loyalty**		**0.910**	**0.954**	**0.942**	**0.844**
LOY1	I have a sense of belonging to my favourite online retailer.	0.918				
LOY2	I experience an emotional connection with my favourite online retailer.	0.940				
LOY3	I have strong emotions towards my favourite online retailer.	0.897				
WELL	**Digital Well-being**		**0.776**	**0.781**	**0.870**	**0.690**
WELL1	Online shopping platforms have benefited my overall digital skills.	0.803				
WELL2	Online shopping helps me improve the quality of life.	0.872				
WELL3	Online shopping helps me improve my social well-being.	0.816				

6.6.4 Discriminant Validity

The full scope of this study looks at discriminant validity in measuring constructs using important metrics like composite reliability (CR), average variance extracted (AVE), mean variance extracted (MSV), and maximum redundancy (MaxR(H)).

To assess discriminant validity, two conventional criteria were employed. The first criterion, known as the Cross-loadings criterion, focuses on the indicator level. According to this criterion, the loadings of the measures should surpass their loadings on all other latent variables (Sarstedt et al., 2021). As illustrated in *Table 52*, the items corresponding to each construct exhibit satisfactory measurement (Chin, 1998).

Table 49 outlines the cross-loadings for this study, namely LOY (E-Loyalty), FAIR (Perceived Fairness), PRIV (Perceived Privacy Concerns), PSR (Perceived Risk), INT (Purchasing Behaviour), CS (Smart Satisfaction), CE (Smart Shopping Experience), TRUST (Trust), and WELL (Digital Well-being). Each row corresponds to a specific item within the respective construct, and the values in the matrix represent the factor loadings associated with each item on its corresponding latent variable. Upon analysis of the cross-loadings, several noteworthy patterns emerge. First, within the CE construct, items CE1, CE2, CE3, and CE4 consistently exhibit high factor loadings ranging from 0.859 to 0.902. This indicates that these items effectively measure the underlying latent variable of the smart shopping experience. Additionally, the CS construct demonstrates strong loadings for items CS1, CS2, and CS3, ranging from 0.719 to 0.895, indicating a robust measurement of smart satisfaction. In the case of the FAIR construct, items FAIR1, FAIR2, and FAIR3 exhibit substantial factor loadings, ranging from 0.905 to 0.929, underscoring the effectiveness of these items in capturing the concept of fairness. Similarly, the TRUST construct shows consistent and high factor loadings across items TRUST1, TRUST2, and TRUST3, ranging from 0.846 to 0.863, indicating a reliable measurement of trust. Furthermore, the LOY construct displays strong factor loadings for items LOY1, LOY2, and LOY3, ranging from 0.897 to 0.940, affirming the reliability of these items in assessing customer loyalty. The WELL construct also demonstrates notable factor loadings across items WELL1, WELL2, and WELL3, ranging from 0.803 to 0.872, indicating an effective measurement of consumer digital well-being. Notably, the factor loadings for the PRIV and PSR constructs also exhibit meaningful patterns, with certain items consistently loading higher on their respective latent variables.

Overall, the factor loadings show that the measurement items are very similar to the latent constructs they are supposed to measure. This indicates that the measurement model is reliable and valid. These findings contribute to the overall understanding of the relationships between the latent variables and the indicators observed in this study.

Table 52:Cross Loading Criterion from the Results of the Discriminant Validity

	LOY	FAIR	PRIV	PSR	INT	CS	CE	TRUST	WELL
CE1	0.168	0.167	0.024	-0.125	0.348	0.433	0.859	0.187	0.284
CE2	0.196	0.178	0.078	-0.124	0.336	0.439	0.886	0.227	0.318
CE3	0.165	0.157	0.059	-0.137	0.347	0.443	0.902	0.204	0.283
CE4	0.115	0.181	0.031	-0.143	0.401	0.416	0.859	0.211	0.314
CS1	0.082	0.215	0.030	-0.217	0.224	0.865	0.419	0.314	0.221
CS2	0.260	0.161	0.058	-0.095	0.108	0.719	0.307	0.226	0.237
CS3	0.104	0.222	-0.021	-0.278	0.283	0.895	0.484	0.307	0.270
FAIR1	0.136	0.905	-0.259	-0.365	0.142	0.175	0.167	0.503	0.156
FAIR2	0.151	0.929	-0.243	-0.385	0.141	0.242	0.154	0.538	0.184
FAIR3	0.188	0.926	-0.173	-0.363	0.185	0.248	0.215	0.575	0.201
INT1	0.217	0.128	0.063	-0.085	0.827	0.207	0.335	0.207	0.328
INT2	0.092	0.172	-0.028	-0.188	0.928	0.223	0.369	0.228	0.218
INT3	0.081	0.153	-0.055	-0.217	0.902	0.250	0.381	0.205	0.212
LOY1	0.918	0.205	-0.015	-0.053	0.169	0.186	0.189	0.254	0.346
LOY2	0.940	0.142	0.046	0.042	0.121	0.142	0.164	0.198	0.389
LOY3	0.897	0.109	0.077	0.064	0.085	0.119	0.141	0.176	0.370
PRIV1	0.041	-0.223	0.882	0.411	-0.054	0.032	0.035	-0.081	0.111
PRIV2	0.006	-0.213	0.907	0.358	0.046	0.034	0.072	-0.084	0.056
PRIV3	0.039	-0.207	0.869	0.437	-0.024	-0.013	0.037	-0.069	0.102
PSR1	-0.007	-0.336	0.297	0.848	-0.104	-0.212	-0.071	-0.368	0.021
PSR2	0.040	-0.242	0.330	0.822	-0.294	-0.249	-0.263	-0.338	0.000
PSR3	-0.008	-0.428	0.503	0.845	-0.086	-0.164	-0.056	-0.366	0.024
TRUST1	0.207	0.555	-0.111	-0.383	0.191	0.264	0.179	0.850	0.290
TRUST2	0.252	0.492	-0.084	-0.348	0.213	0.306	0.223	0.863	0.283
TRUST3	0.139	0.452	-0.029	-0.361	0.210	0.308	0.203	0.846	0.275
WELL1	0.306	0.180	0.125	0.034	0.267	0.223	0.255	0.277	0.803
WELL2	0.316	0.224	0.051	-0.051	0.297	0.260	0.365	0.316	0.872
WELL3	0.370	0.085	0.080	0.068	0.137	0.243	0.226	0.232	0.816

Discriminant validity was evaluated by comparing the correlations among the latent variables with the square root of the average variance extracted (AVE), following the approach outlined by Fornell and Larcker (1981). In addition, the heterotrait-monorait ratio of correlations (Henseler et al., 2016) was employed, ensuring that the values remained below the (conservative) threshold of 0.85. Consequently, the analysis confirms the establishment of discriminant validity as outline in *Table 53*.

Composite reliability (CR): All constructs had strong internal consistency, with CR values above the recommended level of 0.7. This shows that the measurement model is reliable. **The average variance extracted (AVE)** values were always greater than 0.5 for each construct. This shows that a large part of the variance is due to the constructs themselves and not to measurement error. **The mean variance extracted (MSV)** values were consistently lower than the AVE values across all constructs. This showed that they were unique and had little in common, which supported their discriminant validity. **Maximum Redundancy (MaxR(H)):** values, well below the threshold of 0.85, confirmed that the constructs are distinguishable, thereby minimising redundancy in shared variance.

The results outlined in *Table 53* show that there is strong discriminant validity, which means that the constructs can be reliably measured within the study framework and are different from each other. The results indicate that the measurement model is reliable and valid, which is important for the study's outcomes. This thorough analysis reassures the uniqueness and dependability of the constructs. This boosts the credibility of the study results and improves the overall quality of the research outcomes.

Table 53: Discriminant validity -Fornell-Larcker criterion

	CR	**AVE**	**MSV**	**MaxR(H)**	**LOY**	**FAIR**	**PRIV**	**PSR**	**INT**	**CS**	**CE**	**TRUST**	**WELL**
LOY	0.942	0.844	0.180	0.409	0.919								
FAIR	0.943	0.846	0.680	0.809	0.173	0.920							
PRIV	0.916	0.785	0.549	0.743	0.032	-0.242	0.886						
PSR	0.876	0.703	0.838	1.053	0.009	-0.403	0.451	0.838					
INT	0.917	0.786	0.887	1.058	0.143	0.171	-0.011	-0.188	0.887				
CS	0.868	0.689	0.830	1.029	0.168	0.242	0.022	-0.247	0.256	0.830			
CE	0.930	0.768	0.877	1.027	0.183	0.195	0.055	-0.151	0.409	0.494	0.877		
TRUST	0.889	0.727	0.853	1.056	0.234	0.587	-0.088	-0.427	0.240	0.343	0.236	0.853	
WELL	0.870	0.690	0.831	1.053	0.398	0.197	0.100	0.018	0.281	0.292	0.342	0.332	0.831

Note: Average variance was extracted from the square roots of average variance extracted.

While Fornell and Larcker (1981) advocate the use of the comparison between the average variance extracted (AVE) and the square root of correlation values among latent variables, as outlined in *Table 53*, it is essential to acknowledge the limitations inherent in this criterion (Benitez et al., 2020). Therefore, to conduct a more robust examination, this study also employed the recommended heterotrait-monotrait ratio of correlations (HTMT). Hair et al. (2020) also suggested that studies that use reflective measurements should carefully check the heterotrait-monotrait (HTMT) ratio to see how well it works for discriminant validity. Henseler et al. (2016) suggested that an HTMT threshold close to 1 means the discriminant validity is not valid, and values above 0.9 mean the discriminant validity is not sufficient. Notably, in models designed for predictive purposes, the HTMT value should not exceed 0.85 (Wong, 2019). None of the constructs in this study exceeded Wong's (2019) recommended threshold. Therefore, the results indicate that discriminant validity is well-established. The HTMT results for the constructs are presented in *Table 54*.

Table 54 offers a comprehensive view of the interrelationships among the latent variables in the examined model, shedding light on the intricate dynamics within the conceptual framework. The analysis of these correlations provides valuable insights into how various constructs coalesce or diverge, thereby contributing to a nuanced understanding of the factors influencing customer perceptions and behaviours.

The LOY construct, notably, exhibits positive correlations with all other constructs, including FAIR (0.180), PRIV (0.057), PSR (0.069), INT (0.158), CS (0.414), CE (0.198), TRUST (0.264), and WELL (0.476). This broad spectrum of positive correlations indicates that e-loyalty is intricately linked to multiple facets of the consumer smart shopping experience, including perceived fairness, perceived privacy concerns, perceived risk, purchasing behaviour, smart satisfaction, and overall consumer digital well-being. The FAIR construct displays positive correlations with all constructs, ranging from 0.180 with LOY to a substantial 0.680 with TRUST. This indicates that perceptions of fairness are integral to the broader spectrum of consumer attitudes and behaviours (affordances), especially in establishing and nurturing trust. The PRIV construct showed positive correlations with LOY

(0.057), FAIR (0.276), PSR (0.549), INT (0.079), CS (0.034), CE (0.061), and TRUST (0.104). This underscores the relevance of addressing privacy concerns in fostering positive consumer relations, as these concerns extend across various dimensions of the smart shopping experience. The PSR construct demonstrated positive correlations with LOY (0.069), FAIR (0.473), PRIV (0.549), INT (0.229), and CS (0.129). Perceived risk appears to significantly contribute to positive consumer sentiments, emphasising the pivotal role of the perception of risk in shaping consumer perception and behaviour. The INT construct exhibited positive correlations with LOY (0.158), FAIR (0.191), PRIV (0.079), PSR (0.229), and CS (0.371). This indicates that consumer purchasing behaviour plays a crucial role in influencing e-loyalty and smart satisfaction. The CS construct was positively correlated with LOY (0.414), FAIR (0.229), PSR (0.129), INT (0.371), and CE (0.393). This robust network of positive associations underscores the central role of consumer smart satisfaction in driving e-loyalty and positive perceptions across various dimensions. The CE construct displayed positive correlations with LOY (0.198), FAIR (0.214), PRIV (0.061), PSR (0.184), INT (0.463), and CS (0.393). This indicates that a positive overall smart shopping experience is closely tied to perceptions of fairness, privacy, risk, purchasing behaviour, and satisfaction. The TRUST construct was positively correlated with LOY (0.264), FAIR (0.680), PRIV (0.104), PSR (0.533), INT (0.287), CS (0.299), and CE (0.277). Trust emerges as a central theme, positively influencing e-loyalty and intertwining with various dimensions of the smart shopping experience.

Finally, the WELL construct exhibited positive correlations with LOY (0.476), FAIR (0.232), PRIV (0.127), PSR (0.081), INT (0.348), CS (0.579), CE (0.406), and TRUST (0.417). This indicates that consumer digital well-being is influenced by a holistic range of factors, emphasising the interconnectedness of consumer perceptions and overall digital well-being. Evidently, the correlation matrix provides a nuanced understanding of the complex relationships within the model. These insights are pivotal for smart retailers seeking to enhance consumer shopping experiences, build trust, and foster loyalty by addressing various dimensions such as perceived fairness, privacy concerns, risk, purchasing behaviour, and overall consumer satisfaction.

Table 54:Discriminant validity: Heterotrait-monotrait ratio (HTMT) - Matrix

	LOY	**FAIR**	**PRIV**	**PSR**	**INT**	**CS**	**CE**	**TRUST**	**WELL**
LOY									
FAIR	0.180								
PRIV	0.057	0.276							
PSR	0.069	0.473	0.549						
INT	0.158	0.191	0.079	0.229					
CS	0.414	0.229	0.034	0.129	0.371				
CE	0.198	0.214	0.061	0.184	0.463	0.393			
TRUST	0.264	0.680	0.104	0.533	0.287	0.299	0.277		
WELL	0.476	0.232	0.127	0.081	0.348	0.579	0.406	0.417	

Note: LOY: E-Loyalty; FAIR:Perceived Fairness; PRIV: Perceived Privacy concerns; PSR: Perceived Risk; INT: Purchasing Behaviour; CS: Smart Satisfaction; CE:Smart Shopping Experience; TRUST: Trust; WELL: Digital Well-being.

6.6.5 Coefficients of Determination (R^2)

The determination of R^2 values serves as a crucial indicator for assessing the model's explanatory strength and in-sample predictive power (Roldán & Sánchez-Franco, 2012; Shmueli et al., 2019). To prevent overfitting, it is recommended that R^2 values do not exceed 0.9 (Hair et al., 2016). These results provide insights into the proportion of variance explained by each construct. Notably, Trust exhibits a substantial R^2 value of 0.411, indicating that the included variables collectively explain 41% of the variance in Trust. Similarly, Smart Satisfaction and Purchasing Behaviour demonstrate R^2 values of 0.298 and 0.171, respectively, reflecting their respective explanatory strengths in the model. These findings contribute to a comprehensive understanding of the predictive power and explanatory capabilities of the model across various constructs.

Table 55: R^2 values of the model

	R-square	R-square adjusted
E-Loyalty	0.028	0.026
Purchasing Behaviour	0.171	0.168
Smart Satisfaction	0.298	0.295
Smart Shopping Experience	0.056	0.054
Trust	0.411	0.407
Digital Well-being	0.085	0.083

6.7 Hypotheses Testing

Following the assessment of the study's measurement model, the results confirm that the model is suitable for hypothesis testing. The chosen method is bootstrapping in partial least squares structural equation modelling (PLS-SEM) (Sarstedt et al., 2022). Multicollinearity-related issues were analysed and confirmed during the data screening process (see *Table 38*), with all the VIF values being well below the recommended threshold of 10 (Kock and Lynn, 2012), which indicates that multicollinearity is not a significant problem among the independent variables. Subsequently, the R^2 values for the endogenous latent variables were determined. The study employed standardised estimates to test hypotheses based on the model's characteristics. Path significance was determined using a p-value threshold of 0.05 (Hair *et al.*, 2019). To ensure stable results, this study employed a bootstrapping technique with 5000 iterations in SmartPLS 4 to calculate the T-values and path coefficients. In addition, the R-square values were obtained from SmartPLS 4. Figure 29 present the results of the structural model tests. Finally, to assess the consistency of this thesis's contribution, the Stone-Geisser value ($Q2$) and the model's effect size ($f2$) were examined (Cohen, 1988). This thesis adds to previous research by looking at the importance-performance matrix (IPMA) with a focus on the dependent variable of purchase intention, E-loyalty and digital well-being (Ringle and Sarstedt, 2016). Figure 5-1 visually presents the results derived from the PLS analysis.

6.7.1 Structural model Assessment

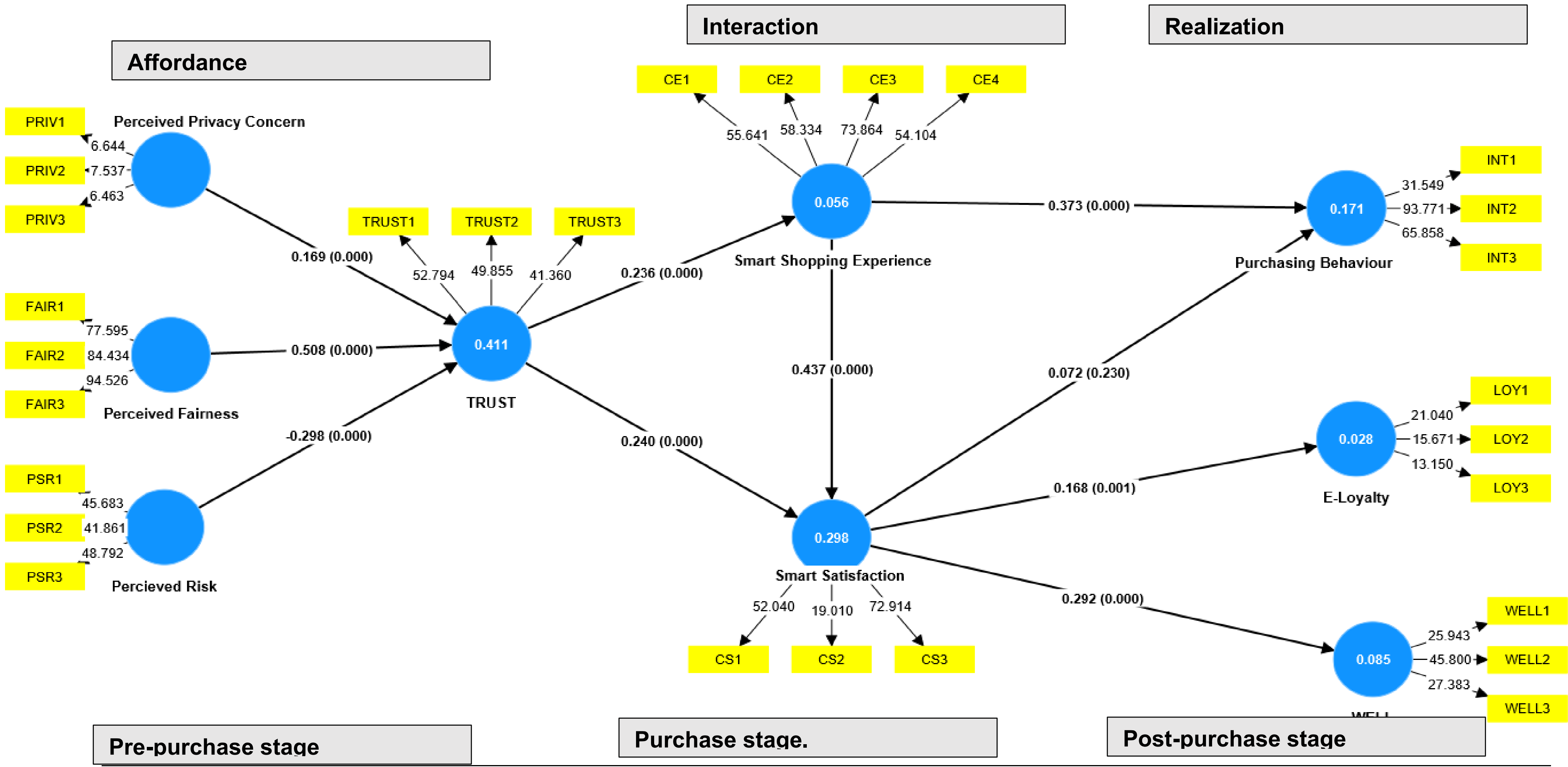
In this hypothesis testing phase, the impact of perceived privacy concerns, perceived fairness, and perceived risk on trust during the pre-purchase stage was examined. The analysis of the structural path model conducted in this study revealed a statistically significant positive correlation between perceived risk, fairness, privacy, and trust levels during retail purchases. These findings highlight the significant influence of consumers' perceptions of risks, fairness, and privacy on brand trust when interacting with smart technology-enabled products, services, or retail environments. The results demonstrated that perceived privacy concerns, affordance, and trust ($\beta = 0.169$, $p < 0.000$) had a positive impact on consumers' trust, thus supporting H1a. Likewise supporting H1b is the strong and positive correlation between perceived fairness affordance ($\beta = 0.508$, $p < 0.000$) and trust. However, perceived risk exhibits a negative and significant association with trust affordance ($\beta = -0.298$, $p < 0.000$), supporting H1c. These findings substantiate H1a–H1c, indicating that perceived privacy concerns, fairness, perceived risk, and affordances significantly impact brand trust during engagement with smart retailing. The results emphasise the necessity for retailers to address privacy concerns and ensure fairness in retail transactions to enhance consumer trust. Given that consumers' trust in a brand is significantly influenced by their perceptions of risk, fairness, and privacy in the retail setting, retailers should prioritise efforts to minimise perceived risk, promote fairness, and protect privacy. This is essential for establishing and maintaining trust with consumers.

Following the exploration of the impact of both the smart experience and satisfaction on consumer purchasing behaviour, e-loyalty, and digital well-being, was the impact of trust (during purchase) on the consumer experience and satisfaction during the purchasing stage of consumer interaction with smart technology-enabled retail products, services, or platforms.

As well, the findings showed that smart shopping experience is significantly and positively correlated with smart satisfaction (β=0.20, p <0.001) and consumer purchasing behaviour (β=0.21, p <0.001); thus, H2a and H2b were supported. The results also showed that consumer digital well-being (β = 0.26, p < 0.001) and e-loyalty (β = − 0.583, p = 0.000) were significantly and positively connected with consumer smart satisfaction in a smart retail context; thus, H3a, H3b, H4b, and H4c were supported. These results show that the two affordance interactions this study explored—smart shopping experience and smart satisfaction during the purchase stage—have a positive effect on consumers' purchasing habits, e-loyalty, and digital well-being when they use smart shopping. However, smart satisfaction is positively associated with purchasing behaviour but lacks statistical significance at conventional levels (β = 0.230, p < 0.072), hence is not supported.

In conclusion, hypothesis testing reveals crucial insights into the relationships between key constructs. Notably, perceived fairness emerges as a robust driver of trust, exerting a substantial positive influence. Perceived privacy concerns, while positively impacting trust, exhibit a more moderate effect. Conversely, perceived risk demonstrates an inverse relationship with trust, emphasising its nuanced role in smart retailing dynamics. Smart satisfaction, although showing a small positive effect on e-loyalty, plays a more pronounced role in influencing digital well-being. The smart shopping experience, a focal point in smart retailing, significantly impacts both purchasing behaviour and overall satisfaction. Trust, as a pivotal factor, has meaningful positive effects on both smart satisfaction and smart shopping experience. These findings collectively underscore the multifaceted nature of smart retailing dynamics, where factors such as fairness, privacy concerns, and trust intricately shape consumer behaviour and satisfaction. Recognising these nuanced relationships is imperative for practitioners and researchers aiming to enhance the effectiveness of smart retail strategies and cultivate positive consumer experiences in this evolving landscape.

Figure 29:Results of Bootstrapping Technique for structural assessment.



6.7.2 Structural Summary Results

Table 56 provides a concise overview of the findings. **Perceived privacy concerns are positively related to trust (H1a).** The estimate of 0.169, which has a significant t-value of 3.678, supports the hypothesis that perceived privacy issues have a beneficial impact on confidence in smart retailing. Based on the findings, customers link trust with intelligent retailers or intelligent retailing goods, services, and platforms that effectively manage their privacy concerns. **Perceived fairness is positively associated with trust in H1b**. The estimate of 0.508, which is highly significant with a t-value of 13.284, confirms that perceived fairness plays a substantial role in establishing confidence in smart retailing. This demonstrates that ethical practices are essential for influencing consumer confidence. **Perceived Risk --> Trust (H1c):** The significant negative estimate of -0.298, with a substantial t-value of 6.399, supports the hypothesis that perceived risk negatively impacts trust in smart commerce. Lower consumer trust correlates with higher perceived risks.

Trust has a strong positive impact on a smart purchasing experience, as indicated by a positive estimate of 0.236 and a significant t-value of 4.916. Establishing reliable ties with consumers enhances the overall buying experience. The analysis shows that trust has a considerable and positive effect on smart satisfaction, as indicated by the estimated coefficient of 0.240 and the t-value of 4.810. Consumers who have confidence in the smart retail system are probably more content with their entire experience.

Smart shopping experience --> Smart satisfaction (H3a): The strong correlation coefficient of 0.437, accompanied by a high t-value of 9.752, provides evidence in favour of the hypothesis that a positive smart shopping experience has a considerable impact on smart satisfaction. Positive shopping experiences frequently lead to satisfied consumers. The analysis shows that a pleasant smart shopping experience has a considerable impact on purchasing behaviour, as indicated by a positive estimate of 0.373 and a large t-value of 7.134. Contented consumers are more inclined to participate in purchasing activities.

Smart Satisfaction --> Purchasing Behaviour (H4a): Surprisingly, the estimated value of 0.072 with a t-value of 1.200 did not have a statistically significant impact. Therefore, it can be inferred that the level of consumer satisfaction with smart retailing does not necessarily directly influence their purchasing habits. **Smart satisfaction--> E-Loyalty (H4b)**, has a positive estimate of 0.168 and a significant t-value of 3.371. This implies that smart satisfaction has a positive influence on electronic loyalty. Content consumers are more inclined to demonstrate loyalty in a smart retail setting. The study found a positive correlation between smart satisfaction and digital well-being, with a significant t-value of 5.428 and an estimated effect size of 0.292. This confirms the hypothesis that smart satisfaction positively impacts digital well-being. Satisfied consumer experience enhanced digital wellness through smart retail interactions.

Table 56: Hypothesis Results summary.

Research Hypotheses		**Estimate (O)**	**SE**	**t**	**LCI**	**UCI**	**Hypothesis support**
H1a	Perceived Privacy Concern -> TRUST	0.169	0.046	3.678	0.079	0.259	Accepted
H1b	Perceived Fairness -> TRUST	0.508	0.038	13.284	0.433	0.583	Accepted
H1c	Perceived Risk -> TRUST	-0.298	0.047	-6.399	-0.390	-0.207	Accepted
H2a	TRUST -> Smart Shopping Experience	0.236	0.048	4.916	0.142	0.331	Accepted
H2b	TRUST -> Smart Satisfaction	0.240	0.050	4.810	0.142	0.337	Accepted
H3a	Smart Shopping Experience -> Smart Satisfaction	0.437	0.045	9.752	0.349	0.525	Accepted
H3b	Smart Shopping Experience -> Purchasing Behaviour	0.373	0.052	7.134	0.271	0.476	Accepted
H4a	Smart Satisfaction -> Purchasing Behaviour	0.072	0.060	1.200	-0.046	0.196	Rejected
H4b	Smart Satisfaction -> E-Loyalty	0.168	0.050	3.371	0.070	0.265	Accepted
H4c	Smart Satisfaction -> Digital Well-being	0.292	0.054	5.428	0.187	0.398	Accepted

6.7.3 f^2 Effect Sizes

The analysis of f-square values provides a nuanced perspective on the effect sizes attributed to specific predictors concerning their respective dependent variables within the model. In this investigation, Cohen's (1988) prescribed methodology was employed to quantify the effect size ($f2$), which is a pivotal metric for elucidating the strength of relationships between constructs. In accordance with the recommendations given by Chin et al. (2003), the findings offer noteworthy insights into the relationships between e-loyalty, perceived fairness, perceived privacy concerns, perceived risk, smart satisfaction, smart shopping experience, and trust.

The results of the analysis indicated that, **Perceived Fairness -> TRUST (0.364):** Perceived fairness substantially influences trust, explaining 36.4% of the variance in trust. **Perceived Privacy Concern -> TRUST (0.038):** Perceived privacy concerns have a weak effect on trust, with only 3.8% of the variance in trust explained. **Perceived Risk -> TRUST (0.107):** Perceived risk moderately affects trust, contributing to 10.7% of the variance in trust. **Smart Satisfaction -> E-Loyalty (0.029):** Smart satisfaction has a minimal effect on e-loyalty, explaining only 2.9% of the variance. **Smart Satisfaction -> Purchasing Behaviour (0.005):** Smart satisfaction has an almost negligible impact on purchasing behaviour, with a mere 0.5% of the variance explained. **Smart Satisfaction -> WELL (0.093):** Smart satisfaction notably influences digital well-being, contributing to 9.3% of the variance in digital well-being. **Smart Shopping Experience -> Purchasing Behaviour (0.127):** The smart shopping experience has a tangible impact on purchasing behaviour, explaining 12.7% of the variance. **Smart Shopping Experience -> Smart Satisfaction (0.257):** The smart shopping experience significantly influences smart satisfaction, explaining a substantial 25.7% of the variance. **TRUST -> Smart Satisfaction (0.077):** Trust has a discernible effect on smart satisfaction, contributing to 7.7% of the variance. **TRUST -> Smart Shopping Experience (0.059):** Trust moderately influences the smart shopping experience, explaining approximately 5.9% of the variance.

In summary, the results demonstrates that perceived fairness significantly influences trust (0.364, explaining 36.4% of trust variance), whereas perceived privacy concerns have a weak effect (0.038, 3.8% variance). Perceived risk moderately affects trust (0.107, 10.7% variance). Smart satisfaction has a minimal impact on e-loyalty (0.029, 2.9% variance) and purchasing behaviour (0.005, 0.5% variance). However, it notably influences digital well-being (0.093, 9.3% variance). The tangible impact of the smart shopping experience impacts purchasing behaviour (0.127, 12.7% variance) and significantly influences smart satisfaction (0.257, 25.7% variance). Trust affects smart satisfaction (0.077, 7.7% variance) and moderately influences the smart shopping experience (0.059, 5.9% variance).

6.7.4 Predictive Relevance (Q^2)

In this study, the analysis of predictive relevance employed the blindfolding procedure to assess the Stone-Geisser's Q^2 values, indicating the extent to which each construct predicts the model's endogenous latent variable (Hair *et al.*, 2013). The omission distance was set to 7, following the recommendation by Geisser (1974). The results, summarised in *Table 57*, indicate that all constructs achieved at least a medium Q^2 value, signifying their predictive relevance in the model. Each of the constructs analysed in the study has a level of impact on predicting consumers purchase intention. Trust stands out as being significant, indicating that it plays a role in predicting purchase intention. Smart satisfaction follows with a level of significance indicating that it also influences purchase intention, but to a greater extent than trust. The smart shopping experience has an impact compared to smart satisfaction, while purchasing behaviour shows weaker but still notable predictive relevance. Digital well-being and E-loyalty has a lower impact on predicting purchase intention, with digital well-being being moderately influential and E-loyalty having the least impact among the constructs. In summary, constructs with Q2 values substantially contribute to the prediction of the model's endogenous latent variable, i.e., the individual's purchase intention. The analysis indicates that constructs with a Q2 value impact individuals' intention to make a purchase within the model context.

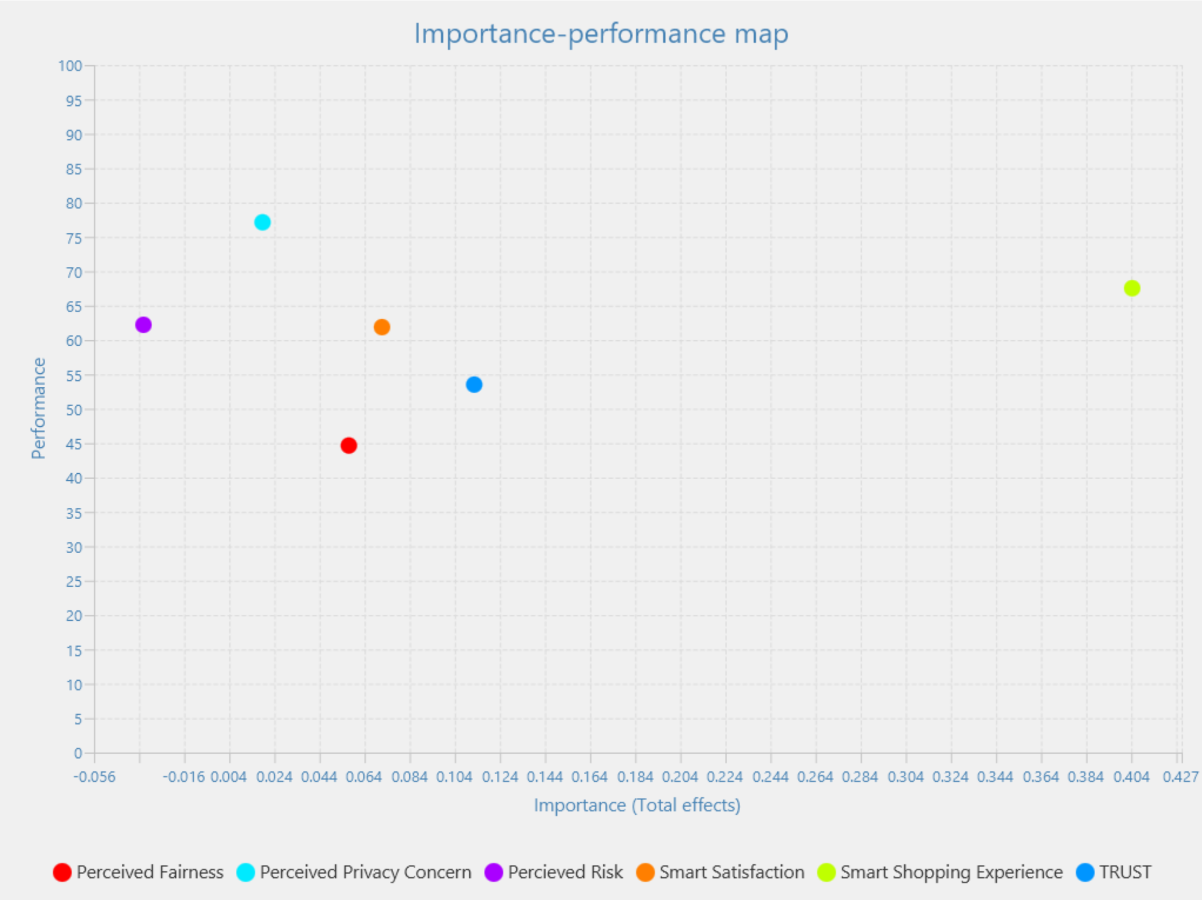
Table 57:The Results of Predictive Relevance Test

CONSTRUCTS	$Q^2 = (1 - sse / sso)$
E-LOYALTY	0.008
PURCHASING BEHAVIOUR	0.026
SMART SATISFACTION	0.086
SMART SHOPPING EXPERIENCE	0.047
TRUST	0.403
WELL	0.018

6.7.5 Importance-Performance Map Analysis (IPMA)

The Importance-Performance Matrix (IPMA) served as an additional analysis with purchase intention as the target construct. The aim of this analysis is to enhance the outcome of the target variable by comparing each construct's total effect with the average values of its performance scores (Ringle and Sarstedt, 2016). IPMA provides a valuable two-dimensional grid, considering both the total effects and the constructs' performance concerning the target variable (Martilla and James, 1977). One key criterion for IPMA is to ensure that all the model's outer weights values are positive. In the current analysis, no problematic values were identified, indicating the absence of issues in this regard. The robustness of the IPMA results adds a strategic dimension to the management approach, facilitating a comprehensive understanding of the constructs' impact and performance in relation to the target variable.

Figure 30: IPMA Results with Purchasing Behaviour



When analysing the correlation between purchasing behaviour and the key elements, it is essential to fully understand the performance rate and the complex interconnections within the conceptual framework. Perceived fairness (0.057): There appears to be a correlation between perceived fairness and purchase behaviour. Consumers exhibit positive purchasing patterns when they perceive equity in their interactions with smart retail platforms. The presence of a small positive correlation implies a subtle correlation between perceived privacy concerns and purchase activity. Heightened worries about privacy have a direct impact on consumer buying patterns. Perceived Risk (0.034): The negative correlation signifies a reverse connection between perceived risk and purchase activity. Consumers are more likely to participate in positive purchasing behaviour when their perception of risk is lower. Smart satisfaction (0.072): A slight positive correlation demonstrated that smart satisfaction impacts purchasing behaviour. Increased satisfaction with product attributes leads to favourable buying behaviour. The data show a strong positive correlation between smart shopping experience and purchase behaviour, indicating a clear relationship between the two. An affirmative and improved shopping experience plays a crucial role in influencing purchasing habits. The positive correlation (0.113) demonstrated that trust influences purchasing behaviour. As consumer confidence increases, individuals are more likely to display favourable purchasing patterns. When examining these relationships, it is crucial to consider the rate of performance. The factor demonstrates a link of 0.405 between smart shopping experience and purchase behaviour. Understanding these correlations is essential for enhancing initiatives that seek to enhance purchasing behaviour in the context of smart retail.

6.7.6 Mediation Analysis

The mediation analysis showed several significant pathways that elucidated the intricate relationships among the key variables in this study. Each path signifies the mediator's impact on the relationship between the independent and dependent variables, thus providing valuable insights into the underlying mechanisms at play. Here is a detailed discussion of the findings presented in *Table 58*.

TRUST -> Smart Shopping Experience -> Smart Satisfaction -> Purchasing Behaviour: The indirect effect of trust (β = 0.016, T statistic = 3.127, p value = 0.002) is positive, indicating that trust has a significant indirect effect on purchasing behaviour through the sequential mediation of smart shopping experience and smart satisfaction. This implies that as trust increases, the sequential impact on shopping experience, satisfaction, and purchasing behaviour is positively influenced.

Perceived Privacy Concern -> TRUST -> Smart Shopping Experience -> Purchasing Behaviour: The indirect effect of perceived privacy concern (β = 0.013, T Statistic = 2.555, p Value = 0.011) is positive, indicating that perceived privacy concern positively influences purchasing behaviour through the mediating effects of trust, smart shopping experience, and smart satisfaction. This implies that higher levels of trust, when coupled with privacy concerns, contribute positively to the subsequent shopping experience and, consequently, purchasing behaviour.

Perceived Privacy Concern -> Trust -> Smart Satisfaction: The indirect effect of perceived privacy concern (β = 0.031, T statistic: 2.598, p value: 0.009) is positive, signifying that perceived privacy concern contributes to smart satisfaction through the mediation of trust. This implies that privacy concerns, when considered in tandem with trust, positively influence the subsequent level of satisfaction.

Perceived fairness, -> TRUST -> Smart Satisfaction -> Digital Well-being: The indirect effect of perceived fairness (β= 0.047, T Statistic= 3.065, p Value =0.002) is positive, signifying that perceived fairness positively influences well-being through the sequential mediation of trust and smart satisfaction. This posits that perceived fairness, in conjunction with trust, positively impacts subsequent digital well-being through increased satisfaction.

Perceived Privacy Concern -> TRUST -> Smart Shopping Experience -> Smart Satisfaction: The indirect effect of perceived privacy concern (β= 0.013, T Statistic= 2.515, p Value= 0.012) is positive, signifying a positive effect of perceived privacy concern on smart satisfaction through the mediation of trust and smart shopping experience. This implies that trust, coupled with privacy concerns, positively influences subsequent satisfaction through the shopping experience.

Perceived Fairness -> TRUST -> Smart Shopping Experience: The indirect effect of perceived fairness (β=0.120, T Statistic= 4.586, p Value= 0.000) demonstrates the strong positive influence of perceived fairness on smart shopping experience through the mediation of trust. This indicates that trust, when paired with perceived fairness, significantly enhances the subsequent smart shopping experience.

Perceived Fairness -> TRUST -> Smart Shopping Experience -> Smart Satisfaction: The indirect effect of perceived fairness (β=0.038, T Statistic=3.537, p Value= 0.000) indicates that perceived fairness has a positive indirect effect on smart satisfaction through the sequential mediation of trust and smart shopping experience. This posits that perceived fairness, in conjunction with trust, significantly influences subsequent satisfaction through the shopping experience.

Perceived Privacy Concern -> Trust -> Smart Satisfaction -> Purchasing Behaviour: The indirect effect of perceived privacy concern (β= 0.007, T Statistic= 2.110, p Value= 0.035) is positive, implying a modest positive impact of perceived privacy concern on purchasing behaviour through the mediation of trust and smart satisfaction. This implies that privacy concerns, when combined with trust, positively influence subsequent purchasing behaviour through increased satisfaction.

Perceived Risk -> Trust -> Smart Satisfaction -> E-Loyalty: The indirect effect of perceived risk (β= -0.021, T Statistic=2.956, p Value= 0.003) indicates that perceived risk negatively influences e-loyalty through the sequential mediation of trust and smart satisfaction. This suggests that trust, when coupled with perceived risk, negatively influences subsequent e-Loyalty through decreased satisfaction.

TRUST -> Smart Shopping Experience -> Smart Satisfaction -> Digital Well-being: The indirect effect of trust (β = 0.037, T statistic = 3.382, p value = 0.001) implies that trust positively affects well-being through the sequential mediation of smart shopping experiences and smart satisfaction. This implies that trust, when coupled with a positive shopping experience and satisfaction, significantly impacts subsequent well-being.

In summary, these mediation analyses shed light on the nuanced pathways through which trust, perceived fairness, perceived privacy concern, and perceived risk collectively influence various outcomes such as satisfaction, well-being, e-loyalty, and purchasing behaviour in the context of smart retailing. The positive and negative mediation effects highlight the importance of considering these factors in tandem to comprehensively understand and predict consumer behaviour in smart retail environments.

Table 58: Mediation analysis results

Path	Path Coefficient (β)	p-value	Impact
TRUST -> Smart Shopping Experience -> Smart Satisfaction -> Purchasing Behaviour	0.016	0.002	Positive
Perceived Privacy Concern -> TRUST -> Smart Shopping Experience -> Purchasing Behaviour	0.013	0.011	Positive
Perceived Privacy Concern -> TRUST -> Smart Satisfaction	0.031	0.009	Positive
Perceived Fairness -> TRUST -> Smart Satisfaction -> Digital Well-being	0.047	0.002	Positive
Perceived Privacy Concern -> TRUST -> Smart Shopping Experience -> Smart Satisfaction	0.013	0.012	Positive
Perceived Fairness -> TRUST -> Smart Shopping Experience	0.120	0.000	Positive
Perceived Fairness -> TRUST -> Smart Shopping Experience -> Smart Satisfaction	0.038	0.000	Positive
Perceived Privacy Concern -> TRUST -> Smart Satisfaction -> Purchasing Behaviour	0.007	0.035	Positive
Perceived Risk -> TRUST -> Smart Satisfaction -> E-Loyalty	-0.021	0.003	Negative
TRUST -> Smart Shopping Experience -> Smart Satisfaction -> Digital Well-being	0.037	0.001	Positive

Chapter 7: Discussion of Findings and Conclusions

7.1 DISCUSSION

Smart retail technologies have recently driven a transformative wave in the retail industry, introducing innovations such as smart mirrors, shopping assistants, chatbots, and RFID technology (Müller-Seitz et al., 2009; Roy et al., 2017; Cukier, 2021; Chen and Chang, 2023). Smart retail technologies and platforms have grown increasingly autonomous, enabling them to perform tasks and make decisions for consumers (de Bellis and Venkataramani Johar, 2020), catalysing societal shifts (Huang and Rust, 2018; Puntoni *et al.*, 2021). However, the use of these emerging technologies and platforms can lead to unintended consequences, including addiction, decreased competence, and erosion of manual skills (Sohn, 2024). Concerns about negative information disclosure and ethical concerns like fairness and privacy coupled with perceived risk have been shown to diminish trust in technology (Okazaki et al., 2009, 2020). Yet, these technologies and platforms can also have positive effects, such as convenient shopping and improving satisfaction, and are often serendipitous in nature (Sohn, 2024). For instance, smart, technology-driven shopping platforms might lead to more deliberate and less impulsive shopping habits, potentially lowering consumers' financial risks. Likewise, these could improve overall satisfaction with smart shopping experiences, albeit consumers may not attribute this directly to the platform's decision-making process (Botti and Iyengar, 2004; Sohn, 2024).

The findings of this study reveal a robust positive correlation between perceived fairness and trust within the original sample. This underscores the foundational role of fairness in shaping consumer trust in smart retailing. The results address a critical gap in existing literature, emphasising the significance of balanced fairness perceptions and trust. The results of this study demonstrate that perceived fairness, honesty, and reasonable management of consumer information play pivotal roles in shaping consumer trust in smart retailing. In the ever-evolving landscape of smart retail, where technology interfaces directly with consumer experiences, the perception of fairness becomes a cornerstone for establishing trust. Consumers interacting with smart retail systems expect a fair and transparent exchange of value. This perception encompasses various dimensions, such as personalised recommendations and data privacy. A positive perception of these factors establishes a strong foundation for trust, influencing consumers to engage confidently in online transactions and interactions. This finding corroborates those of previous studies that indicate that fairness exerts significant effects on consumers' trust (Chen and Chou, 2012; Zhao, Guan and Zhang, 2023) and also validates the inclusion of perceived fairness in the model.

Second, this study revealed that perceived privacy concerns directly affect consumer trust, emphasising the crucial need to address privacy considerations to foster trust in this technologically advanced retail landscape. In other words, perceived consumer privacy concerns are a crucial variable that explains consumer trust and behavioural outcomes in smart retail settings. Consumers who experience uncertainty about smart retail technologies and platforms' success qualities have less trust in the platform and, as a result, perceive a high privacy risk, which in turn reduces their trust in the platform. Existing studies have explored the relationship between privacy protection, trust, and behavioural intention in limited areas, such as e-commerce (Wolfinbarger and Gilly, 2003), online-to-offline (O2O) business (Kim, Wang and Roh, 2021), and social commerce (Abbas *et al.*, 2023). However, this study focused on this relationship in the context of smart retailing, where consumers directly make purchases in smart technology-enabled retail environments.

This study found that perceived privacy concerns affect consumer trust in smart retailing. This result indicates that privacy protection is a decisive factor in consumer trust and smart shopping experiences. Consumers' sensitivity to how their personal information is handled, their insistence on keeping their privacy safe, and the prioritisation of personal privacy as a key ethical factor collectively contribute to the establishment and maintenance of trust. Smart retailers must prioritise robust privacy policies, transparent data practices, and effective security measures to address these concerns and foster a trustworthy online shopping environment. At a time when digital consumers place an increasing value on privacy, meeting these expectations can both increase consumer trust and contribute to the long-term success of smart retailing platforms. These findings will be helpful for future research exploring the role of trust-based privacy protection in smart retailing. In line with affordance theory (Gibson, 1977), this study supports the notion that the perceived properties of an environment or system (in this case, smart retailing platforms) influence how individuals (consumers) interact with them.

In contrast, the inverse relationship between perceived risk and trust emphasises the difficulty that higher perceived risk poses to the development of trust in smart retail scenarios. This finding corroborates those of previous studies that have conceptualised consumer digital ethical concerns and perceived risk as barriers and validates the inclusion of risk to trust in the model (Featherman and Hajli, 2016; Park and Tussyadiah, 2017; Sohn, 2024). The results underline specific concerns related to misinformation, general worry, and the potential misuse of personal privacy, all of which contribute to a sense of risk for consumers engaging in smart technology-enabled retail transactions. This finding further supports existing research that has demonstrated that perceived risk in using smart retail technologies and platforms undermines consumers' willingness to adopt them (Kleijnen, de Ruyter and Wetzels, 2007; Pizzi and Scarpi, 2020). It emphasises the importance of viewing consumer digital ethical concerns and perceived risk as a multidimensional factor in understanding technology adoption, rather than relying on a unidimensional model or compound conceptualizations. Specifically, this study tested and confirmed digital ethics and perceived risk as a multidimensional factor with four dimensions. The results demonstrate the perceived digital ethics and perceived risk associated with the use of smart technologies in retail as a second-order concept with a significant impact on trust.

7.1.1 Research Question One

In answering research question 1: How does the integration of smart technology in retail influence consumers' perceptions of privacy, fairness, risk, and trust?

The findings of this study reveal that the integration of smart technology in retail has a nuanced impact on consumers' perceptions. Perceived fairness emerges as a significant driver of consumer trust (explaining 36.4% of the variance in trust). This implies that consumers place significant importance on fairness in their interactions with smart retail platforms, which in turn influences their trust in the system, indicating that equitable practices in smart retail operations are crucial for fostering trust and loyalty. While perceived privacy concerns are present, they have a weaker effect on trust (with only 3.8% of the variance in trust explained) compared to fairness. This indicates that while consumers may have some concerns about privacy in the context of smart retail technology, it does not significantly impact their trust in the system. Additionally, perceived risk moderately affects trust (contributing to 10.7% of the variance in trust), highlighting the importance of addressing consumer apprehensions to build trust in smart retail environments. This indicates that consumers do consider the risks associated with smart retail technologies and platforms when forming trust, but to a lesser extent compared to fairness. Perceived risk, on the other hand, moderately affects trust (explaining 10.7% of the of the variance in trust). The negative coefficient between perceived risk and trust (-0.416) indicates that as consumers perceive higher risks associated with smart retailing, their trust in the platform decreases. This highlights the importance of mitigating perceived risks in the integration of smart technology to foster trust among consumers.

Overall, the results confirm that the integration of smart technology in retail significantly influences consumers' perceptions of privacy, fairness, risk, and trust. While it can enhance perceptions of fairness and trust, it may also raise concerns about privacy and perceived risks. Thus, understanding and addressing these factors are crucial for the successful implementation and acceptance of smart retailing technology.

7.1.2 Research Question Two

In answering research question 2: How does trust shape the smart shopping experience and satisfaction for consumers using smart retail technologies and platforms?

The findings of this study reveal that Trust moderately influences the smart shopping experience, explaining approximately 5.9% of the variance. This confirms that trust plays a role in shaping consumers' perceptions and experiences during their smart shopping interactions, in line with existing literature (Kim, Ferrin and Rao, 2008; Aguirre et al., 2015b; Mofokeng, 2023). In the same vein, Trust has a discernible effect on smart satisfaction, contributing to 7.7% of the variance. This indicates that higher levels of trust in the smart retailing system are associated with increased satisfaction with the overall smart retailing experience. The findings demonstrate the complex, multifaceted relationship among trust, smart satisfaction, and smart shopping experience. Trust affects consumer perceptions and behaviours in smart retail settings, as shown by the strong positive path coefficients of 0.287 for smart satisfaction and 0.277 for smart shopping experience. These findings indicate that trusting a smart retail platform increases consumer satisfaction and positive shopping experiences. The variation in consumer smart satisfaction and smart shopping experience shows how important it is in shaping consumer views and behaviours. Trust improves smart retail shopping satisfaction and experience.

7.1.3 Research Question Three

In answering research question 3: In what ways does the smart shopping experience contribute to smart satisfaction among consumers?

The empirical findings of this study unequivocally establish a positive and significant relationship between consumers’ smart shopping experience and their smart satisfaction, thereby offering robust support for the hypotheses expressed in Hypothesis 3. This fundamental association underscores the crucial role that smart shopping experience calibre within smart retail environments plays in determining consumers’ overall satisfaction levels.

Importantly, these empirical results align with and reinforce extant scholarly literature (Vakulenko *et al.*, 2019; Holmlund *et al.*, 2020; Pei *et al.*, 2020; Lee and Ko, 2021), albeit within the distinct context of smart retailing. The ability of smart technologies to facilitate a seamless, effective, and personalised shopping experience has emerged as a powerful driver of customer satisfaction, successfully meeting the varied needs and preferences of consumers. In the contemporary, technologically driven retail landscape, the consumer's smart shopping experience assumes paramount significance as a determinant of smart satisfaction. Significantly, the empirical evidence underscores that consumer smart satisfaction serves as a critical indicator of a smart retailer's successful and sustainable long-term competitiveness. Moreover, the findings illuminate the consumer's smart shopping experience as a pivotal source of sustainable competitive advantage for smart retailers, whether operating within physical brick-and-mortar stores or virtual online platforms. These results underscore the transformative potential of the consumer smart shopping experience in various shopping contexts and its significance in driving consumer satisfaction and loyalty.

Furthermore, the empirical insights underscore the imperative for smart retailers to strategically prioritize the differentiation of the consumer experience, leveraging smart technologies to craft unique and compelling shopping encounters. This strategic emphasis on enhancing consumer satisfaction and loyalty resonates with the scholarly literature (Holmlund *et al.*, 2020), particularly in the domains of online commerce and big data analytics. In essence, this study contributes methodologically rigorous empirical evidence to our understanding of the intricate interplay between consumers' smart shopping experiences and their smart satisfaction, shedding light on its profound implications for smart retailers' competitiveness and sustainability. By recognising and strategically harnessing the transformative potential of superior customer experiences facilitated by smart technologies, retailers can fortify their market position and thrive among evolving consumer preferences and technological advancements.

7.1.4 Research Question Four

In answering research question 4: To what extent does satisfaction impact consumer purchasing behaviour and contribute to e-loyalty and digital well-being in smart retailing?

Based on the empirical findings of this study, smart satisfaction emerges as a pivotal determinant with profound implications across multiple dimensions within the context of smart retailing. This study presents valuable insights into the intricate interplay between consumer satisfaction and its consequential impact on purchasing behaviour, e-loyalty, and digital well-being. The robust statistical analyses provide compelling evidence, thereby advancing our understanding of consumer behaviour within the dynamic context of smart retailing.

The findings underscore that while the influence of consumer smart satisfaction on purchasing behaviour may initially seem modest ($\beta = 0.072$), its significance in fostering e-loyalty ($\beta = 0.168$) and contributing to digital well-being ($\beta = 0.292$) is unequivocally noteworthy, thereby offering robust support for the hypotheses expressed in Hypotheses 4b and 4c. This nuanced relationship highlights the multifaceted nature of satisfaction as a pivotal driver of consumer behaviour within the smart retail environment. Despite not being the sole determinant, satisfaction plays a pivotal role in cultivating repeat purchases and brand loyalty, echoing established scholarly discourse (Rita et al., 2019). Moreover, the analysis unveils insightful dynamics surrounding the relationship between satisfaction and consumer loyalty in the context of smart retailing. Despite the relatively moderate impact of satisfaction on consumer loyalty ($\beta = 0.192$), the positive coefficient indicates that satisfied consumers are significantly more inclined to exhibit loyalty towards smart brands or platforms. This underscores the strategic imperative of prioritising customer satisfaction as a foundational element in nurturing and sustaining a loyal customer base, as corroborated by prior research (Lin and Sun, 2009; Camilleri and Filieri, 2023). In addition, the study reveals the broader implications of smart satisfaction for consumer digital well-being, emphasising its pivotal role in enhancing consumers' overall quality of life within the digital retail landscape. Satisfaction with the smart retail experience significantly contributes to consumers' digital well-being, fostering sentiments of contentment, convenience, and positive emotions derived from interactions with smart retail technologies.

Overall, the results highlight the significant impact of smart satisfaction in shaping consumer behaviour and well-being within the dynamic milieu of smart retailing. Satisfied consumers exhibit more favourable purchasing behaviours, demonstrate heightened loyalty towards smart brands, and experience enhanced digital well-being. This study enriches the scholarly discourse by unravelling the intricate interplay between satisfaction and consumer outcomes in the context of smart retailing, providing invaluable insights for retailers and policymakers striving to optimise consumer experiences and drive business success. In the future, research could focus on further exploring the mechanisms and limits of the connection between satisfaction and consumer behaviour in a smart retail setting. Investigating other variables that might impact or intervene in this connection could provide a better understanding of improving consumer experiences and promoting long-lasting relationships in the constantly changing environment of smart retailing.

7.2 AN AFFORDANCE-BASED EXPLORATION OF FINDINGS

Affordance theory, which is rooted in the idea that technology features offer invitations for certain actions or behaviours, serves as a comprehensive lens to understand the intricate relationships among various factors in the context of smart retailing. The results from the analysis of perceived fairness, perceived privacy concern, perceived risk, smart satisfaction, trust, smart shopping experience, purchasing behaviour, e-loyalty, and consumer digital well-being provide rich insights into how consumers perceive and interact with smart retailing technologies. Perceived fairness, an affordance in the smart retailing ecosystem, is positively correlated with trust. The affordability theory posits that consumers perceive fairness as an invitation for trust-building actions. This finding is critical for smart retailers because it underscores the importance of transparent and ethical practises, which can be considered affordances that enhance user trust. As consumers trust the platform more, they are more likely to engage in positive smart shopping experiences, fostering smart satisfaction.

The affordance of perceived privacy concerns emerges as a significant factor positively influencing trust in the smart retailing environment. Consumers, being increasingly cautious about their privacy, perceive the features related to privacy protection as crucial affordances. This insight highlights the necessity for smart retailers to prioritise privacy-preserving features and communicate them effectively to build and maintain user trust. Conversely, perceived risk negatively impacts trust in smart retailing. The affordance theory perspective indicates that features perceived as risky do not afford the trust-building actions that users seek. Therefore, minimising perceived risks associated with the use of smart technology is paramount for establishing and maintaining user trust. Smart satisfaction, an affordance arising from positive interactions with the smart retailing platform, positively influences e-loyalty and digital well-being. This indicates that users perceive satisfaction as an invitation to engage more loyally and experience improved digital well-being. Smart retailers should prioritise features that enhance user satisfaction to foster loyalty and contribute positively to users' overall well-being.

The affordance of the smart shopping experience, which is influenced by the features and functionalities of the smart retailing platform, positively impacts purchasing behaviour Users perceive a positive shopping experience as an invitation for further engagement, leading to increased purchasing behaviour Smart retailers should focus on creating seamless, enjoyable shopping experiences that encourage users to make more purchases. Trust, as an affordance, plays a pivotal role in influencing both smart satisfaction and smart shopping experiences. Consumers who perceive trust as an affordance are likely to engage more satisfactorily and have positive shopping experiences. Trust is foundational to the success of smart retailing platforms, and its affordance contributes to overall positive outcomes for consumers.

Overall, applying affordance theory to the analysis of smart retailing variables provides a robust framework for understanding user perceptions and behaviours The results contribute significantly to the existing knowledge by unravelling the complex relationships among perceived fairness, perceived privacy concern, perceived risk, smart satisfaction, trust, smart shopping experience, purchasing behaviour, e-loyalty, and consumer digital well-being. Smart retailers can leverage these insights to refine their platforms, ensuring that the affordances perceived by consumers align with their expectations and preferences. This holistic understanding of consumer smart shopping experiences in the digital commerce landscape is essential for shaping the future of smart retailing and enhancing consumer digital well-being.

7.2.1 The legal and regulatory landscape surrounding smart retailing, including current laws and guidelines that govern its use.

The widespread adoption of smart technologies such as smartphones, internet-connected gadgets, and sensors has resulted in the creation of a significant consumer digital footprint, a trend that is expected to continue (Arya et al., 2019). The term "digital footprint" refers to the trail, traces, or "footprints" that people leave online, either knowingly or unknowingly, after their interactions with smart retailing portals or other Internet-based media channels. This information can be collected and used in a variety of ways (Muhammad, Dey and Weerakkody, 2018; Arya, Sethi and Paul, 2019) despite the growing ethical concerns such as trust and data privacy among stakeholders (Jaspers and Pearson, 2022; Jayaswal and Parida, 2023; Ying *et al.*, 2023). Digital footprints are not only consumer identities but also memories, moments, and consumer behaviours. Smart retailers, like other businesses, amass these massive digital chronicles in order to better understand how and why consumers behave and purchase on digital platforms based on their behaviour and purchase histories, among others (Wedel and Kannan, 2016; Bradlow *et al.*, 2017; Martins *et al.*, 2019). However, this has prompted regulatory concerns regarding data ownership and privacy protection (Houston, 2016; Eggers, Turley and Kishnani, 2018; Palmatier and Martin, 2019). Determining whether the consumer or the service provider (smart retailer) is the owner of the data is one of the most critical challenges. Given the unprecedented and exponential growth in the amount of consumer data collected by retailers across a variety of customer touchpoints, safeguarding data privacy and other ethical views has become one of the key priorities in the smart retail industry (Martin and Murphy, 2017; Bleier, Goldfarb and Tucker, 2020; Martin and Palmatier, 2020; Martin *et al.*, 2020). Data privacy in retail contexts requires convergence among three key stakeholders: the consumer, the retailer, and the regulatory. Each of these parties has a distinct role to play and perspective to offer.

Prior studies have established that, there is not a single global agreement on AI policies including data protection, and the various regulatory agencies take a variety of stances with regard to these topics (Eggers et al., 2018; K. D. Martin et al., 2020). Recently, governments worldwide have begun paying attention to and promoting AI-related research and policy documents in this area. Eggers, Turley and Kishnani (2018) in their work, argued that almost one-third of countries do not have any data protection laws, and those that do often have inconsistent provisions. The General Data Protection Regulation (GDPR) of the European Union, for example, codifies the principle of privacy by imposing stringent controls over the transmission of data across international borders and by granting citizens the right to "be forgotten." (Eggers et al., 2018; Mwesiumo et al., 2021; Roe et al., 2022) A survey revealed that 82% of Europeans intend to make use of their newly acquired rights to view, restrict, or delete their personal data (Eggers et al., 2018). In the United States, however, the emphasis is on industry-specific regulations, such as those governing the retail, banking, and healthcare industries, in addition to state legislation. On the other hand, this approach has been criticised because the country lacks a comprehensive federal law that governs data protection. As a result, several states have passed their own data privacy laws, resulting in a patchwork of regulations that businesses must explore. The Illinois Biometric Information Privacy Act (BIPA), for instance, mandates that businesses obtain written consent from consumers before collecting their biometric information, which includes facial recognition information (Eggers et al., 2018).

Numerous lawsuits against businesses that were accused of collecting biometric data without getting proper consent have been based on BIPA (Bilyk, 2021; Nasiri, 2022). Another example is the California Consumer Privacy Act (CCPA), which grants California residents the right to know what personal information is being collected about them and the right to request that it be deleted. Before selling personal information to third parties, the CCPA also requires enterprises to get explicit consent (Mulgund *et al.*, 2021). Furthermore, some industry players and privacy advocates have produced guidelines and best practises. The National Telecommunications and Information Administration (NTIA), for example, has published a set of voluntary privacy rules for facial recognition technologies. Businesses should be upfront about their use of face recognition technology, acquire informed consent from consumers, and limit the use of facial recognition technology to particular purposes, according to these rules (Congressional Research Service, 2022). Thus, it is of the paramount importance to establish a comprehensive and uniform legal framework that protects consumer data while allowing for the development of innovative technology and its use in retail.

Table 59: Comparison of some privacy Acts.

	BIPA The Illinois Biometric Information Privacy Act	CCPA California Consumer Privacy Act	GDPR General Data Protection Regulation
Year passed	2008	2018	2016
Year Enforced	2019	2020	2018
Scope	BIPA regulates private entities' collection, use, and storage of biometric data in Illinois and allows individuals to sue privately to enforce their legal rights.	Businesses subject to the CCPA must provide California residents with a privacy policy that describes the types of personal information collected, how it is used, and the third parties with whom it is shared or sold. Businesses must also secure personal data.	The GDPR applies to all businesses, including those outside the EU, that process EU residents' personal data. GDPR covers all personal data processing, including collection, use, storage, and transfer. Personal data includes names, emails, location data, and online identifiers under the GDPR.
Penalties	The Illinois Attorney General has the authority to enforce BIPA and may bring a lawsuit against a private entity that violates the law, subject to civil penalties of up to $5,000 for each violation.	CCPA breaches cost $2,500, and intentional violations cost $7,500. Data breaches can cost businesses $100 to $750 per California resident per incident or actual damages (whichever is greater).	The GDPR imposes significant fines for non-compliance, with fines of up to 4% of a business's global annual revenue or €20 million (whichever is greater).
Private right of action	Individuals and businesses	Individuals and businesses	Individuals and businesses
Consent rules	BIPA requires private entities to obtain informed written consent from individuals before collecting, using, or disclosing their biometric data and provide them with a written policy detailing the entity's retention schedule and guidelines for permanently destroying biometric data. The law also prohibits employers, vendors, and service providers from requiring biometric data consent.	The CCPA prohibits businesses from discriminating against consumers who opt out of selling their personal data. Businesses cannot deny goods or services, charge different prices, or provide different service to CCPA-eligible consumers.	Regardless of consent, GDPR requires businesses to ensure that personal data processing is necessary and proportionate for the purposes for which it is collected. Businesses must use legitimate interests or contractual necessity if consent is not a legal basis.

7.2.2 Research Contribution

This study contributes to the understanding of smart technology in the retail landscape by specifically employing affordance theory as a theoretical lens. The investigation explores the intricate dynamics of consumer interactions within smart retail environments, shedding light on the impact of smart technology on perceived risk, privacy, and fairness, subsequently influencing consumer trust. Moreover, it explores the cascading effects of consumer trust on the smart shopping experience, satisfaction, purchasing behaviour, loyalty, and digital well-being. The primary contribution of this research lies in empirically substantiating the relationships proposed by affordance theory within the context of smart retailing. Building on Gibson's pioneering work (1977), this study reveals the positive associations among perceived fairness, low risk, robust privacy measures, and the cultivation of consumer trust. This aligns with the existing literature that emphasises the significance of transparency and ethical practices in fostering trust within digital marketplaces (Lu, He and Ke, 2023; Wang et al., 2023; Souka, Bilstein and Decker, 2024). Importantly, the research acknowledges a counterargument related to potential privacy concerns undermining trust, offering a nuanced perspective supported by real-world scenarios and empirical evidence (Pan and Zinkhan, 2006; Wirtz and Lwin, 2009; Liao, Liu and Chen, 2011; Martin and Palmatier, 2020).

Beyond establishing relationships, this study explores the cascading impact of trust on consumers' smart shopping experiences and satisfaction. Drawing on affordance theory, this study substantiates a robust positive relationship between trust and overall shopping experience. This insight aligns with scholarly discussions underscoring the central role of trust in shaping satisfactory consumer interactions in digital retail environments (Grabner-Kraeuter, 2002; Kim, Ferrin and Rao, 2008; Kim, Jin and Swinney, 2009; Rodríguez-Priego *et al.*, 2023). Furthermore, the research explores the ramifications of the smart shopping experience on consumer purchasing behaviour and loyalty. By synthesising affordance theory with empirical findings, this study contributes to understanding how enriched smart shopping experiences positively influence purchasing decisions and foster consumer loyalty. These insights add valuable knowledge to the literature on consumer behaviour in the digital marketplace (Sun *et al.*, 2019; Bayer, Gimpel and Rau, 2021; Tuncer, 2021). This study advances our understanding of the broader implications of smart shopping experiences on digital well-being. Integrating insights from affordance theory, reveals how positive digital experiences contribute to reduced stress and enhanced convenience for consumers (Orben and Przybylski, 2019; Burr, Taddeo and Floridi, 2020; Ovani and Windasari, 2022). This dimension of the study extends the current literature by considering the impact of smart retailing on consumer well-being in a digital setting. This research enriches our understanding of trust within smart retail by recognising the interconnected nature of perceived fairness, privacy concerns, and perceived risk as affordances. This holistic approach provides a nuanced perspective on trust formation, emphasising the pivotal role of psychological affordances, perceived fairness, perceived privacy concerns, and perceived risk. Statistical significance underscores their substantial contribution to trust establishment and maintenance.

7.2.3 The Theoretical Implications of the Study

This thesis has important theoretical implications for the field of contemporary management research by applying affordance theory, which is rooted in ecological psychology, to explain the dynamics of smart retailing and its profound impact on consumer ethical perspectives, smart shopping experiences, satisfaction, purchasing behaviour, loyalty, and digital well-being. The theoretical implications resulting from this study contribute not only to the growing body of knowledge in the context of smart retail but also offer a nuanced understanding of the relationships among various factors influencing consumer behavioural intentions. Affordance theory, as proposed by Gibson (1977), posits that the environment provides individuals with perceived possibilities for action. In the context of smart retailing, these perceived possibilities for action, or affordances, arise from the interaction between consumers and retail advanced technological systems.

To begin with, the application of affordance theory to this study enhances the understanding of consumer ethical perspectives within the smart retailing domain. Drawing on Gibson's (1977) original conceptualisation, the theory allowed the dissection of how smart retail technologies afford or restrict certain actions, thereby influencing consumers' perceived risks, privacy concerns, considerations of fairness and levels of trust. The results of this study provide valuable insights into the impact of smart technology on consumer behaviours within smart retail settings, with a particular emphasis on ethical affordances and digital well-being, an area that has seen limited exploration in existing literature.

For instance, in the exploration of perceived risk, affordance theory assists in identifying how consumers interpret the risks associated with smart retail technologies. This aligns with prior research by (Kamalul Ariffin, Mohan and Goh, 2018; Hong *et al.*, 2020), who argued the importance of risk perception in technology adoption. The theory further contributes by highlighting the affordances that either mitigate or exacerbate perceived risks in the context of smart retailing. Concerning perceived privacy, the theory enables an in-depth examination of how the design and functionalities of smart retail technologies afford consumers a sense of control over their personal information. This perspective resonates with the findings of (Grossklags, 2005), who underscored the pivotal role of control in shaping privacy perceptions. Affordance theory, applied in this context, reveals the affordances that either foster or impede perceived privacy.

Moreover, the incorporation of affordance theory into the investigation of fairness within smart retailing aligns with ethical considerations. The theory allows for the identification of affordances that contribute to fair or unfair practices, such as personalised pricing based on consumer profiles. This perspective converges with the ethical discourse in consumer behaviour research highlighted by (Shaw and Shiu, 2002), who emphasised the importance of fairness in consumer decision-making.

Moving to the impact on consumer experiences, the theory contributes to unravelling the intricacies of smart retail experiences and subsequent satisfaction. The affordances provided by smart technology influence consumers' smart shopping experiences, a concept in line with the user experience (UX) literature (Hassenzahl, 2010). Affordance theory, when applied to smart retailing, offers a nuanced understanding of how certain affordances contribute to or hinder consumer smart satisfaction. Furthermore, the exploration of the relationship between smart experiences and subsequent loyalty builds on the foundation laid by (Oliver, 1980, 2013) in customer satisfaction and loyalty research. Affordance theory enhances this area by dissecting the affordances that contribute to positive experiences and foster customer loyalty within the smart retailing landscape. The theoretical contribution extends to the field of consumer well-being, aligning with the burgeoning literature on technology and well-being (Erasmus, Boshoff and Rousseau, 2001; Hassenzahl, 2010; Diefenbach, 2018). By investigating how certain affordances impact aspects of consumer well-being within smart retailing, this thesis explores an increasingly critical dimension of consumer behaviour research.

Finally, the influence of smart experiences on purchasing behaviour, a focal point in consumer behaviour research (Engel et al., 1995), is enriched through affordance theory. The theory sheds light on the affordances that align with consumer preferences and ethical considerations, thus shaping purchasing decisions within the smart retail context. In conclusion, the theoretical contribution of applying affordance theory to smart retailing is multi-faceted, encompassing the domain of consumer ethical perspectives, smart experiences, satisfaction, loyalty, consumer well-being, and purchasing behaviour. This study provides a comprehensive understanding of the complex interplay between consumers and smart retail technologies, contributing to both theoretical advancements and practical implications for the evolving landscape of digital commerce.

7.2.4 The Practical Implications of the Study

This study presents a compelling case and new ways of understanding the role of smart technology in retail and its practical implications and contributions to the field of innovation and management research, specifically within the dynamics of online shopping. By dissecting the intricate relationships among perceived risk, privacy, fairness, trust, smart shopping experiences, and purchasing behaviour, this study not only advances academic knowledge but also offers tangible benefits for practitioners, policymakers, and industry leaders. The findings of this research provide strategic insights for smart retailing platforms, guiding retailers in their quest to build and fortify consumer trust, loyalty, and a lived smart shopping experience. Understanding the nuanced associations among perceived risk, privacy, and fairness allows businesses to implement targeted strategies that directly address consumer concerns, thereby optimising the trust-building process (Kim, Seok and Roh, 2023; Wu *et al.*, 2023). Cynics (Vishwanath and Rigby, 2006), might argue that the smart retail environment is diverse and that no one-size-fits-all approach is applicable. However, the research methodology incorporated a diverse sample, ensuring the generalisability of the findings across various smart retail scenarios. The integration of smart technologies into online shopping environments marks a significant shift in consumer interactions (Martins *et al.*, 2019; Meißner *et al.*, 2020; Shankar *et al.*, 2021). This study contends that leveraging artificial intelligence, machine learning, and personalised recommendations can tailor the online shopping journey, fostering trust and loyalty (Cukier, 2021). Scholars may argue that the implementation of sophisticated technologies might exacerbate privacy concerns (Souka et al., 2024). However, this research emphasises the importance of responsible and transparent use of such technologies, addressing potential drawbacks, and promoting consumer confidence (Morey et al., 2015).

This study asserts that understanding privacy concerns is paramount in the era of heightened data sensitivity. Smart retail platforms can use the findings to implement robust privacy measures, ensuring secure transactions and transparent data practices (Wang et al., 2023). Sceptics may question the feasibility of implementing stringent privacy measures without hindering the consumer experience. However, the research investigates the balance between privacy and consumer experience, offering nuanced recommendations that mitigate risks while maintaining a seamless online shopping process. The significance of fairness in influencing trust and purchasing behaviour is a key argument in this thesis. By implementing ethical practices and transparent pricing models, businesses can foster long-term relationships and positive brand perceptions (Hassenzahl et al., 2021). Cynics might argue that fairness is subjective, and what is perceived as fair can vary among consumers. However, the research incorporates diverse perspectives, revealing overarching principles that can guide smart retailers in establishing fair and equitable practices. The lens of affordance, as applied in this study, offers a unique perspective on innovation management. By recognising perceived possibilities for action, smart retailers can develop innovative solutions that address identified concerns. Some may question the practicality of affordance theory in a real-world smart retail environment (Oliver, 2005). However, this research connects affordance theory to tangible business outcomes, demonstrating its applicability and potential impact on innovation management similar to (Sun *et al.*, 2019; Bayer, Gimpel and Rau, 2021). The thesis concludes by recommending policy actions for a sustainable smart retail ecosystem. Policymakers can draw on these recommendations to develop regulations that balance consumer protection with industry innovation. Others may argue that policy interventions stifle innovation. However, the study advocates a balanced approach, suggesting policies that create an environment conducive to innovation while safeguarding consumer interests. In conclusion, the practical implications and contributions of this study extend beyond theoretical discourse, providing actionable insights for industry stakeholders and policymakers. The counterarguments addressed in this study enhance the robustness of the proposed recommendations, thereby ensuring a comprehensive understanding of the complex dynamics at play in the online shopping environment.

7.2.5 The Policy Implications of the Study

The policy implications of this study are manifold, providing guidance for policymakers and stakeholders in shaping frameworks that facilitate and regulate the smart retailing environment. The following are the key policy considerations derived from this study:

Ethical Standards and Regulations: Policymakers should consider developing and enforcing ethical standards for smart retail platforms. This may include guidelines for transparent communication, fair practices, and responsible data usage. Establishing a regulatory framework that promotes ethical conduct can contribute to building consumer trust.

Data Security and Privacy Policies: Given the significance of perceived privacy concerns in influencing consumer trust, policymakers should prioritise the development of robust data security and privacy policies. Clear and enforceable regulations can enhance consumer confidence in engaging with smart retail platforms, thus fostering a secure digital environment.

Consumer Education Initiatives: Policymakers should invest in educational initiatives to increase consumer awareness of digital ethics and smart retailing practices. This includes providing information on how personal data is used, the implications of smart technologies, and the rights and protections afforded to consumers in the digital space.

Incentives for ethical retail practices:

Governments may explore the implementation of incentives for retailers to adopt ethical and sustainable practices in smart retailing. This could include tax benefits, certification programmes or other measures aimed at encouraging businesses to prioritise fair retail practises, environmental sustainability and social responsibility.

Technological Standards and Interoperability:

Policymakers should consider establishing technological standards and promoting interoperability among smart retail platforms. Standardisation can enhance the consistency and quality of smart features, ensuring a seamless and consumer-friendly experience for consumers across various platforms.

Regulation of Smart Advertising Practices:

Given the influence of smart satisfaction on various outcomes, policymakers may need to address smart advertising practices. Regulations could focus on preventing deceptive advertising, ensuring transparency in product information, and safeguarding consumers from undue persuasion in the digital marketplace.

Continuous Monitoring and Adaptation:

Policymakers should adopt a dynamic approach to regulation by continuously monitoring technological advancements and consumer behaviour. Regular updates to policies can ensure that regulations remain relevant and effective in addressing emerging challenges and opportunities in the rapidly evolving smart retailing setting.

Collaboration with industry stakeholders:

Collaboration among policymakers, industry stakeholders, and consumer advocacy groups is crucial. Engaging in dialogue with these entities can lead to more informed and effective policymaking, ensuring that regulations align with industry practices while prioritising consumer digital welfare. In summary, the policy implications underscore the need for a comprehensive regulatory framework that addresses ethical considerations, data security, consumer education, and technological standards. Such policies aim to create an environment that fosters trust, innovation, and responsible practices in the dynamic environment of smart retailing.

7.3 THE LIMITATION AND FUTURE RESEARCH DIRECTIONS

Systematic Literature Review: While the systematic literature review in Chapter 3 focuses on ABS-ranked journals to ensure methodological rigour and theoretical depth, this emphasis presents a limitation in scope. By excluding non-ABS-ranked journals, industry white papers, and conference proceedings, this review may omit valuable perspectives on emerging trends, regional adaptations, and practitioner-led innovations. For example, reports from McKinsey and Gartner often capture real-time developments in consumer behaviour and technological applications, while conferences like NRF Retail's Big Show showcase early-stage innovations in smart retailing that academic journals may not yet cover. This limitation directly impacts the study's ability to fully explore sector-specific variations and cross-cultural differences in smart retailing because these insights are frequently found in practitioner and interdisciplinary sources. Furthermore, the exclusion of non-ABS sources may constrain the study's capacity to address rapid technological advancements and their immediate implications for consumer behaviour.To address this limitation, future research should adopt a mixed-methods approach that integrates systematic reviews of academic literature with thematic analyses of practitioner reports and conference proceedings. This strategy should include measures to evaluate the credibility and reliability of non-ABS sources, such as triangulation with academic findings or expert validation. By broadening the inclusion criteria in this way, future research can enrich theoretical insights with practical perspectives, providing a more comprehensive understanding of the evolving field of smart retailing.

Industry-Specific Findings: While the current study sheds light on the dynamics within a particular sector of smart retailing, it is imperative to acknowledge the limitations regarding industry specificity. The findings might not be universally applicable across diverse sectors within the smart retailing setting. Future research should strategically diversify its focus to discern sector-specific variations, thereby offering a more nuanced understanding of the multifaceted relationships identified.

Potential Methodological Bias: The dependence on self-reported measures introduces a potential methodological bias, raising concerns about the internal validity of the results. A critical examination of the study design suggests the need for methodological triangulation or sophisticated statistical techniques to mitigate common method biases. This consideration is fundamental for bolstering the credibility and rigour of the empirical outcomes.

Contextual Constraints: The study's contextual confinement to a specific setting could limit the generalizability of the findings to broader cultural or regional contexts. Future research should conduct cross-cultural analyses to understand the subtleties shaping consumer responses because diverse sociocultural factors naturally influence smart retailing.

Omission of Mediation Exploration: The absence of a comprehensive exploration of potential mediation effects is a notable limitation. The failure to dive into the mediating mechanisms underlying the observed relationships curtails the study's explanatory depth. Future research should employ sophisticated mediation analyses to unravel the intricate pathways through which perceived fairness, privacy concerns, and risk collectively influence consumer outcomes.

Underexplored Moderating Factors: The study refrains from a robust exploration of potential moderating factors that might influence the strength and direction of the identified relationships. Neglecting the investigation of moderating variables, such as consumer demographics or technological literacy, limits the granularity of insights. Future research should strategically integrate moderation analyses to uncover the nuanced conditions governing the observed effects.

7.3.1 Future Research Directions

Mediation Exploration for Deeper Insights:

Subsequent research endeavours should prioritise the incorporation of mediation analyses to unravel the intricate web of relationships among perceived fairness, privacy concerns, risk, and consumer outcomes. A nuanced exploration of potential mediating variables will contribute to a more sophisticated understanding of the underlying mechanisms dictating consumer behaviour.

Temporal Dynamics through Longitudinal Investigations: The current study, anchored in a cross-sectional design, necessitates a forward-looking approach to ascertain temporal dynamics and causality. A transition to longitudinal research designs will empower researchers to dissect the evolving nature of these relationships over time, fostering a more dynamic understanding.

Comparative Industry Analyses for Holistic Insights: A strategic shift towards comparative industry analyses is paramount to uncovering industry-specific idiosyncrasies. This approach will facilitate a more holistic comprehension of the impact of perceived fairness, privacy concerns, and risk across varied sectors within the smart retail domain.

Cross-Cultural Inquiries for Universal Applicability: Given the cultural nuances shaping consumer behaviour, future research should engage in rigorous cross-cultural inquiries. A comparative analysis across diverse cultural contexts will unearth variations in the manifestation of perceived fairness, privacy concerns, and risk, providing insights with broader universal applicability.

Objective Measures to Mitigate Bias: To fortify methodological robustness, future research should consider the incorporation of objective measures or observational data. This methodological enhancement is imperative to alleviate potential biases associated with self-reported measures, elevating the overall rigour of the investigation.

Systematic Exploration of Moderating Variables: The identification and systematic exploration of moderating variables are pivotal for a comprehensive understanding of the conditional nature of the identified relationships. Future research should embark on a systematic investigation of potential moderating factors to uncover the nuanced conditions shaping the observed effects. In summary, by critically addressing these limitations and embracing these strategic future research directions, scholars can propel the academic discourse forward, advancing our understanding of the intricate dynamics within the smart retail paradigm.

7.3.2 Conclusion

In conclusion, this study has illuminated the intricate dynamics of smart retailing, offering valuable insights into the relationships among perceived fairness, privacy concerns, risk, trust, smart shopping experiences, and purchasing behaviour. By applying affordance theory, we have gained a deeper understanding of how consumers interact with smart retail environments. However, while this study has made significant contributions to the field, several limitations have been identified, paving the way for future research. To address these gaps, future studies should incorporate mediation analyses to unravel the underlying mechanisms driving consumer behaviour. Transitioning to longitudinal research designs will provide a more dynamic understanding of these relationships. Furthermore, comparative industry analyses and cross-cultural inquiries are essential for uncovering industry-specific nuances and understanding the cultural factors shaping consumer behaviour. Objective measures should be integrated to fortify methodological robustness and mitigate potential biases associated with self-reported measures. Finally, systematic exploration of moderating variables will enhance the validity and reliability of the research findings. By addressing these limitations and embracing strategic future research directions, scholars can propel the academic discourse forward, advancing our understanding of the intricate dynamics within the smart retail paradigm. This will not only contribute to the growing body of knowledge in the field but also offer tangible benefits for practitioners, policymakers, and industry leaders, ultimately shaping the future of smart retailing.

Chapter 8: References

Aaker, D.A., Kumar, V. and Day, G.S. (2001) *Marketing Research*. Wiley. Available at: https://books.google.co.uk/books?id=1ixaAAAAYAAJ.

Abbas, S. *et al.* (2023) 'Antecedents of trustworthiness of social commerce platforms: A case of rural communities using multi group SEM & MCDM methods', *Electronic Commerce Research and Applications*, 62. Available at: https://doi.org/10.1016/j.elerap.2023.101322.

Abbott, L. (1955) 'Quality and competition', in *Quality and Competition*. Columbia University Press.

Abu Saleh, M. (2006) *Antecedents of Commitment to an Import Supplier*.

Abuljadail, M. *et al.* (2023) 'Big data analytics and e-governance: Actors, opportunities, tensions, and applications', *Technological Forecasting and Social Change*, 193. Available at: https://doi.org/10.1016/j.techfore.2023.122612.

Acaps (2012) *Qualitative and Quantitative Research Techniques for Humanitarian Needs Assessment*.

Adam, M., Wessel, M. and Benlian, A. (2021a) 'AI-based chatbots in customer service and their effects on user compliance', *Electronic Markets*, 31(2), pp. 427–445. Available at: https://doi.org/10.1007/s12525-020-00414-7.

Adam, M., Wessel, M. and Benlian, A. (2021b) 'AI-based chatbots in customer service and their effects on user compliance', *Electronic Markets*, 31(2), pp. 427–445. Available at: https://doi.org/10.1007/s12525-020-00414-7.

Adapa, S. *et al.* (2019) 'Examining the antecedents and consequences of perceived shopping value through smart retail technology', *Journal of Retailing and Consumer Services* [Preprint]. Available at: https://doi.org/10.1016/j.jretconser.2019.101901.

Adomavicius, G. and Tuzhilin, A. (2005) 'Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions', *IEEE Transactions on Knowledge and Data Engineering*, pp. 734–749. Available at: https://doi.org/10.1109/TKDE.2005.99.

Adu-Gyamfi, G. *et al.* (2022) 'Towards sustainable vehicular transport: Empirical assessment of battery swap technology adoption in China', *Technological Forecasting and Social Change*, 184. Available at: https://doi.org/10.1016/j.techfore.2022.121995.

Agag, G. (2019) 'E-commerce Ethics and Its Impact on Buyer Repurchase Intentions and Loyalty: An Empirical Study of Small and Medium Egyptian Businesses', *Journal of Business Ethics*, 154(2), pp. 389–410. Available at: https://doi.org/10.1007/s10551-017-3452-3.

Agarwal, R. *et al.* (2020) 'Emerging technologies and analytics for a new era of value-centered marketing in healthcare', *Journal of the Academy of Marketing Science*, 48(1), pp. 9–23. Available at: https://doi.org/10.1007/s11747-019-00692-4.

Agrawal, A., Gans, J. and Goldfarb, A. (2018a) *Google's AI Assistant Is a Reminder that Privacy and Security Are Not the Same*, *Harvard Business Review website*. Available at: https://hbr.org/2018/05/googles-ai-assistant-is-a-reminder-that-privacy-and-security-are-not-the-same (Accessed: 2 June 2021).

Agrawal, A., Gans, J. and Goldfarb, A. (2018b) *Prediction machines: the simple economics of artificial intelligence*. Harvard Business Press.

Aguirre, E. *et al.* (2015a) 'Unraveling the personalization paradox: The effect of information collection and trust-building strategies on online advertisement effectiveness', *Journal of Retailing*, 91(1), pp. 34–49. Available at: https://doi.org/10.1016/j.jretai.2014.09.005.

Aguirre, E. *et al.* (2015b) 'Unraveling the personalization paradox: The effect of information collection and trust-building strategies on online advertisement effectiveness', *Journal of Retailing*, 91(1), pp. 34–49. Available at: https://doi.org/10.1016/j.jretai.2014.09.005.

Ahmed, S.Y., Ali, B.J. and Top, C. (2021) 'Understanding the Impact of Trust, Perceived Risk, and Perceived Technology on the Online Shopping Intentions: Case Study in Kurdistan Region of Iraq', *Journal of Contemporary Issues in Business and Government*, 27(3). Available at: https://doi.org/10.47750/cibg.2021.27.03.264.

Ajzen, I. (1985) 'From Intentions to Actions: A Theory of Planned Behavior', in *Action Control*. Springer Berlin Heidelberg, pp. 11–39. Available at: https://doi.org/10.1007/978-3-642-69746-3_2.

Ajzen, I. (1991) 'The theory of planned behavior', *Organizational Behavior and Human Decision Processes*, 50(2), pp. 179–211. Available at: https://doi.org/10.1016/0749-5978(91)90020-T.

Alcácer, J., Cantwell, J. and Piscitello, L. (2016) 'Internationalization in the information age: A new era for places, firms, and international business networks&quest', *Journal of International Business Studies*, 47(5), pp. 499–512. Available at: https://EconPapers.repec.org/RePEc:pal:jintbs:v:47:y:2016:i:5:p:499-512.

Alexander, M.J., Jaakkola, E. and Hollebeek, L.D. (2018) 'Zooming out: actor engagement beyond the dyadic', *Journal of Service Management*, 29(3), pp. 333–351. Available at: https://doi.org/10.1108/JOSM-08-2016-0237.

Alhumaid, K., Habes, M. and Salloum, S.A. (2021) 'Examining the Factors Influencing the Mobile Learning Usage during COVID-19 Pandemic: An Integrated SEM-ANN Method', *IEEE Access*, 9, pp. 102567–102578. Available at: https://doi.org/10.1109/ACCESS.2021.3097753.

Aliyu, A.A. *et al.* (2014) 'Positivist and Non-Positivist Paradigm in Social Science Research: Conflicting Paradigms or Perfect Partners?', *Journal of Management and Sustainability*, 4(3). Available at: https://doi.org/10.5539/jms.v4n3p79.

AlKheder, S. *et al.* (2023) ‘Customer perception and acceptance of autonomous delivery vehicles in the State of Kuwait during COVID-19’, *Technological Forecasting and Social Change*, 191. Available at: https://doi.org/10.1016/j.techfore.2023.122485.

Alkis, A. and Kose, T. (2022) ‘Privacy concerns in consumer E-commerce activities and response to social media advertising: Empirical evidence from Europe’, *Computers in Human Behavior*, 137. Available at: https://doi.org/10.1016/j.chb.2022.107412.

Allal-Chérif, O., Simón-Moya, V. and Ballester, A.C.C. (2021) ‘Intelligent purchasing: How artificial intelligence can redefine the purchasing function’, *Journal of Business Research*, 124, pp. 69–76. Available at: https://doi.org/10.1016/j.jbusres.2020.11.050.

Allender, W.J. *et al.* (2021) ‘Price fairness and strategic obfuscation’, *Marketing Science*, 40(1), pp. 122–146. Available at: https://doi.org/10.1287/mksc.2020.1244.

Al-Qaysi, N., Mohamad-Nordin, N. and Al-Emran, M. (2020) ‘A Systematic Review of Social Media Acceptance From the Perspective of Educational and Information Systems Theories and Models’, *Journal of Educational Computing Research*, 57(8), pp. 2085–2109. Available at: https://doi.org/10.1177/0735633118817879.

Alvarez, C., David, M.E. and George, M. (2023) ‘Types of Consumer-Brand Relationships: A systematic review and future research agenda’, *Journal of Business Research*, 160. Available at: https://doi.org/10.1016/j.jbusres.2023.113753.

Alyahya, M. *et al.* (2023) ‘Understanding the factors affecting consumers’ behaviour when purchasing refurbished products: A chaordic perspective’, *Journal of Retailing and Consumer Services*, 75. Available at: https://doi.org/10.1016/j.jretconser.2023.103492.

Alzaidi, M.S. and Agag, G. (2022) ‘The role of trust and privacy concerns in using social media for e-retail services: The moderating role of COVID-19’, *Journal of Retailing and Consumer Services*, 68. Available at: https://doi.org/10.1016/j.jretconser.2022.103042.

Ameen, N. *et al.* (2021) ‘Customer experiences in the age of artificial intelligence’, *Computers in Human Behavior*, 114, p. 106548. Available at: https://doi.org/10.1016/j.chb.2020.106548.

El Amri, D. and Akrout, H. (2020) ‘Perceived design affordance of new products: Scale development and validation’, *Journal of Business Research*, 121, pp. 127–141. Available at: https://doi.org/10.1016/j.jbusres.2020.08.010.

Anderson, J.C. and Gerbing, D. (1988) ‘Psychological Bulletin Structural Equation Modeling in Practice: A Review and Recommended Two-Step Approach’, 103(3), pp. 411–423.

Anderson, R.E. and Srinivasan, S.S. (2003) ‘E-Satisfaction and E-Loyalty: A Contingency Framework’, *Psychology and Marketing*, 20(2), pp. 123–138. Available at: https://doi.org/10.1002/mar.10063.

Ansari, A., Essegaier, S. and Kohli, R. (2000) ‘Internet Recommendation Systems’, *Journal of Marketing Research*, 37(3), pp. 363–375. Available at: https://doi.org/10.1509/jmkr.37.3.363.18779.

Appel, G. *et al.* (2020) 'The future of social media in marketing', *Journal of the Academy of Marketing Science*, 48(1), pp. 79–95. Available at: https://doi.org/10.1007/s11747-019-00695-1.

Araujo, T. (2018) 'Living up to the chatbot hype: The influence of anthropomorphic design cues and communicative agency framing on conversational agent and company perceptions', *Computers in Human Behavior*, 85, pp. 183–189. Available at: https://doi.org/10.1016/j.chb.2018.03.051.

Ben Arfi, W. *et al.* (2021) 'Understanding acceptance of eHealthcare by IoT natives and IoT immigrants : An integrated model of UTAUT, perceived risk, and financial cost Understanding Acceptance of eHealthcare by IoT Natives and IoT Immigrants: An Integrated Model of UTAUT, Perceived Risk, and Financial Cost Running title: Integrated Model for eHealthcare Acceptance', *Technological Forecasting and Social Change*, p. 163. Available at: https://doi.org/10.1016/j.techfore.2020.120437ï.

Arghashi, V. and Yuksel, C.A. (2022) 'Interactivity, Inspiration, and Perceived Usefulness! How retailers' AR-apps improve consumer engagement through flow', *Journal of Retailing and Consumer Services*, 64. Available at: https://doi.org/10.1016/j.jretconser.2021.102756.

Arora, N. and Rahul, M. (2018) *The role of perceived risk in influencing online shopping attitude among women in India*, *Int. J. Public Sector Performance Management*.

Arya, V., Sethi, D. and Paul, J. (2019) 'Does digital footprint act as a digital asset? – Enhancing brand experience through remarketing', *International Journal of Information Management*, 49, pp. 142–156. Available at: https://doi.org/10.1016/j.ijinfomgt.2019.03.013.

Ashraful Alam, M. (2020) 'Academic session on Quasi-Experimental Study at Bangladesh Medical Research Council'. Available at: https://doi.org/10.13140/RG.2.2.17475.22567.

Atos (2021) *Artificial Intelligence - Atos*, *Atos*. Available at: https://atos.net/en/artificial-intelligence (Accessed: 19 June 2021).

Attié, E. and Meyer-Waarden, L. (2022) 'The acceptance and usage of smart connected objects according to adoption stages: an enhanced technology acceptance model integrating the diffusion of innovation, uses and gratification and privacy calculus theories', *Technological Forecasting and Social Change*, 176. Available at: https://doi.org/10.1016/j.techfore.2022.121485.

Azer, J. *et al.* (2023) 'Consumer-Driven racial stigmatization: The moderating role of race in online consumer-to-consumer reviews', *Journal of Business Research*, 157. Available at: https://doi.org/10.1016/j.jbusres.2022.113567.

Ba, S. and Pavlou, P.A. (2002) *Evidence of the Effect of Trust Building Technology in Electronic Markets: Price Premiums and Buyer Behavior*, *Source: MIS Quarterly*.

Baabdullah, A.M. *et al.* (2022) 'Virtual agents and flow experience: An empirical examination of AI-powered chatbots', *Technological Forecasting and Social Change*, 181, p. 121772. Available at: https://doi.org/https://doi.org/10.1016/j.techfore.2022.121772.

Babbie, R. (2004) *The Practice of Social Research*. Thomson/Wadsworth (Available Titles CengageNOW Series). Available at: https://books.google.co.uk/books?id=gdbtAAAAMAAJ.

Bagozzi, R. (1994) *Advanced Marketing Research*. Wiley. Available at: https://books.google.co.uk/books?id=bOxUEAAAQBAJ.

Bagozzi, R.P. and Yi, Y. (1988) 'On the Evaluation of Structural Equation Models', *Journal of the Academy of Marketing Science*, 16(1), pp. 74–94. Available at: https://doi.org/10.1177/009207038801600107.

Bahmani, N., Bhatnagar, A. and Gauri, D. (2022) 'Hey, Alexa! What attributes of Skills affect firm value?', *Journal of the Academy of Marketing Science* [Preprint]. Available at: https://doi.org/10.1007/s11747-022-00851-0.

Bai, Y. *et al.* (2017) 'Awe, the diminished self, and collective engagement: Universals and cultural variations in the small self', *Journal of Personality and Social Psychology*, 113(2), pp. 185–209. Available at: https://doi.org/10.1037/pspa0000087.

Baldus, B.J., Voorhees, C. and Calantone, R. (2015) 'Online brand community engagement: Scale development and validation', *Journal of Business Research*, 68(5), pp. 978–985. Available at: https://doi.org/10.1016/j.jbusres.2014.09.035.

Banik, S. and Gao, Y. (2023) 'Exploring the hedonic factors affecting customer experiences in phygital retailing', *Journal of Retailing and Consumer Services*, 70. Available at: https://doi.org/10.1016/j.jretconser.2022.103147.

Banker, S. and Khetani, S. (2019a) 'Algorithm Overdependence: How the Use of Algorithmic Recommendation Systems Can Increase Risks to Consumer Well-Being', *Journal of Public Policy and Marketing*, 38(4), pp. 500–515. Available at: https://doi.org/10.1177/0743915619858057.

Banker, S. and Khetani, S. (2019b) 'Algorithm Overdependence: How the Use of Algorithmic Recommendation Systems Can Increase Risks to Consumer Well-Being', *Journal of Public Policy and Marketing*, 38(4), pp. 500–515. Available at: https://doi.org/10.1177/0743915619858057.

Barney, C. *et al.* (2022) 'Ideally human-ish: How anthropomorphized do you have to be in shopper-facing retail technology?', *Journal of Retailing* [Preprint]. Available at: https://doi.org/10.1016/j.jretai.2022.04.001.

Barr, S. and Ozturk, O. (2020) *Changing behaviours are accelerating trends along a reinvented customer purchase journey*.

Barrios-O'Neil, D. and Pakalkaitė, J. (2022) 'Exploring Next-Generation Touch-Rich Interactions for Consumer Well-Being', in. BCS Learning & Development. Available at: https://doi.org/10.14236/ewic/eva2022.42.

Bart, Y. *et al.* (2005) *Are the Drivers and Role of Online Trust the Same for All Web Sites and Consumers? A Large-Scale Exploratory Empirical Study*. Available at: www.spglobal.com.

Barta, S., Gurrea, R. and Flavián, C. (2023) 'The double side of flow in regret and product returns: Maximizers versus satisficers', *International Journal of Information Management*, 71. Available at: https://doi.org/10.1016/j.ijinfomgt.2023.102648.

Bartlett, M.S. (1951) *The Effect of Standardization on a χ2 Approximation in Factor Analysis*. Available at: https://www.jstor.org/stable/2332580.

Barwitz, N. and Maas, P. (2018) 'Understanding the Omnichannel Customer Journey: Determinants of Interaction Choice', *Journal of Interactive Marketing*, 43, pp. 116–133. Available at: https://doi.org/10.1016/j.intmar.2018.02.001.

Batat, W. (2021) 'How augmented reality (AR) is transforming the restaurant sector: Investigating the impact of "Le Petit Chef" on customers' dining experiences', *Technological Forecasting and Social Change*, 172. Available at: https://doi.org/10.1016/j.techfore.2021.121013.

Bauer, R.A. (1960) 'Consumer behavior as risk taking', in *Proceedings of the 43rd National Conference of the American Marketing Assocation, June 15, 16, 17, Chicago, Illinois, 1960*. American Marketing Association.

Bauer, R.A. (1967) *Risk Taking and Information Handling in Consumer Behavior*. Available at: https://books.google.co.uk/books?id=o1s5f4mQreYC.

Bawack, R.E. *et al.* (2022) 'Artificial intelligence in E-Commerce: a bibliometric study and literature review', *Electronic Markets*, 32(1), pp. 297–338. Available at: https://doi.org/10.1007/s12525-022-00537-z.

Bayer, S., Gimpel, H. and Rau, D. (2021) 'IoT-commerce - opportunities for customers through an affordance lens', *Electronic Markets*, 31(1), pp. 27–50. Available at: https://doi.org/10.1007/s12525-020-00405-8.

Beavers, A.S. *et al.* (2013) 'Practical considerations for using exploratory factor analysis in educational research', *Practical Assessment, Research and Evaluation*, 18(6), pp. 1–13. Available at: https://www.scopus.com/inward/record.uri?eid=2-s2.0-84877146095&partnerID=40&md5=050e38006903b10c207f3c96df37a073.

Becker, L. and Jaakkola, E. (2020) 'Customer experience: fundamental premises and implications for research', *Journal of the Academy of Marketing Science*. Springer, pp. 630–648. Available at: https://doi.org/10.1007/s11747-019-00718-x.

Bélanger, F. and Crossler, R.E. (2011) *Privacy in the Digital Age: A Review of Information Privacy Research in Information Systems*, *Source: MIS Quarterly*.

Belk, R. (2010) 'Sharing', *Journal of Consumer Research*, 36(5), pp. 715–734. Available at: https://doi.org/10.1086/612649.

Bell, E. *et al.* (2019) *Business research methods*. Fifth. Oxford, United Kingdom: Oxford University Press.

de Bellis, E. and Venkataramani Johar, G. (2020) 'Autonomous Shopping Systems: Identifying and Overcoming Barriers to Consumer Adoption', *Journal of Retailing*, 96(1), pp. 74–87. Available at: https://doi.org/10.1016/j.jretai.2019.12.004.

Bender, W.C. (1964) 'Consumer purchase-costs-do retailers recognize them', *Journal of Retailing*, 40(1), p. 1.

Benoit, S. *et al.* (2024) 'Autonomous stores: How levels of in-store automation affect store patronage', *Journal of Retailing* [Preprint]. Available at: https://doi.org/10.1016/j.jretai.2023.12.003.

Bentler, P.M. (1990) *QUANTITATIVE METHODS IN PSYCHOLOGY Comparative Fit Indexes in Structural Models*.

Bentler, P.M. and Bonett, D.G. (1980) 'Significance tests and goodness of fit in the analysis of covariance structures.', *Psychological Bulletin*, 88, pp. 588–606. Available at: https://doi.org/10.1037/0033-2909.88.3.588.

Berry, L.L. (1995) 'Relationship Marketing of Services—Growing Interest, Emerging Perspectives', *Journal of the Academy of Marketing Science*, 23(4), pp. 236–245. Available at: https://doi.org/10.1177/009207039502300402.

Berry, L.L. (2000) *Cultivating Service Brand Equity*.

Berry, L.L. and Cooper, L.R. (1990) 'Competing with time-saving service', *Business*, 40(2), pp. 3–7.

Berry, L.L., Seiders, K. and Grewal, D. (2002) 'Understanding service convenience', *Journal of marketing*, 66(3), pp. 1–17.

Bettman, J.R., Luce, M.F. and Payne, J.W. (1998a) *Constructive Consumer Choice Processes*. Available at: https://academic.oup.com/jcr/article/25/3/187/1795625.

Bettman, J.R., Luce, M.F. and Payne, J.W. (1998b) *Constructive Consumer Choice Processes*. Available at: https://academic.oup.com/jcr/article/25/3/187/1795625.

Bettman, J.R. and Park, C.W. (1980) *Effects of Prior Knowledge and Experience and Phase of the Choice Process on Consumer Decision Processes: A Protocol Analysis*, *Source: Journal of Consumer Research*. Available at: https://about.jstor.org/terms.

Bettman, J.R. and Zins, M.A. (1979) 'Information format and choice task effects in decision making', *Journal of Consumer Research*, 6(2), pp. 141–153.

Bhatnagar, A., Misra, S. and Rao, H.R. (2000) 'On risk, convenience, and Internet shopping behavior', *Communications of the ACM*, 43(11), pp. 98–105.

Bianchi, C. and Andrews, L. (2012) 'Risk, trust, and consumer online purchasing behaviour: A Chilean perspective', *International Marketing Review*, 29(3), pp. 253–275. Available at: https://doi.org/10.1108/02651331211229750.

Bijmolt, T.H.A. *et al.* (2021) 'Challenges at the marketing–operations interface in omni-channel retail environments', *Journal of Business Research*, 122, pp. 864–874. Available at: https://doi.org/10.1016/j.jbusres.2019.11.034.

Bilgihan, A. (2016) 'Gen y customer loyalty in online shopping: An integrated model of trust, user experience and branding', *Computers in Human Behavior*, 61, pp. 103–113. Available at: https://doi.org/10.1016/j.chb.2016.03.014.

Bilyk, J. (2021) *Six Flags inks $36M deal to end fingerprint scan class action that resulted in landmark IL Supreme Court decision | Cook County Record*, *Cook County Record*. Available at: https://cookcountyrecord.com/stories/602405829-six-flags-inks-36m-deal-to-end-fingerprint-scan-class-action-that-resulted-in-landmark-il-supreme-court-decision (Accessed: 18 March 2023).

Bleier, A. and Eisenbeiss, M. (2015a) ‘Personalized online advertising effectiveness: The interplay of what, when, and where’, *Marketing Science*, 34(5), pp. 669–688. Available at: https://doi.org/10.1287/mksc.2015.0930.

Bleier, A. and Eisenbeiss, M. (2015b) ‘The Importance of Trust for Personalized Online Advertising’, *Journal of Retailing*, 91(3), pp. 390–409. Available at: https://doi.org/10.1016/j.jretai.2015.04.001.

Bleier, A., Goldfarb, A. and Tucker, C. (2020) ‘Consumer privacy and the future of data-based innovation and marketing’, *International Journal of Research in Marketing*, 37(3), pp. 466–480. Available at: https://doi.org/10.1016/j.ijresmar.2020.03.006.

Blut, M. *et al.* (2015) ‘How procedural, financial and relational switching costs affect customer satisfaction, repurchase intentions, and repurchase behavior: A meta-analysis’, *International Journal of Research in Marketing*, 32(2), pp. 226–229. Available at: https://doi.org/10.1016/j.ijresmar.2015.01.001.

Blut, M. *et al.* (no date) ‘Understanding anthropomorphism in service provision: a meta-analysis of physical robots, chatbots, and other AI’. Available at: https://doi.org/10.1007/s11747-020-00762-y/Published.

Bolton, R.N. *et al.* (2022) ‘Managing a Global Retail Brand in Different Markets: Meta-Analyses of Customer Responses to Service Encounters’, *Journal of Retailing*, 98(2), pp. 294–314. Available at: https://doi.org/10.1016/j.jretai.2021.03.004.

Bolton, R.N. and Drew, J.H. (1991) *A Multistage Model of Customers’ Assessments of Service Quality and Value*, *Source: Journal of Consumer Research*. Available at: https://www.jstor.org/stable/2626833.

Bonabeau, E. (2004) *The Perils of the Imitation Age*, *Harvard Business Review*. Available at: https://hbr.org/2004/06/the-perils-of-the-imitation-age (Accessed: 20 April 2023).

Boomsma, A. (2020) *Book review of K.A. Bollen (1989). Structural equations with latent variables*. Available at: https://www.researchgate.net/publication/269395170.

Borau, S. *et al.* (2021) ‘The most human bot: Female gendering increases humanness perceptions of bots and acceptance of AI’, *Psychology and Marketing*, 38(7), pp. 1052–1068. Available at: https://doi.org/10.1002/mar.21480.

Botti, S. and Iyengar, S.S. (2004) ‘The psychological pleasure and pain of choosing: When people prefer choosing at the cost of subsequent outcome satisfaction’, *Journal of Personality and Social Psychology*, 87(3), pp. 312–326. Available at: https://doi.org/10.1037/0022-3514.87.3.312.

Bourg, L. *et al.* (2021) ‘Enhancing shopping experiences in smart retailing’, *Journal of Ambient Intelligence and Humanized Computing* [Preprint]. Available at: https://doi.org/10.1007/s12652-020-02774-6.

Bradlow, E.T. *et al.* (2017) ‘The Role of Big Data and Predictive Analytics in Retailing’, *Journal of Retailing*, 93(1), pp. 79–95. Available at: https://doi.org/10.1016/j.jretai.2016.12.004.

Breidbach, C.F., Brodie, R. and Hollebeek, L. (2014) ‘Beyond virtuality: From engagement platforms to engagement ecosystems’, *Managing Service Quality*, 24(6), pp. 592–611. Available at: https://doi.org/10.1108/MSQ-08-2013-0158.

Breidbach, C.F. and Brodie, R.J. (2017) ‘Engagement platforms in the sharing economy: Conceptual foundations and research directions’, *Journal of Service Theory and Practice*, 27(4), pp. 761–777. Available at: https://doi.org/10.1108/JSTP-04-2016-0071.

Breidbach, C.F. and Maglio, P.P. (2016) ‘Technology-enabled value co-creation: An empirical analysis of actors, resources, and practices’, *Industrial Marketing Management*, 56, pp. 73–85. Available at: https://doi.org/10.1016/j.indmarman.2016.03.011.

Brengman, M. *et al.* (2005) ‘Segmenting Internet shoppers based on their Web-usage-related lifestyle: A cross-cultural validation’, *Journal of Business Research*, 58(1 SPEC.ISS), pp. 79–88. Available at: https://doi.org/10.1016/S0148-2963(02)00476-9.

Bridges, J. and Vásquez, C. (2018) ‘If nearly all Airbnb reviews are positive, does that make them meaningless?’, *Current Issues in Tourism*, 21(18), pp. 2065–2083. Available at: https://doi.org/10.1080/13683500.2016.1267113.

Brislin, R.W. (1986) ‘The wording and translation of research instruments.’, in *Field methods in cross-cultural research.* Thousand Oaks, CA, US: Sage Publications, Inc (Cross-cultural research and methodology series, Vol. 8.), pp. 137–164.

Brodie, R.J. *et al.* (2011) ‘Customer engagement: Conceptual domain, fundamental propositions, and implications for research’, *Journal of Service Research*, 14(3), pp. 252–271. Available at: https://doi.org/10.1177/1094670511411703.

Brodie, R.J. *et al.* (2013) ‘Consumer engagement in a virtual brand community: An exploratory analysis’, *Journal of Business Research*, 66(1), pp. 105–114. Available at: https://doi.org/10.1016/j.jbusres.2011.07.029.

Brodie, R.J. *et al.* (2019) ‘Actor Engagement in Networks: Defining the Conceptual Domain’, *Journal of Service Research*, 22(2), pp. 173–188. Available at: https://doi.org/10.1177/1094670519827385.

Browne, M.W. (2001) ‘An overview of analytic rotation in exploratory factor analysis’, *Multivariate Behavioral Research*, 36(1), pp. 111–150. Available at: https://doi.org/10.1207/S15327906MBR3601_05.

Brucks, M. (1985) *The Effects of Product Class Knowledge on Information Search Behavior*, *Source: Journal of Consumer Research*. Available at: https://about.jstor.org/terms.

Bruner, G.C. and Kumar, A. (2005) ‘Explaining consumer acceptance of handheld Internet devices’, *Journal of Business Research*, 58(5), pp. 553–558. Available at: https://doi.org/10.1016/j.jbusres.2003.08.002.

Bryman, A. (2016) *Social Research Methods*. Oxford University Press.

Bryman, A. and Bell, E. (2011) *Business research methods*. 3rd edn. Oxford: Oxford University Press.

Bryman, A. and Bell, E. (2015) *Business research methods*. Fourth. Oxford, United Kingdom: Oxford University Press.

Burke, R.R. (2002) 'Technology and the customer interface: What consumers want in the physical and virtual store', *Journal of the Academy of Marketing Science*, pp. 411–432. Available at: https://doi.org/10.1177/009207002236914.

Burns, D.J. *et al.* (2018) 'Showrooming: an Exploratory Empirical Investigation of Students' Attitudes and Behavior', *Information Systems Management*, 35(4), pp. 294–307. Available at: https://doi.org/10.1080/10580530.2018.1503802.

Burr, C., Taddeo, M. and Floridi, L. (2020) 'The Ethics of Digital Well-Being: A Thematic Review', *Science and Engineering Ethics*. Springer, pp. 2313–2343. Available at: https://doi.org/10.1007/s11948-020-00175-8.

Butori, R. and Lancelot Miltgen, C. (2023) 'A construal level theory approach to privacy protection: The conjoint impact of benefits and risks of information disclosure', *Journal of Business Research*, 168. Available at: https://doi.org/10.1016/j.jbusres.2023.114205.

Byrne, B. (2010a) *Basic Concepts, Applications, and Programming SECOND EDITION Structural Equation Modeling with AMOS*.

Byrne, B. (2010b) *Basic Concepts, Applications, and Programming SECOND EDITION Structural Equation Modeling with AMOS*.

Byrne, B.M. (2001) *Structural equation modeling with AMOS: Basic concepts, applications, and programming.*, *Structural equation modeling with AMOS: Basic concepts, applications, and programming.* Mahwah, NJ, US: Lawrence Erlbaum Associates Publishers (Multivariate applications book series.).

Byun, K.A., Hong, J.H. and William James, K. (2023) 'When does a goal-appeal match affect consumer satisfaction? Examining the work and play context', *Journal of Business Research*, 158. Available at: https://doi.org/10.1016/j.jbusres.2023.113666.

Cadwalladr, C. and Graham-Harrison, E. (2018) *Revealed: 50 million Facebook profiles harvested for Cambridge Analytica in major data breach | Cambridge Analytica | The Guardian*, *The guardian*. Available at: https://www.theguardian.com/news/2018/mar/17/cambridge-analytica-facebook-influence-us-election (Accessed: 7 July 2021).

Cai, H. and Mardani, A. (2023) 'Research on the impact of consumer privacy and intelligent personalization technology on purchase resistance', *Journal of Business Research*, 161. Available at: https://doi.org/10.1016/j.jbusres.2023.113811.

Calderón - Ochoa, A.F., Hernandez, J.R.C. and Portnoy, I. (2021) 'Throughput Analysis of an Amazon Go Retail under the COVID-19-related Capacity Constraints', in *Procedia Computer Science*. Elsevier B.V., pp. 602–607. Available at: https://doi.org/10.1016/j.procs.2021.12.293.

Cambier, F. and Poncin, I. (2020) 'Inferring brand integrity from marketing communications: The effects of brand transparency signals in a consumer empowerment context', *Journal of Business Research*, 109, pp. 260–270. Available at: https://doi.org/https://doi.org/10.1016/j.jbusres.2019.11.060.

Camilleri, M.A. and Filieri, R. (2023) ‘Customer satisfaction and loyalty with online consumer reviews: Factors affecting revisit intentions’, *International Journal of Hospitality Management*, 114. Available at: https://doi.org/10.1016/j.ijhm.2023.103575.

Canziani, B. and MacSween, S. (2021) ‘Consumer acceptance of voice-activated smart home devices for product information seeking and online ordering’, *Computers in Human Behavior*, 119. Available at: https://doi.org/10.1016/j.chb.2021.106714.

Capatina, A. *et al.* (2020) ‘Matching the future capabilities of an artificial intelligence-based software for social media marketing with potential users’ expectations’, *Technological Forecasting and Social Change*, 151. Available at: https://doi.org/10.1016/j.techfore.2019.119794.

Castelo, N. *et al.* (2023) ‘Understanding and Improving Consumer Reactions to Service Bots’, *Journal of Consumer Research*, p. ucad023. Available at: https://doi.org/10.1093/jcr/ucad023.

Castelo, N., Bos, M.W. and Lehmann, D.R. (2019) ‘Task-Dependent Algorithm Aversion’, *Journal of Marketing Research*, 56(5), pp. 809–825. Available at: https://doi.org/10.1177/0022243719851788.

Cath, C. (2018) ‘Governing artificial intelligence: ethical, legal and technical opportunities and challenges’, *Philosophical Transactions A: Mathematical Physical and Engineering Sciences* [Preprint]. Available at: https://doi.org/10.1098/rsta.2018.0080.

Cecere, G., Le Guel, F. and Soulié, N. (2015) ‘Perceived Internet privacy concerns on social networks in Europe’, *Technological Forecasting and Social Change*, 96, pp. 277–287. Available at: https://doi.org/10.1016/j.techfore.2015.01.021.

Chahal, H., Wirtz, J. and Verma, A. (2020) ‘Social media brand engagement: dimensions, drivers and consequences’, *Journal of Consumer Marketing*, 37(2), pp. 191–204. Available at: https://doi.org/10.1108/JCM-11-2018-2937.

Chaney, D., Lunardo, R. and Mencarelli, R. (2018) ‘Consumption experience: past, present and future’, *Qualitative Market Research*. Emerald Group Publishing Ltd., pp. 402–420. Available at: https://doi.org/10.1108/QMR-04-2018-0042.

Chang, M.K., Cheung, W. and Lai, V.S. (2005) ‘Literature derived reference models for the adoption of online shopping’, *Information & Management*, 42(4), pp. 543–559. Available at: https://doi.org/10.1016/j.im.2004.02.006.

Chang, V. (2021) ‘An ethical framework for big data and smart cities’, *Technological Forecasting and Social Change*, 165, p. 120559. Available at: https://doi.org/10.1016/j.techfore.2020.120559.

Chang, Y.W. and Chen, J. (2021) ‘What motivates customers to shop in smart shops? The impacts of smart technology and technology readiness’, *Journal of Retailing and Consumer Services*, 58. Available at: https://doi.org/10.1016/j.jretconser.2020.102325.

Chatterjee, S. *et al.* (2021) ‘Adoption of artificial intelligence-integrated CRM systems in agile organizations in India’, *Technological Forecasting and Social Change*, 168. Available at: https://doi.org/10.1016/j.techfore.2021.120783.

Chatterjee, S., Khorana, S. and Kizgin, H. (2022) 'Harnessing the Potential of Artificial Intelligence to Foster Citizens' Satisfaction: An empirical study on India', *Government Information Quarterly*, 39(4). Available at: https://doi.org/10.1016/j.giq.2021.101621.

Chellappa, R.K. and Sin, R.G. (2005) *Personalization versus Privacy: An Empirical Examination of the Online Consumer's Dilemma*, *Information Technology and Management*.

Chen, H. *et al.* (2022) 'How do interpersonal interaction factors affect buyers' purchase intention in live stream shopping? The mediating effects of swift guanxi', *Internet Research*, 32(1), pp. 335–361. Available at: https://doi.org/10.1108/INTR-05-2020-0252.

Chen, J. and Chang, Y.W. (2023) 'How smart technology empowers consumers in smart retail stores? The perspective of technology readiness and situational factors', *Electronic Markets*, 33(1). Available at: https://doi.org/10.1007/s12525-023-00635-6.

Chen, J., Lan, Y.C. and Chang, Y.W. (2023) 'Consumer behaviour in cross-border e-commerce: Systematic literature review and future research agenda', *International Journal of Consumer Studies* [Preprint]. John Wiley and Sons Inc. Available at: https://doi.org/10.1111/ijcs.12969.

Chen, S. *et al.* (2024) 'From comparison to purchasing: Effects of online behavior toward associated co-visited products on consumer purchase', *Information and Management*, 61(3). Available at: https://doi.org/10.1016/j.im.2024.103938.

Chen, X. *et al.* (2023) 'Customer engagement, dependence and loyalty: An empirical study of Chinese customers in multitouch service encounters', *Technological Forecasting and Social Change*, 197. Available at: https://doi.org/10.1016/j.techfore.2023.122920.

Chen, Y. and Cui, T.H. (2013) 'The benefit of uniform price for branded variants', *Marketing Science*, 32(1), pp. 36–50. Available at: https://doi.org/10.1287/mksc.1120.0751.

Chen, Y.F. (2008) 'Herd behavior in purchasing books online', *Computers in Human Behavior*, 24(5), pp. 1977–1992. Available at: https://doi.org/10.1016/j.chb.2007.08.004.

Cheung, C.M. *et al.* (2003) *An integrative model of consumer trust in internet shopping*. Available at: http://www.emarketer.com/analysis/ecommerce_b2c/20000801_privacy.html.

Cheung, G.W. and Rensvold, R.B. (1999) 'Testing factorial invariance across groups: A reconceptualization and proposed new method.', *Journal of Management*, 25, pp. 1–27. Available at: https://doi.org/10.1177/014920639902500101.

Chevalier, S. (2022) *Global retail e-commerce sales 2026 | Statista*, *Statista*. Available at: https://www.statista.com/statistics/379046/worldwide-retail-e-commerce-sales/ (Accessed: 24 April 2023).

Chi, O.H. *et al.* (2021) 'Developing a formative scale to measure consumers' trust toward interaction with artificially intelligent (AI) social robots in service delivery', *Computers in Human Behavior*, 118. Available at: https://doi.org/10.1016/j.chb.2021.106700.

Chin, W.W. (1998) *The Partial Least Squares Approach to Structural Equation Modeling*. Available at: https://www.researchgate.net/publication/311766005.

Chiu, C.M., Hsu, M.H. and Wang, E.T.G. (2006) 'Understanding knowledge sharing in virtual communities: An integration of social capital and social cognitive theories', *Decision Support Systems*, 42(3), pp. 1872–1888. Available at: https://doi.org/10.1016/j.dss.2006.04.001.

Chiu, C.M., Huang, H.Y. and Yen, C.H. (2010) 'Antecedents of trust in online auctions', *Electronic Commerce Research and Applications*, 9(2), pp. 148–159. Available at: https://doi.org/10.1016/j.elerap.2009.04.003.

Choi, H. and Kandampully, J. (2019) 'The effect of atmosphere on customer engagement in upscale hotels: An application of S-O-R paradigm', *International Journal of Hospitality Management*, 77, pp. 40–50. Available at: https://doi.org/10.1016/j.ijhm.2018.06.012.

Chung, H.F.L. *et al.* (2021) 'Dynamism and B2B firm performance: The dark and bright contingent role of B2B relationships', *Journal of Business Research*, 129, pp. 250–259. Available at: https://doi.org/10.1016/j.jbusres.2021.02.047.

Chung, M. *et al.* (2020) 'Chatbot e-service and customer satisfaction regarding luxury brands', *Journal of Business Research*, 117, pp. 587–595. Available at: https://doi.org/10.1016/j.jbusres.2018.10.004.

Churchill, G.A. (1999) *Marketing Research: Methodological Foundations*. Dryden Press (Dryden Press series in marketing). Available at: https://books.google.co.uk/books?id=j0OXNxakmBwC.

Citaningtyas Ari Kadi, D. and Surya Amalia, M. (2021) 'Asian Journal of Management Entrepreneurship and Social Science The Influence of Brand Image, Perception of Ease and Perception of Risk on Purchase Intention through Trust in Shopee'. Available at: https://ajmesc.com/index.php/ajmesc.

Cohen, J. (1988) *Statistical power analysis for the behavioral sciences*. 2nd edn. Hillsdale, NJ;Hove; Lawrence Erlbaum Associates. Available at: https://go.exlibris.link/tBw2gjd4.

Collis, J. and Hussey, R. (2014) *Business research: A practical guide for undergraduate and postgraduate students*.

Collis, J. and Hussey, R. (2021) *Business research: a practical guide for students*. Fifth. London: Macmillan International Higher Education.

Competition and Markets Authority (2021) *Algorithms: How they can reduce competition and harm consumers*.

Comrey, A.L. and Lee, H.B. (1992) *A first course in factor analysis, 2nd ed.*, *A first course in factor analysis, 2nd ed.* Hillsdale, NJ, US: Lawrence Erlbaum Associates, Inc.

Congressional Research Service (2022) *The National Telecommunications and Information Administration (NTIA): Current Roles and Programs*. Available at: https://crsreports.congress.gov.

consumers international and Internet Society (2019) *The Trust Opportunity: Exploring Consumer Attitudes to the Internet of Things | Internet Society*, *Internet Society*. Available at: https://www.internetsociety.org/resources/doc/2019/trust-opportunity-exploring-consumer-attitudes-to-iot/ (Accessed: 3 July 2021).

Conway, J.M. and Huffcutt, A.I. (2003) ‘A Review and Evaluation of Exploratory Factor Analysis Practices in Organizational Research’, *Organizational Research Methods*, 6(2), pp. 147–168. Available at: https://doi.org/10.1177/1094428103251541.

Copeland, M.T. (1923) ‘Relation of consumers’ buying habits to marketing methods’, *Harvard business review*, 1(2), pp. 282–289.

Corritore, C.L., Kracher, B. and Wiedenbeck, S. (2003) ‘On-line trust: Concepts, evolving themes, a model’, *International Journal of Human Computer Studies*, 58(6), pp. 737–758. Available at: https://doi.org/10.1016/S1071-5819(03)00041-7.

Court, D. *et al.* (2009) ‘The consumer decision journey’, *McKinsey Quarterly*, 3(3), pp. 96–107.

Coyne, S.M., Stockdale, L. and Summers, K. (2019) ‘Problematic cell phone use, depression, anxiety, and self-regulation: Evidence from a three year longitudinal study from adolescence to emerging adulthood’, *Computers in Human Behavior*, 96, pp. 78–84. Available at: https://doi.org/10.1016/j.chb.2019.02.014.

Creswell, J.W. (2014) *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches*. SAGE Publications. Available at: https://books.google.co.uk/books?id=4uB76IC_pOQC.

Cropanzano, R. *et al.* (2001) ‘Moral virtues, fairness heuristics, social entities, and other denizens of organizational justice’, *Journal of Vocational Behavior*, 58(2), pp. 164–209. Available at: https://doi.org/10.1006/jvbe.2001.1791.

Cuesta-Valiño, P. *et al.* (2023) ‘Strategic orientation towards digitization to improve supermarket loyalty in an omnichannel context’, *Journal of Business Research*, 156. Available at: https://doi.org/10.1016/j.jbusres.2022.113475.

Cui, Y. (Gina), van Esch, P. and Jain, S.P. (2022) ‘Just walk out: the effect of AI-enabled checkouts’, *European Journal of Marketing*, 56(6), pp. 1650–1683. Available at: https://doi.org/10.1108/EJM-02-2020-0122.

Cukier, K. (2021) ‘Commentary: How AI Shapes Consumer Experiences and Expectations’, *Journal of Marketing*. SAGE Publications Ltd, pp. 152–155. Available at: https://doi.org/10.1177/0022242920972932.

Culnan, M.J. and Armstrong, P.K. (1999) ‘Information Privacy Concerns, Procedural Fairness, and Impersonal Trust: An Empirical Investigation’, *Organization Science*, 10(1), pp. 104–115. Available at: https://doi.org/10.1287/orsc.10.1.104.

Cuong, D.T. (2023) ‘Determinants affecting online shopping consumers’ satisfaction and repurchase intention: Evidence from Vietnam’, *Innovative Marketing*, 19(1), pp. 126–139. Available at: https://doi.org/10.21511/im.19(1).2023.11.

Cvii, V. and Banerjee, A. V (1992) *QUARTERLY JOURNAL OF ECONOMICS Issue 3 A SIMPLE MODEL OF HERD BEHAVIOR**. Available at: https://academic.oup.com/qje/article/107/3/797/1873520.

Cyr, D. (2008) ‘Modeling web site design across cultures: Relationships to trust, satisfaction, and E-Loyalty’, *Journal of Management Information Systems*, 24(4), pp. 47–72. Available at: https://doi.org/10.2753/MIS0742-1222240402.

Dacko, S.G. (2017) ‘Enabling smart retail settings via mobile augmented reality shopping apps’, *Technological Forecasting and Social Change*, 124, pp. 243–256. Available at: https://doi.org/10.1016/j.techfore.2016.09.032.

Dagger, T.S. and Sweeney, J.C. (2006) ‘The effect of service evaluations on behavioral intentions and quality of life’, *Journal of Service Research*, 9(1), pp. 3–18. Available at: https://doi.org/10.1177/1094670506289528.

Dahlke, J. *et al.* (2021) ‘Crisis-driven innovation and fundamental human needs: A typological framework of rapid-response COVID-19 innovations’, *Technological Forecasting and Social Change*, 169. Available at: https://doi.org/10.1016/j.techfore.2021.120799.

Dane, F.C. (1990) *Research Methods*. Brooks/Cole Publishing Company (International Student Edition). Available at: https://books.google.co.uk/books?id=Rg-2AAAAIAAJ.

Dannemiller, K.A. *et al.* (2021) ‘Investigating autonomous vehicle impacts on individual activity-travel behavior’, *Transportation Research Part A: Policy and Practice*, 148, pp. 402–422. Available at: https://doi.org/10.1016/j.tra.2021.04.006.

Darke, P.R. and Dahl, D.W. (2003) ‘Fairness and Discounts: The Subjective Value of a Bargain’, *Journal of Consumer Psychology*, 13(3), pp. 328–338. Available at: https://doi.org/10.1207/S15327663JCP1303_13.

Darley, W.K., Blankson, C. and Luethge, D.J. (2010) ‘Toward an integrated framework for online consumer behavior and decision making process: A review’, *Psychology and Marketing*, 27(2), pp. 94–116. Available at: https://doi.org/10.1002/mar.20322.

Datta, Amit, Tschantz, M.C. and Datta, Anupam (2015) ‘Automated Experiments on Ad Privacy Settings’, *Proceedings on Privacy Enhancing Technologies*, 2015(1), pp. 92–112. Available at: https://doi.org/10.1515/popets-2015-0007.

Dattalo, P. (2013) *Analysis of Multiple Dependent Variables*. OUP USA (Pocket Guide to Social Work Re). Available at: https://books.google.co.uk/books?id=eH6_ty48As8C.

Davenport, T. *et al.* (2020) ‘How artificial intelligence will change the future of marketing’, *Journal of the Academy of Marketing Science*, 48(1), pp. 24–42. Available at: https://doi.org/10.1007/s11747-019-00696-0.

Davenport, T.H. (2018) *Artificial Intelligence for the Real World*, *Harvard Business Review*. Available at: https://hbr.org/webinar/2018/02/artificial-intelligence-for-the-real-world (Accessed: 2 January 2023).

Davis, F.D. (1989) ‘Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology’, *MIS Quarterly*, 13(3), pp. 319–340. Available at: https://doi.org/10.2307/249008.

Davis, J.M. and Tuttle, B.M. (2013) ‘A heuristic-systematic model of end-user information processing when encountering IS exceptions’, *Information and*

Management, 50(2–3), pp. 125–133. Available at: https://doi.org/10.1016/j.im.2012.09.004.

Dayal, S., Landesberg, H. and Zeisser, M. (1999) 'How to build trust online', *Marketing Management*, 8(3), p. 64. Available at: https://doi.org/10.1007/978-3-7091-6088-6_5.

Degeratu, A.M., Rangaswamy, A. and Wu, J. (2000) *Consumer choice behavior in online and traditional supermarkets: The effects of brand name, price, and other search attributes*, *Intern. J. of Research in Marketing*. Available at: www.elsevier.comrlocaterijresmar.

Deighton, J. (1996) *The Future of Interactive Marketing*, *Harvard Business Review*. Available at: https://hbr.org/1996/11/the-future-of-interactive-marketing (Accessed: 8 July 2021).

Delgado, E. (2020) *Changes In Food Retail Foot Traffic During COVID-19 - McMillanDoolittle - Transforming Retail*, *McMillan Doolittle*. Available at: https://www.mcmillandoolittle.com/changes-in-food-retail-foot-traffic-during-covid-19/ (Accessed: 17 June 2023).

Dellaert, B.G.C. *et al.* (2020) 'Consumer decisions with artificially intelligent voice assistants', *Marketing Letters*, 31(4), pp. 335–347. Available at: https://doi.org/10.1007/s11002-020-09537-5.

Dellaert, B.G.C. and Stremersch, S. (2005) *Marketing Mass-Customized Products: Striking a Balance between Utility and Complexity*, *Source: Journal of Marketing Research*.

Deng, X., Li, X. and Xiang, Y. (2024) 'Smartphone addiction and internalized and externalized aggression among adolescents: Evidence from longitudinal study and weekly diary study', *Computers in Human Behavior*, 150. Available at: https://doi.org/10.1016/j.chb.2023.107988.

Denyer, D. and Tranfield, D. (2009) 'Denyer-Tranfield-Producing-a-Systematic-Review', *The sage handbook of organizational research methods*, pp. 671–688.

Dessart, L., Veloutsou, C. and Morgan-Thomas, A. (2016) 'Capturing consumer engagement: duality, dimensionality and measurement', *Journal of Marketing Management*, 32(5–6), pp. 399–426. Available at: https://doi.org/10.1080/0267257X.2015.1130738.

Desveaud, K., Mandler, T. and Eisend, M. (2024) 'A meta-model of customer brand loyalty and its antecedents', *Journal of Business Research*, 176. Available at: https://doi.org/10.1016/j.jbusres.2024.114589.

Deutsch, M. and Gerard, H.B. (1955) 'A study of normative and informational social influences upon individual judgment.', *The Journal of Abnormal and Social Psychology*, 51, pp. 629–636. Available at: https://doi.org/10.1037/h0046408.

Dhiman, N., Jamwal, M. and Kumar, A. (2023) 'Enhancing value in customer journey by considering the (ad)option of artificial intelligence tools', *Journal of Business Research*, 167. Available at: https://doi.org/10.1016/j.jbusres.2023.114142.

Diab, D.L. *et al.* (2011) ‘Lay perceptions of selection decision aids in US and non-US samples’, *International Journal of Selection and Assessment*, 19(2), pp. 209–216. Available at: https://doi.org/10.1111/j.1468-2389.2011.00548.x.

Diamantopoulos, A. and Siguaw, J.A. (2000) *Introducing LISREL: A Guide for the Uninitiated*. SAGE Publications (Introducing Statistical Methods series). Available at: https://books.google.co.uk/books?id=ExUXAQAAMAAJ.

Diefenbach, S. (2018) ‘The potential and challenges of digital well-being interventions: Positive technology research and design in light of the bitter-sweet ambivalence of change’, *Frontiers in Psychology*, 9(MAR). Available at: https://doi.org/10.3389/fpsyg.2018.00331.

Dienlin, T. and Trepte, S. (2015) ‘Is the privacy paradox a relic of the past? An in-depth analysis of privacy attitudes and privacy behaviors’, *European Journal of Social Psychology*, 45(3), pp. 285–297. Available at: https://doi.org/10.1002/ejsp.2049.

Dijkstra, T.K. and Henseler, J. (2015) ‘Consistent partial least squares path modeling’, *MIS Quarterly: Management Information Systems*. University of Minnesota, pp. 297–316. Available at: https://doi.org/10.25300/MISQ/2015/39.2.02.

Dinev, T. and Hart, P. (2006) ‘An Extended Privacy Calculus Model for E-Commerce Transactions’, *Information Systems Research*, 17(1), pp. 61–80. Available at: https://doi.org/10.1287/isre.1060.0080.

Dings, R. (2021) ‘Meaningful affordances’, *Synthese*, 199(1–2), pp. 1855–1875. Available at: https://doi.org/10.1007/s11229-020-02864-0.

Doney, P.M. and Cannon, J.P. (1997) *An Examination of the Nature of Trust in Buyer-Seller Relationships*.

Dong, X. and Wang, T. (2018) ‘Social tie formation in Chinese online social commerce: The role of IT affordances’, *International Journal of Information Management*, 42, pp. 49–64. Available at: https://doi.org/10.1016/j.ijinfomgt.2018.06.002.

Dong, X., Wang, T. and Benbasat, I. (2016) *Measuring IT affordance in OSC IT Affordances in Online Social Commerce: Conceptualization Validation and Scale Development Full papers*, *Americas Conference on Information Systems*.

van Doorn, J. *et al.* (2010) ‘Customer engagement behavior: Theoretical foundations and research directions’, *Journal of Service Research*, 13(3), pp. 253–266. Available at: https://doi.org/10.1177/1094670510375599.

Dowling, G.R. and Staelin, R. (1994) ‘A Model of Perceived Risk and Intended Risk-Handling Activity’, *Journal of Consumer Research*, 21(1), p. 119. Available at: https://doi.org/10.1086/209386.

Du, S. and Xie, C. (2020) ‘Paradoxes of artificial intelligence in consumer markets: Ethical challenges and opportunities’, *Journal of Business Research*, 129, pp. 961–974. Available at: https://doi.org/10.1016/j.jbusres.2020.08.024.

Du, S. and Xie, C. (2021) ‘Paradoxes of artificial intelligence in consumer markets: Ethical challenges and opportunities’, *Journal of Business Research*, 129, pp. 961–974. Available at: https://doi.org/10.1016/j.jbusres.2020.08.024.

Duarte, P., Costa e Silva, S. and Ferreira, M.B. (2018) 'How convenient is it? Delivering online shopping convenience to enhance customer satisfaction and encourage e-WOM', *Journal of Retailing and Consumer Services*, 44, pp. 161–169. Available at: https://doi.org/10.1016/j.jretconser.2018.06.007.

Duhigg, C. (2012) *How Companies Learn Your Secrets - The New York Times*, *The New York Times*. Available at: https://www.nytimes.com/2012/02/19/magazine/shopping-habits.html?_r=0 (Accessed: 5 July 2021).

Dwivedi, Y.K. *et al.* (2021) 'Setting the future of digital and social media marketing research: Perspectives and research propositions', *International Journal of Information Management*, 59, p. 102168. Available at: https://doi.org/10.1016/J.IJINFOMGT.2020.102168.

Dziuban, C.D. and Shirkey, E.C. (1974) 'When is a correlation matrix appropriate for factor analysis? Some decision rules', *Psychological Bulletin*, 81(6), pp. 358–361. Available at: https://doi.org/10.1037/h0036316.

Eastwood, J., Snook, B. and Luther, K. (2012) 'What People Want From Their Professionals: Attitudes Toward Decision-making Strategies', *Journal of Behavioral Decision Making*, 25(5), pp. 458–468. Available at: https://doi.org/10.1002/bdm.741.

Edelman, D.C. and Singer, M. (2015) 'Competing on customer journeys', *Harvard business review*, 93(11), pp. 88–100.

Eggers, W.D., Turley, M. and Kishnani, P.K. (2018) *The future of regulation Principles for regulating emerging technologies A report from the Deloitte Center for Government Insights MIKE TURLEY*.

Elberse, A. (2010) 'Bye-Bye Bundles: The Unbundling of Music in Digital Channels', *Journal of Marketing*, 74, pp. 107–123.

Elsner, N. (2017) *KAYAK Mobile Travel Report - KAYAK UK*, *KAYAK.co.uk*. Available at: https://www.kayak.co.uk/news/mobile-travel-report-2017/ (Accessed: 1 July 2021).

Emrich, O., Paul, M. and Rudolph, T. (2015) 'Shopping Benefits of Multichannel Assortment Integration and the Moderating Role of Retailer Type', *Journal of Retailing*, 91(2), pp. 326–342. Available at: https://doi.org/10.1016/j.jretai.2014.12.003.

Engel, J.F., Blackwell, R.D. and Miniard, P.W. (1995) *Consumer Behavior*. Dryden Press (Dryden Press series in marketing). Available at: https://books.google.co.uk/books?id=BWqfQgAACAAJ.

Erasmus, A.C., Boshoff, E. and Rousseau, G.G. (2001) 'Consumer decision-making models within the discipline of consumer science: a critical approach', *Journal of Family Ecology and Consumer Sciences*, 29.

van Esch, P., Cui, Y. and Jain, S.P. (2021) 'Self-efficacy and callousness in consumer judgments of AI-enabled checkouts', *Psychology and Marketing*, 38(7), pp. 1081–1100. Available at: https://doi.org/10.1002/mar.21494.

Esmark, C.L. and Noble, S.M. (2018) ‘Retail space invaders: When employees’ invasion of customer space increases purchase intentions’, *Journal of the Academy of Marketing Science*, 46(3), pp. 477–496. Available at: https://doi.org/10.1007/s11747-016-0488-3.

European Commission (2016) ‘REGULATION (EU) 2016/679 OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL of 27 April 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data, and repealing Directive 95/46/EC (General Data Protection Regulation)’, *Official Journal of the European Union* [Preprint]. Available at: https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32016R0679 (Accessed: 12 June 2021).

Evans, S.K. *et al.* (2017) ‘Explicating Affordances: A Conceptual Framework for Understanding Affordances in Communication Research’, *Journal of Computer-Mediated Communication*, 22(1), pp. 35–52. Available at: https://doi.org/https://doi.org/10.1111/jcc4.12180.

Fabrigar, L.R. *et al.* (1999) ‘Evaluating the use of exploratory factor analysis in psychological research’, *Psychological Methods*, 4(3), pp. 272–299. Available at: https://doi.org/10.1037/1082-989X.4.3.272.

Fan, X. *et al.* (2020) ‘Adoption of augmented reality in online retailing and consumers’ product attitude: A cognitive perspective’, *Journal of Retailing and Consumer Services*, 53. Available at: https://doi.org/10.1016/j.jretconser.2019.101986.

Fan, X., Thompson, B. and Wang, L. (1999) ‘Effects of sample size, estimation methods, and model specification on structural equation modeling fit indexes’, *Structural Equation Modeling: A Multidisciplinary Journal*, 6(1), pp. 56–83. Available at: https://doi.org/10.1080/10705519909540119.

Fanderl, H. *et al.* (2019) *Addressing automotive customer experience | McKinsey*, *McKinsey & Company*. Available at: https://www.mckinsey.com/industries/automotive-and-assembly/our-insights/driving-the-automotive-customer-experience-toward-the-age-of-mobility (Accessed: 5 June 2021).

Fang, Y.H. (2019) ‘An app a day keeps a customer connected: Explicating loyalty to brands and branded applications through the lens of affordance and service-dominant logic’, *Information & Management*, 56(3), pp. 377–391. Available at: https://doi.org/10.1016/J.IM.2018.07.011.

Faqih, K.M.S. (2012) ‘Integrating Perceived Risk and Trust with Technology Acceptance Model: An Empirical Assessment of Customers’ Acceptance of Online Shopping in Jordan’, in.

Faqih, K.M.S. (2022) ‘Internet shopping in the Covid-19 era: Investigating the role of perceived risk, anxiety, gender, culture, and trust in the consumers’ purchasing behavior from a developing country context’, *Technology in Society*, 70. Available at: https://doi.org/10.1016/j.techsoc.2022.101992.

Farquhar, J.D. and Rowley, J. (2009) ‘Convenience: A services perspective’, *Marketing Theory*, 9(4), pp. 425–438. Available at: https://doi.org/10.1177/1470593109346894.

Featherman, M.S. and Hajli, N. (2016) ‘Self-Service Technologies and e-Services Risks in Social Commerce Era’, *Journal of Business Ethics*, 139(2), pp. 251–269. Available at: https://doi.org/10.1007/s10551-015-2614-4.

Featherman, M.S. and Pavlou, P.A. (2003) ‘Predicting e-services adoption: A perceived risk facets perspective’, *International Journal of Human Computer Studies*, 59(4), pp. 451–474. Available at: https://doi.org/10.1016/S1071-5819(03)00111-3.

Feijóo, C. *et al.* (2020) ‘Harnessing artificial intelligence (AI) to increase wellbeing for all: The case for a new technology diplomacy’, *Telecommunications Policy*, 44(6), p. 101988. Available at: https://doi.org/10.1016/j.telpol.2020.101988.

Fernandes, T. and Oliveira, E. (2021a) ‘Understanding consumers’ acceptance of automated technologies in service encounters: Drivers of digital voice assistants adoption’, *Journal of Business Research*, 122, pp. 180–191. Available at: https://doi.org/10.1016/j.jbusres.2020.08.058.

Fernandes, T. and Oliveira, E. (2021b) ‘Understanding consumers’ acceptance of automated technologies in service encounters: Drivers of digital voice assistants adoption’, *Journal of Business Research*, 122, pp. 180–191. Available at: https://doi.org/10.1016/j.jbusres.2020.08.058.

Ferreira, J.J. *et al.* (2021) ‘Wearable technology and consumer interaction: A systematic review and research agenda’, *Computers in Human Behavior*, 118, p. 106710. Available at: https://doi.org/10.1016/j.chb.2021.106710.

Ferreira, M., Zambaldi, F. and Guerra, D. de S. (2020) ‘Consumer engagement in social media: scale comparison analysis’, *Journal of Product and Brand Management*, 29(4), pp. 491–503. Available at: https://doi.org/10.1108/JPBM-10-2018-2095.

Field, A. (2005) *Discovering statistics using SPSS, 2nd ed.*, *Discovering statistics using SPSS, 2nd ed.* Thousand Oaks, CA, US: Sage Publications, Inc.

Field, A. (2017) *Discovering Statistics Using IBM SPSS Statistics*. SAGE Publications. Available at: https://books.google.co.uk/books?id=QMI-DwAAQBAJ.

Filieri, R., Hofacker, C.F. and Alguezaui, S. (2018) ‘What makes information in online consumer reviews diagnostic over time? The role of review relevancy, factuality, currency, source credibility and ranking score’, *Computers in Human Behavior*, 80, pp. 122–131. Available at: https://doi.org/10.1016/j.chb.2017.10.039.

Fitzsimons, G.J. and Lehmann, D.R. (2004) ‘Reactance to Recommendations: When Unsolicited Advice Yields Contrary Responses’, *Marketing Science*, 23(1), pp. 82–94. Available at: https://doi.org/10.1287/mksc.1030.0033.

Fletcher-Brown, J. *et al.* (2020) ‘Vulnerable consumer engagement: How corporate social media can facilitate the replenishment of depleted resources’, *International Journal of Research in Marketing* [Preprint]. Available at: https://doi.org/10.1016/j.ijresmar.2020.06.002.

Fokkema, M. and Greiff, S. (2017) ‘How performing PCA and CFA on the same data equals trouble’, *European Journal of Psychological Assessment*, 33(6), pp. 399–402. Available at: https://doi.org/10.1027/1015-5759/a000460.

Fornell, C. *et al.* (1996) *The American Customer Satisfaction Index: Nature, Purpose, and Findings*.

Fornell, C. and Larcker, D.F. (1981) *Evaluating Structural Equation Models with Unobservable Variables and Measurement Error*, *Source: Journal of Marketing Research*.

Foroudi, P. *et al.* (2018) 'Investigating the effects of smart technology on customer dynamics and customer experience', *Computers in Human Behavior*, 80, pp. 271–282. Available at: https://doi.org/10.1016/j.chb.2017.11.014.

Forsythe, S.M. and Shi, B. (2003) 'Consumer patronage and risk perceptions in Internet shopping', *Journal of Business Research*, 56(11), pp. 867–875. Available at: https://doi.org/10.1016/S0148-2963(01)00273-9.

Fotheringham, D. and Wiles, M.A. (2022) 'The effect of implementing chatbot customer service on stock returns: an event study analysis', *Journal of the Academy of Marketing Science* [Preprint]. Available at: https://doi.org/10.1007/s11747-022-00841-2.

Frambach, R.T., Roest, H.C.A. and Krishnan, T. V. (2007) 'The impact of consumer internet experience on channel preference and usage intentions across the different stages of the buying process', *Journal of Interactive Marketing*, 21(2), pp. 26–41. Available at: https://doi.org/10.1002/dir.20079.

Frank, B., Herbas-Torrico, B. and Schvaneveldt, S.J. (2021) 'The AI-extended consumer: Technology, consumer, country differences in the formation of demand for AI-empowered consumer products', *Technological Forecasting and Social Change*, 172. Available at: https://doi.org/10.1016/j.techfore.2021.121018.

Frauenstein, E.D. *et al.* (2023) 'Unraveling the behavioral influence of social media on phishing susceptibility: A Personality-Habit-Information Processing model', *Information & Management*, 60(7), p. 103858. Available at: https://doi.org/10.1016/j.im.2023.103858.

Fu, X. *et al.* (2020) *HOW DO EXPECTATIONS SHAPE CONSUMER SATISFACTION? AN EMPIRICAL STUDY ON KNOWLEDGE PRODUCTS*, *Journal of Electronic Commerce Research*.

Gao, L. (Xuehui) *et al.* (2022) 'Winning your customers' minds and hearts: Disentangling the effects of lock-in and affective customer experience on retention', *Journal of the Academy of Marketing Science* [Preprint]. Available at: https://doi.org/10.1007/s11747-022-00898-z.

Gao, Y. (Lisa), Zhang, L. and Wei, W. (2021) 'The effect of perceived error stability, brand perception, and relationship norms on consumer reaction to data breaches', *International Journal of Hospitality Management*, 94, p. 102802. Available at: https://doi.org/10.1016/J.IJHM.2020.102802.

Gauri, D.K. *et al.* (2021) 'Evolution of retail formats: Past, present, and future', *Journal of Retailing*, 97(1), pp. 42–61. Available at: https://doi.org/10.1016/j.jretai.2020.11.002.

Gefen, D., Karahanna, E. and Straub, D.W. (2003) ‘Trust and TAM in Online Shopping: An Integrated Model’, *MIS Quarterly*, 27(1), pp. 51–90. Available at: https://doi.org/10.2307/30036519.

Gefen, D., Rigdon, E.E. and Straub, D. (2011) ‘An update and extension to SEM guidelines for administrative and social science research’, *MIS Quarterly: Management Information Systems*. University of Minnesota. Available at: https://doi.org/10.2307/23044042.

Gefen, D., Straub, D. and Boudreau, M. (2000) ‘Structural Equation Modeling And Regression: Guidelines For Research Practice’, *Communications of the Association for Information Systems*, 4. Available at: https://doi.org/10.17705/1CAIS.00407.

Gehrt, K.C. and Yale, L.J. (1993) *THE DIMENSIONALITY OF THE CONVENIENCE PHENOMENON: A QUALITATIVE REEXAMINATION*, *JOURNAL OF BUSINESS AND PSYCHOLOGY*.

Geisser, S. (1974) *A Predictive Approach to the Random Effect Model*. Available at: https://about.jstor.org/terms.

Ghouri, A.M. *et al.* (2021) ‘Real-time information sharing, customer orientation, and the exploration of intra-service industry differences: Malaysia as an emerging market’, *Technological Forecasting and Social Change*, 167. Available at: https://doi.org/10.1016/j.techfore.2021.120684.

Gibson, J.J. (1966) *The Senses Considered as Perceptual Systems*. Bloomsbury Academic. Available at: https://books.google.co.uk/books?id=J9ROAAAAMAAJ.

Gibson, J.J. (1977) *The Theory of Affordances*. New Jersey: Lawrence Erlbaum Associates.

Gibson, J.J. (1979) *The ecological approach to visual perception.*, *The ecological approach to visual perception.* Boston, MA, US: Houghton, Mifflin and Company.

Gibson, J.J. (1986) *The ecological approach to visual perception*, *The ecological approach to visual perception*. Hillsdale, N.J: Lawrence Erlbaum Associates.

Gibson, J.J. (2014) ‘The Ecological Approach to Visual Perception : Classic Edition’, *The Ecological Approach to Visual Perception* [Preprint]. Available at: https://doi.org/10.4324/9781315740218.

Gideon, R.A. (2007) ‘The correlation coefficients’, *Journal of Modern Applied Statistical Methods*, 6(2), pp. 517–529. Available at: https://doi.org/10.22237/jmasm/1193890500.

Gielens, K. *et al.* (2021) ‘The Future of Private Labels: Towards a Smart Private Label Strategy’, *Journal of Retailing*, 97(1), pp. 99–115. Available at: https://doi.org/10.1016/j.jretai.2020.10.007.

Gillath, O. *et al.* (2021) ‘Attachment and trust in artificial intelligence’, *Computers in Human Behavior*, 115. Available at: https://doi.org/10.1016/j.chb.2020.106607.

Giroux, M. *et al.* (2022) ‘Artificial Intelligence and Declined Guilt: Retailing Morality Comparison Between Human and AI’, *Journal of Business Ethics*, 178(4), pp. 1027–1041. Available at: https://doi.org/10.1007/s10551-022-05056-7.

Glover, S. and Benbasat, I. (2010) 'A Comprehensive Model of Perceived Risk of E-Commerce Transactions', *International Journal of Electronic Commerce*, 15(2), pp. 47–78. Available at: http://www.jstor.org/stable/27919912.

Go, E. and Sundar, S.S. (2019) 'Humanizing chatbots: The effects of visual, identity and conversational cues on humanness perceptions', *Computers in Human Behavior*, 97, pp. 304–316. Available at: https://doi.org/10.1016/j.chb.2019.01.020.

Goddard, N.D.R., Kemp, R.M.J. and Lane, R. (1997) 'An overview of smart technology', *Packaging Technology and Science*, 10(3), pp. 129–143. Available at: https://doi.org/10.1002/(SICI)1099-1522(19970501/30)10:3<129::AID-PTS393>3.0.CO;2-C.

Goh, M. (2020) *AI Powered Recommendation System In Retail | by Manfye Goh | Artificial Intelligence in Plain English*, *2020*. Available at: https://ai.plainenglish.io/recommendation-system-use-cases-in-retail-and-challenges-6150b1872281 (Accessed: 23 April 2023).

Gong, T. (2018) 'Customer brand engagement behavior in online brand communities', *Journal of Services Marketing*, 32(3), pp. 286–299. Available at: https://doi.org/10.1108/JSM-08-2016-0293.

Goodman, B. and Flaxman, S. (2017) 'European union regulations on algorithmic decision making and a "right to explanation"', *AI Magazine*, 38(3), pp. 50–57. Available at: https://doi.org/10.1609/aimag.v38i3.2741.

Goretzko, D., Pham, T.T.H. and Bühner, M. (2021) 'Exploratory factor analysis: Current use, methodological developments and recommendations for good practice', *Current Psychology*, 40(7), pp. 3510–3521. Available at: https://doi.org/10.1007/s12144-019-00300-2.

Grabner-Kraeuter, S. (2002) 'The Role of Consumers' Trust in Online-Shopping', *Journal of Business Ethics*, 39(1), pp. 43–50. Available at: https://doi.org/10.1023/A:1016323815802.

Granić, A. and Marangunić, N. (2019) 'Technology acceptance model in educational context: A systematic literature review', *British Journal of Educational Technology*. Blackwell Publishing Ltd, pp. 2572–2593. Available at: https://doi.org/10.1111/bjet.12864.

Greenberg, J. (1987) 'A Taxonomy of Organizational Justice Theories', *Academy of Management Review*, 12(1), pp. 9–22. Available at: https://doi.org/10.5465/amr.1987.4306437.

Grégoire, Y. *et al.* (2009) 'When Customer Love Turns into Lasting Hate: The Effects of Relationship Strength and Time on Customer Revenge and Avoidance', *Journal of Marketing*, 73, pp. 18–32.

Grewal, D. *et al.* (2016a) 'Mobile Advertising: A Framework and Research Agenda', *Journal of Interactive Marketing*, 34, pp. 3–14. Available at: https://doi.org/10.1016/j.intmar.2016.03.003.

Grewal, D. *et al.* (2016b) 'Mobile Advertising: A Framework and Research Agenda', *Journal of Interactive Marketing*, 34, pp. 3–14. Available at: https://doi.org/10.1016/j.intmar.2016.03.003.

Grewal, D., Kroschke, M., *et al.* (2020) 'Frontline Cyborgs at Your Service: How Human Enhancement Technologies Affect Customer Experiences in Retail, Sales, and Service Settings', *Journal of Interactive Marketing*, 51, pp. 9–25. Available at: https://doi.org/10.1016/j.intmar.2020.03.001.

Grewal, D., Noble, S.M., *et al.* (2020) 'The future of in-store technology', *Journal of the Academy of Marketing Science*, 48(1), pp. 96–113. Available at: https://doi.org/10.1007/s11747-019-00697-z.

Grewal, D., Hulland, J., *et al.* (2020) 'The future of technology and marketing: a multidisciplinary perspective', *Journal of the Academy of Marketing Science*. Springer. Available at: https://doi.org/10.1007/s11747-019-00711-4.

Grewal, D., Gauri, D.K., Das, G., *et al.* (2021) 'Retailing and emergent technologies', *Journal of Business Research*, 134, pp. 198–202. Available at: https://doi.org/10.1016/j.jbusres.2021.05.004.

Grewal, D., Gauri, D.K., Roggeveen, A.L., *et al.* (2021) 'Strategizing Retailing in the New Technology Era', *Journal of Retailing*, 97(1), pp. 6–12. Available at: https://doi.org/10.1016/j.jretai.2021.02.004.

Grewal, D. *et al.* (2023) 'Leveraging In-Store Technology and AI: Increasing Customer and Employee Efficiency and Enhancing their Experiences', *Journal of Retailing*, 99(4), pp. 487–504. Available at: https://doi.org/10.1016/j.jretai.2023.10.002.

Grewal, D., Levy, M. and Kumar, V. (2009) 'Customer Experience Management in Retailing: An Organizing Framework', *Journal of Retailing*, 85(1), pp. 1–14. Available at: https://doi.org/10.1016/j.jretai.2009.01.001.

Grewal, D., Monroe, K.B. and Krishnan, R. (1998) *The Effects of Price-Comparison Advertising on Buyers' Perceptions of Acquisition Value, Transaction Value, and Behavioral Intentions*.

Grewal, D., Roggeveen, A.L. and Nordfält, J. (2017) 'The Future of Retailing', *Journal of Retailing*, 93(1), pp. 1–6. Available at: https://doi.org/10.1016/j.jretai.2016.12.008.

Grossklags, J. (2005) *Economics of Information Security Privacy and Rationality in Individual Decision Making*. Available at: www.computer.org/security/.

Grubbs, F.E. (1969) *American Society for Quality Procedures for Detecting Outlying Observations in Samples*.

Guenther, P. *et al.* (2023) 'Improving PLS-SEM use for business marketing research', *Industrial Marketing Management*, 111, pp. 127–142. Available at: https://doi.org/10.1016/j.indmarman.2023.03.010.

Guerrero Quiñones, J.L. (2024) 'Using artificial intelligence to enhance patient autonomy in healthcare decision-making', *AI and Society* [Preprint]. Available at: https://doi.org/10.1007/s00146-024-01956-6.

Guha, A. *et al.* (2021) 'How artificial intelligence will affect the future of retailing', *Journal of Retailing*, 97(1), pp. 28–41. Available at: https://doi.org/10.1016/j.jretai.2021.01.005.

Guha, A. *et al.* (2023) 'How artificiality and intelligence affect voice assistant evaluations', *Journal of the Academy of Marketing Science*, 51(4), pp. 843–866. Available at: https://doi.org/10.1007/s11747-022-00874-7.

Gulfraz, M.B. *et al.* (2022) 'Understanding the impact of online customers' shopping experience on online impulsive buying: A study on two leading E-commerce platforms', *Journal of Retailing and Consumer Services*, 68. Available at: https://doi.org/10.1016/j.jretconser.2022.103000.

Guo, B. and Wang, D. (2023) 'EXPRESS: Will Online Shopping Lead to More Brand Loyalty than Offline Shopping? The Role of Uncertainty Avoidance', *Journal of Marketing Research*, p. 002224372311530. Available at: https://doi.org/10.1177/00222437231153075.

Guo, M. *et al.* (2020) 'Consumer preference analysis: A data-driven multiple criteria approach integrating online information', *Omega (United Kingdom)*, 96. Available at: https://doi.org/10.1016/j.omega.2019.05.010.

Guo, M. *et al.* (2023) 'The impact of perceived risk of online takeout packaging and the moderating role of educational level', *Humanities and Social Sciences Communications*, 10(1). Available at: https://doi.org/10.1057/s41599-023-01732-9.

Guo, S. *et al.* (2018) 'Inspiring awe in consumers: Relevance, triggers, and consequences', *Asian Journal of Social Psychology*, 21(3), pp. 129–142. Available at: https://doi.org/10.1111/ajsp.12215.

Guo, X. and Jiang, B. (2016) 'Signaling through price and quality to consumers with fairness concerns', *Journal of Marketing Research*, 53(6), pp. 988–1000. Available at: https://doi.org/10.1509/jmr.15.0323.

Gupta, B.B., Gaurav, A. and Panigrahi, P.K. (2023) 'Analysis of retail sector research evolution and trends during COVID-19', *Technological Forecasting and Social Change*, 194, p. 122671. Available at: https://doi.org/10.1016/j.techfore.2023.122671.

Gupta, R., Mukherjee, S. and Jayarajah, K. (2021) 'Role of group cohesiveness in targeted mobile promotions', *Journal of Business Research*, 127, pp. 216–227. Available at: https://doi.org/10.1016/j.jbusres.2021.01.030.

Gutierrez, A. *et al.* (2023) 'Retailers, don't ignore me on social media! The importance of consumer-brand interactions in raising purchase intention - Privacy the Achilles heel', *Journal of Retailing and Consumer Services*, 72. Available at: https://doi.org/10.1016/j.jretconser.2023.103272.

Haenlein, M. and Kaplan, A. (2021) 'Artificial intelligence and robotics: Shaking up the business world and society at large', *Journal of Business Research*, 124, pp. 405–407. Available at: https://doi.org/10.1016/j.jbusres.2020.10.042.

Hair, J.F. *et al.* (2007) 'Research Methods for Business', *Education + Training*, 49(4), pp. 336–337. Available at: https://doi.org/10.1108/et.2007.49.4.336.2.

Hair, J.F. *et al.* (2013) *Multivariate Data Analysis*. Pearson Education Limited (Always learning). Available at: https://books.google.co.uk/books?id=VvXZnQEACAAJ.

Hair, J.F. *et al.* (2014) 'Partial least squares structural equation modeling (PLS-SEM): An emerging tool in business research', *European Business Review*. Emerald Group

Publishing Ltd., pp. 106–121. Available at: https://doi.org/10.1108/EBR-10-2013-0128.

Hair, J.F. *et al.* (2019) ‘When to use and how to report the results of PLS-SEM’, *European Business Review*, 31(1), pp. 2–24. Available at: https://doi.org/10.1108/EBR-11-2018-0203.

Hair, J.F., Black, W.C. and Babin, B.J. (2010a) *Multivariate Data Analysis: A Global Perspective*. Pearson Education (Global Edition). Available at: https://books.google.co.uk/books?id=SLRPLgAACAAJ.

Hair, J.F., Black, W.C. and Babin, B.J. (2010b) *Multivariate Data Analysis: A Global Perspective*. Pearson Education (Global Edition). Available at: https://books.google.co.uk/books?id=SLRPLgAACAAJ.

Hair Jr, J. *et al.* (2021) *Classroom Companion: Business Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R AAWorkbook*. Available at: http://www.

Hair JR, J.F. *et al.* (2010) *Multivariate Data Analysis*. 7th edn.

Hall, A. and Towers, N. (2017) ‘Understanding how Millennial shoppers decide what to buy: Digitally connected unseen journeys’, *International Journal of Retail and Distribution Management*, 45(5), pp. 498–517. Available at: https://doi.org/10.1108/IJRDM-11-2016-0206.

Hall, M.C. *et al.* (2021) ‘Beyond panic buying: consumption displacement and COVID-19’, *Journal of Service Management*, 32(1), pp. 113–128. Available at: https://doi.org/10.1108/JOSM-05-2020-0151.

Hamzah, M.I. and Pontes, N. (2022) ‘What drives car buyers to accept a rejuvenated brand? the mediating effects of value and pricing in a consumer-brand relationship’, *Journal of Strategic Marketing* [Preprint]. Available at: https://doi.org/10.1080/0965254X.2022.2129749.

Hann, I.-H. *et al.* (2007) ‘Overcoming Online Information Privacy Concerns: An Information-Processing Theory Approach’, *Journal of Management Information Systems*, 24(2), pp. 13–42. Available at: https://doi.org/10.2753/MIS0742-1222240202.

Harmeling, C.M. *et al.* (2017) ‘Toward a theory of customer engagement marketing’, *Journal of the Academy of Marketing Science*, 45(3), pp. 312–335. Available at: https://doi.org/10.1007/s11747-016-0509-2.

van Harreveld, F., van der Pligt, J. and Nordgren, L. (2008) ‘The relativity of bad decisions: Social comparison as a means to alleviate regret.’, *British Journal of Social Psychology*, 47, pp. 105–117. Available at: https://doi.org/10.1348/014466607X260134.

Harwood, S. and Eaves, S. (2020) ‘Conceptualising technology, its development and future: The six genres of technology’, *Technological Forecasting and Social Change*, 160, p. 120174. Available at: https://doi.org/10.1016/j.techfore.2020.120174.

Hasan, R., Shams, R. and Rahman, M. (2021) ‘Consumer trust and perceived risk for voice-controlled artificial intelligence: The case of Siri’, *Journal of Business Research*, 131, pp. 591–597. Available at: https://doi.org/10.1016/j.jbusres.2020.12.012.

Hassan, A.M. *et al.* (2006) ‘CONCEPTUALIZATION AND MEASUREMENT OF PERCEIVED RISK IN ONLINE SHOPPING.’, *Marketing Management Journal*, 16(1), pp. 138–147. Available at: https://search.ebscohost.com/login.aspx?direct=true&AuthType=ip,shib&db=buh&AN=21517925&site=ehost-live&scope=site&custid=s1123049.

Hassenzahl, M. (2010) ‘Experience Design: Technology for All the Right Reasons’, *Synthesis Lectures on Human-Centered Informatics*, 3(1), pp. 1–95. Available at: https://doi.org/10.2200/s00261ed1v01y201003hci008.

Hassenzahl, M., Burmester, M. and Koller, F. (2021) ‘User Experience Is All There Is Twenty Years of Designing Positive Experiences and Meaningful Technology’, *i-com*, 20(3), pp. 197–213. Available at: https://doi.org/10.1515/icom-2021-0034.

Hawes, J.M. and Lumpkin, J.R. (1986) ‘Perceived risk and the selection of a retail patronage mode’, *Journal of the Academy of Marketing Science*, 14(4), pp. 37–42. Available at: https://doi.org/10.1007/BF02721814.

Hawkins, M.A. (2019) ‘The effect of activity identity fusion on negative consumer behavior’, *Psychology and Marketing*, 36(4), pp. 395–409. Available at: https://doi.org/10.1002/mar.21186.

El Hedhli, K., Chebat, J.C. and Sirgy, M.J. (2013) ‘Shopping well-being at the mall: Construct, antecedents, and consequences’, *Journal of Business Research*, 66(7), pp. 856–863. Available at: https://doi.org/10.1016/j.jbusres.2011.06.011.

Heitmann, M., Lehmann, D.R. and Herrmann, A. (2007) *Choice Goal Attainment and Decision and Consumption Satisfaction*, *Journal of Marketing Research*. Available at: http://www.marketingpower.com/jmrblog.

Heller, J. *et al.* (2019) ‘Touching the Untouchable: Exploring Multi-Sensory Augmented Reality in the Context of Online Retailing’, *Journal of Retailing*, 95(4), pp. 219–234. Available at: https://doi.org/10.1016/j.jretai.2019.10.008.

Henseler, J., Hubona, G. and Ray, P.A. (2016) ‘Using PLS path modeling in new technology research: Updated guidelines’, *Industrial Management and Data Systems*, 116(1), pp. 2–20. Available at: https://doi.org/10.1108/IMDS-09-2015-0382.

Herrmann, R.O. and Beik, L.L. (1968) ‘Shoppers’ movements outside their local retail area’, *Journal of Marketing*, 32(4_part_1), pp. 45–51.

Herzallah, D., Muñoz Leiva, F. and Liébana-Cabanillas, F. (2022) ‘To buy or not to buy, that is the question: understanding the determinants of the urge to buy impulsively on Instagram Commerce’, *Journal of Research in Interactive Marketing*, 16(4), pp. 477–493. Available at: https://doi.org/10.1108/JRIM-05-2021-0145.

Hess, N.J. *et al.* (2020) ‘Getting Personal in Public!? How Consumers Respond to Public Personalized Advertising in Retail Stores’, *Journal of Retailing*, 96(3), pp. 344–361. Available at: https://doi.org/10.1016/j.jretai.2019.11.005.

Higueras-Castillo, E., Liébana-Cabanillas, F.J. and Villarejo-Ramos, Á.F. (2023) 'Intention to use e-commerce vs physical shopping. Difference between consumers in the post-COVID era', *Journal of Business Research*, 157. Available at: https://doi.org/10.1016/j.jbusres.2022.113622.

Hilken, T. *et al.* (2017) 'Augmenting the eye of the beholder: exploring the strategic potential of augmented reality to enhance online service experiences', *Journal of the Academy of Marketing Science*, 45(6), pp. 884–905. Available at: https://doi.org/10.1007/s11747-017-0541-x.

Hinsch, C., Felix, R. and Rauschnabel, P.A. (2020) 'Nostalgia beats the wow-effect: Inspiration, awe and meaningful associations in augmented reality marketing', *Journal of Retailing and Consumer Services*, 53. Available at: https://doi.org/10.1016/j.jretconser.2019.101987.

Hirschman, E.C. and Holbrook, M.B. (1982) *Hedonic Consumption: Emerging Concepts, Methods and Propositions*, *Source: Journal of Marketing , Summer*.

Ho, X.H. *et al.* (2022) 'Customer engagement in the context of retail mobile apps: A contingency model integrating spatial presence experience and its drivers', *Journal of Retailing and Consumer Services*, 66. Available at: https://doi.org/10.1016/j.jretconser.2022.102950.

Hoelter, J.O.N.W. (1983) 'The Analysis of Covariance Structures: Goodness-of-Fit Indices', *Sociological Methods & Research*, 11(3), pp. 325–344. Available at: https://doi.org/10.1177/0049124183011003003.

Hoffman, D.L. and Novak, T.P. (2018a) 'Consumer and object experience in the internet of things: An assemblage theory approach', *Journal of Consumer Research*, 44(6), pp. 1178–1204. Available at: https://doi.org/10.1093/jcr/ucx105.

Hoffman, D.L. and Novak, T.P. (2018b) 'Consumer and object experience in the internet of things: An assemblage theory approach', *Journal of Consumer Research*, 44(6), pp. 1178–1204. Available at: https://doi.org/10.1093/jcr/ucx105.

Hoffman, D.L., Novak, T.P. and Peralta, M. (1999) *COMMUNICATIONS OF THE ACM*.

Holbrook, M.B. and Hirschman, E.C. (1982) *The Experiential Aspects of Consumption: Consumer Fantasies, Feelings, and Fun*, *Source: Journal of Consumer Research*. Available at: https://www.jstor.org/stable/2489122.

Hollebeek, L.D. *et al.* (2019) 'Customer engagement in evolving technological environments: synopsis and guiding propositions', *European Journal of Marketing*. Emerald Group Holdings Ltd., pp. 2018–2023. Available at: https://doi.org/10.1108/EJM-09-2019-970.

Hollebeek, L.D. *et al.* (2020) 'Virtual reality through the customer journey: Framework and propositions', *Journal of Retailing and Consumer Services*, 55. Available at: https://doi.org/10.1016/j.jretconser.2020.102056.

Hollebeek, L.D. and Belk, R. (2021) 'Consumers' technology-facilitated brand engagement and wellbeing: Positivist TAM/PERMA- vs. Consumer Culture Theory perspectives', *International Journal of Research in Marketing* [Preprint]. Available at: https://doi.org/10.1016/j.ijresmar.2021.03.001.

Hollebeek, L.D., Glynn, M.S. and Brodie, R.J. (2014) ‘Consumer brand engagement in social media: Conceptualization, scale development and validation’, *Journal of Interactive Marketing*, 28(2), pp. 149–165. Available at: https://doi.org/10.1016/j.intmar.2013.12.002.

Hollebeek, L.D., Juric, B. and Tang, W. (2017) ‘Virtual brand community engagement practices: a refined typology and model’, *Journal of Services Marketing*, 31(3), pp. 204–217. Available at: https://doi.org/10.1108/JSM-01-2016-0006.

Hollebeek, L.D. and Macky, K. (2019) ‘Digital Content Marketing’s Role in Fostering Consumer Engagement, Trust, and Value: Framework, Fundamental Propositions, and Implications’, *Journal of Interactive Marketing*, 45, pp. 27–41. Available at: https://doi.org/10.1016/j.intmar.2018.07.003.

Hollebeek, L.D., Srivastava, R.K. and Chen, T. (2019) ‘S-D logic–informed customer engagement: integrative framework, revised fundamental propositions, and application to CRM’, *Journal of the Academy of Marketing Science*, 47(1), pp. 161–185. Available at: https://doi.org/10.1007/s11747-016-0494-5.

Holmes-Smith, P., Coote, L. and Cunningham, E. (2006) ‘Structural equation modeling: From the fundamentals to advanced topics’, *Melbourne: Sreams* [Preprint].

Holmlund, M. *et al.* (2020) ‘Customer experience management in the age of big data analytics: A strategic framework’, *Journal of Business Research*, 116, pp. 356–365. Available at: https://doi.org/10.1016/j.jbusres.2020.01.022.

Holtzman, S. (1989) *Intelligent decision systems / Samuel Holtzman.* Reading, Mass. ; Addison-Wesley (Teknowledge series in knowledge engineering).

Homburg, C. and Giering, A. (2001) ‘Personal characteristics as moderators of the relationship between customer satisfaction and loyalty - An empirical analysis’, *Psychology and Marketing*, 18(1), pp. 43–66. Available at: https://doi.org/10.1002/1520-6793(200101)18:1<43::AID-MAR3>3.0.CO;2-I.

Homburg, C., Jozić, D. and Kuehnl, C. (2017a) ‘Customer experience management: toward implementing an evolving marketing concept’, *Journal of the Academy of Marketing Science*, 45(3), pp. 377–401. Available at: https://doi.org/10.1007/s11747-015-0460-7.

Homburg, C., Jozić, D. and Kuehnl, C. (2017b) ‘Customer experience management: toward implementing an evolving marketing concept’, *Journal of the Academy of Marketing Science*, 45(3), pp. 377–401. Available at: https://doi.org/10.1007/s11747-015-0460-7.

Hong, I.B. and Cho, H. (2011) ‘The impact of consumer trust on attitudinal loyalty and purchase intentions in B2C e-marketplaces: Intermediary trust vs. seller trust’, *International Journal of Information Management*, 31(5), pp. 469–479. Available at: https://doi.org/10.1016/j.ijinfomgt.2011.02.001.

Hong, L.M. *et al.* (2020) ‘Online store image effect on perceived risks towards online purchasing behaviour’, *International Journal of Business Information Systems*, 35(1), pp. 27–44. Available at: https://doi.org/10.1504/IJBIS.2020.109530.

Hong, W., Chan, F.K.Y. and Thong, J.Y.L. (2021) ‘Drivers and Inhibitors of Internet Privacy Concern: A Multidimensional Development Theory Perspective’, *Journal of*

Business Ethics, 168(3), pp. 539–564. Available at: https://doi.org/10.1007/s10551-019-04237-1.

Hong, Y. and Pavlou, P.A. (2014) ‘Product fit uncertainty in online markets: Nature, effects, and antecedents’, *Information Systems Research*, 25(2), pp. 328–344. Available at: https://doi.org/10.1287/isre.2014.0520.

Hopkins, J.L. (2021) ‘An investigation into emerging industry 4.0 technologies as drivers of supply chain innovation in Australia’, *Computers in Industry*, 125. Available at: https://doi.org/10.1016/j.compind.2020.103323.

Horton, R.L. (1976) *The Structure of Perceived Risk: Some Further Progress*.

Houston, M.B. (2016) ‘Is “strategy” a dirty word?’, *Journal of the Academy of Marketing Science*. Springer New York LLC, pp. 557–561. Available at: https://doi.org/10.1007/s11747-016-0481-x.

Howard, J.A. and Sheth, J.N. (1969a) ‘The theory of buyer behavior’, *New York*, 63, p. 145.

Howard, J.A. and Sheth, J.N. (1969b) ‘The theory of buyer behavior’, *New York*, 63, p. 145.

Howard, M.C. (2023) ‘A systematic literature review of exploratory factor analyses in management’, *Journal of Business Research*, 164. Available at: https://doi.org/10.1016/j.jbusres.2023.113969.

Hoyer, W.D. *et al.* (2020) ‘Transforming the Customer Experience Through New Technologies’, *Journal of Interactive Marketing*, 51, pp. 57–71. Available at: https://doi.org/10.1016/j.intmar.2020.04.001.

Hoyle, R.H. (2012) *Handbook of Structural Equation Modeling*. Guilford Publications. Available at: https://books.google.co.uk/books?id=qC4aMfXL1JkC.

Hsu, C.P., Chiang, Y.F. and Huang, H.C. (2012) ‘How experience-driven community identification generates trust and engagement’, *Online Information Review*, 36(1), pp. 72–88. Available at: https://doi.org/10.1108/14684521211206971.

Hu, L. and Bentler, P.M. (1999) ‘Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives.’, *Structural Equation Modeling*, 6, pp. 1–55. Available at: https://doi.org/10.1080/10705519909540118.

Hu, M., Pantano, E. and Stylos, N. (2023) ‘“Home alone” no more: How does the internet of things (IoT) enhance travellers’ subjective well-being’, *Technological Forecasting and Social Change*, 192. Available at: https://doi.org/10.1016/j.techfore.2023.122563.

Hu, Y. and Min, H. (Kelly) (2023) ‘The dark side of artificial intelligence in service: The “watching-eye” effect and privacy concerns’, *International Journal of Hospitality Management*, 110. Available at: https://doi.org/10.1016/j.ijhm.2023.103437.

Huang, D., Jin, X. and Coghlan, A. (2021) ‘Advances in consumer innovation resistance research: A review and research agenda’, *Technological Forecasting and Social Change*, 166. Available at: https://doi.org/10.1016/j.techfore.2021.120594.

Huang, M.-H. and Rust, R.T. (2018) ‘Artificial Intelligence in Service’, *Journal of Service Research*, 21(2), pp. 155–172. Available at: https://doi.org/10.1177/1094670517752459.

Huang, T.L. and Liao, S. (2015) ‘A model of acceptance of augmented-reality interactive technology: the moderating role of cognitive innovativeness’, *Electronic Commerce Research*, 15(2), pp. 269–295. Available at: https://doi.org/10.1007/s10660-014-9163-2.

Huang, T.L. and Liu, B.S.C. (2021) ‘Augmented reality is human-like: How the humanizing experience inspires destination brand love’, *Technological Forecasting and Social Change*, 170. Available at: https://doi.org/10.1016/j.techfore.2021.120853.

Hubert, M. *et al.* (2017) ‘Acceptance of Smartphone-Based Mobile Shopping: Mobile Benefits, Customer Characteristics, Perceived Risks, and the Impact of Application Context’, *Psychology and Marketing*, 34(2), pp. 175–194. Available at: https://doi.org/10.1002/mar.20982.

Hufnagel, G., Schwaiger, M. and Weritz, L. (2022) ‘Seeking the perfect price: Consumer responses to personalized price discrimination in e-commerce’, *Journal of Business Research*, 143, pp. 346–365. Available at: https://doi.org/10.1016/j.jbusres.2021.10.002.

Hui, M.K., Thakor, M. V. and Gill, R. (1998) ‘The effect of delay type and service stage on consumers’ reactions to waiting’, *Journal of Consumer Research*, 24(4), pp. 469–479. Available at: https://doi.org/10.1086/209522.

Hulland, J. (1999) ‘Use of partial least squares (PLS) in strategic management research: A review of four recent studies’, *Strategic Management Journal*, 20(2), pp. 195–204. Available at: https://doi.org/10.1002/(sici)1097-0266(199902)20:2<195::aid-smj13>3.0.co;2-7.

Hulland, J., Chow, Y.H. and Lam, S. (1996) *Research in Marketing Use of causal models in marketing research: A review*, *Intern. J. of Research in Marketing*.

Hussey, I. *et al.* (2023) *An aberrant abundance of Cronbach’s alpha values at .70*.

Inman, J.J. and Nikolova, H. (2017) ‘Shopper-Facing Retail Technology: A Retailer Adoption Decision Framework Incorporating Shopper Attitudes and Privacy Concerns’, *Journal of Retailing*, 93(1), pp. 7–28. Available at: https://doi.org/10.1016/j.jretai.2016.12.006.

Ismail, N., Kinchin, G. and Edwards, J.-A. (2017) ‘Pilot Study, Does It Really Matter? Learning Lessons from Conducting a Pilot Study for a Qualitative PhD Thesis’, *International Journal of Social Science Research*, 6(1), p. 1. Available at: https://doi.org/10.5296/ijssr.v6i1.11720.

Jacobsen, S. (2018) ‘Why did I buy this?: The effect of WOM and online reviews on post purchase attribution for product outcomes’, *Journal of Research in Interactive Marketing*, 12(3), pp. 370–395. Available at: https://doi.org/10.1108/JRIM-12-2017-0102.

Jahangirian, M. *et al.* (2010) ‘Simulation in manufacturing and business: A review’, *European Journal of Operational Research*, 203(1), pp. 1–13. Available at: https://doi.org/10.1016/j.ejor.2009.06.004.

Jai, T.M., Burns, L.D. and King, N.J. (2013) 'The effect of behavioral tracking practices on consumers' shopping evaluations and repurchase intention toward trusted online retailers', *Computers in Human Behavior*, 29(3), pp. 901–909. Available at: https://doi.org/10.1016/j.chb.2012.12.021.

Janson, A. (2023) 'How to leverage anthropomorphism for chatbot service interfaces: The interplay of communication style and personification', *Computers in Human Behavior*, p. 107954. Available at: https://doi.org/10.1016/j.chb.2023.107954.

Jaspers, E.D.T. and Pearson, E. (2022) 'Consumers' acceptance of domestic Internet-of-Things: The role of trust and privacy concerns', *Journal of Business Research*, 142, pp. 255–265. Available at: https://doi.org/10.1016/j.jbusres.2021.12.043.

Jayaswal, P. and Parida, B. (2023) 'The role of augmented reality in redefining e-tailing: A review and research agenda', *Journal of Business Research*, 160, p. 113765. Available at: https://doi.org/10.1016/j.jbusres.2023.113765.

Jen, M.-Y. (2021) *Investigating Factors Affecting Purchase Intention in Collaborative Consumption: The Antecedents of Social Trust and Self-efficacy*.

Jiang, L. (Alice), Yang, Z. and Jun, M. (2013) 'Measuring consumer perceptions of online shopping convenience', *Journal of Service Management*, 24(2), pp. 191–214. Available at: https://doi.org/10.1108/09564231311323962.

Jiang, Y. and Stylos, N. (2021) 'Triggers of consumers' enhanced digital engagement and the role of digital technologies in transforming the retail ecosystem during COVID-19 pandemic', *Technological Forecasting and Social Change*, 172. Available at: https://doi.org/10.1016/j.techfore.2021.121029.

Jones, K.S. (2003) 'What Is an Affordance?', *Ecological Psychology*, 15(2), pp. 107–114. Available at: https://doi.org/10.1207/S15326969ECO1502_1.

Jones, P. and Comfort, D. (2013) 'Stories and Retailer Brands: A Study of the UK's Leading Retailers', *Leading Retailers. Indonesian Journal of Contemporary Management Research*, (2), pp. 65–77. Available at: https://doi.org/10.33455/ijcmr.v1i2.92.

Jun, S.P., Yoo, H.S. and Choi, S. (2018) 'Ten years of research change using Google Trends: From the perspective of big data utilizations and applications', *Technological Forecasting and Social Change*, 130, pp. 69–87. Available at: https://doi.org/10.1016/j.techfore.2017.11.009.

Kaiser, H.F. (1970) 'A second generation little jiffy', *Psychometrika*, 35(4), pp. 401–415. Available at: https://doi.org/10.1007/BF02291817.

Kaltcheva, V.D. and Weitz, B.A. (2006) *When Should a Retailer Create an Exciting Store Environment?*, *Source: Journal of Marketing*.

Kamalul Ariffin, S., Mohan, T. and Goh, Y.N. (2018) 'Influence of consumers' perceived risk on consumers' online purchase intention', *Journal of Research in Interactive Marketing*, 12(3), pp. 309–327. Available at: https://doi.org/10.1108/JRIM-11-2017-0100.

Kamis, A., Koufaris, M. and Stern, T. (2008) *Using an Attribute-Based Decision Support System for User-Customized Products Online: An Experimental Investigation C^t'fterly Using an Attribute-Based Decision Support System for User-Customized Products Online: An Experimental Investigation1*, *Source: MIS Quarterly*.

Kamoonpuri, S.Z. and Sengar, A. (2023) 'Hi, May AI help you? An analysis of the barriers impeding the implementation and use of artificial intelligence-enabled virtual assistants in retail', *Journal of Retailing and Consumer Services*, 72. Available at: https://doi.org/10.1016/j.jretconser.2023.103258.

Kanika, A. (2015) *Research Methods: The Essential Knowledge Base*. Cengage Learning. Available at: https://books.google.co.uk/books?id=gFdfzgEACAAJ.

Kankanhalli, A., Tan, B.C.Y. and Wei, K.-K. (2005) *Contributing Knowledge to Electronic Knowledge Repositories: An Empirical Investigation*.

Karahanna, E. *et al.* (2018) 'The Needs–affordances–features Perspective for the Use of Social Media', *MIS Q.*, 42(3), pp. 737–756. Available at: https://doi.org/10.25300/MISQ/2018/11492.

Karimi, S., Holland, C.P. and Papamichail, K.N. (2018) 'The impact of consumer archetypes on online purchase decision-making processes and outcomes: A behavioural process perspective', *Journal of Business Research*, 91, pp. 71–82. Available at: https://doi.org/10.1016/j.jbusres.2018.05.038.

Karimi, S., Papamichail, K.N. and Holland, C.P. (2015) 'The effect of prior knowledge and decision-making style on the online purchase decision-making process: A typology of consumer shopping behaviour', *Decision Support Systems*, 77, pp. 137–147. Available at: https://doi.org/10.1016/j.dss.2015.06.004.

Karpoff, J.M. (2021) 'The future of financial fraud', *Journal of Corporate Finance*, 66. Available at: https://doi.org/10.1016/j.jcorpfin.2020.101694.

Kautish, P. and Khare, A. (2022) 'Investigating the moderating role of AI-enabled services on flow and awe experience', *International Journal of Information Management*, 66. Available at: https://doi.org/10.1016/j.ijinfomgt.2022.102519.

Kaya, B. *et al.* (2019) 'The Moderating Role of Website Familiarity in the Relationships Between e-Service Quality, e-Satisfaction and e-Loyalty', *Journal of Internet Commerce*, 18(4), pp. 369–394. Available at: https://doi.org/10.1080/15332861.2019.1668658.

Keaveney, S.M. (1995) *Customer Switching Behavior in Service Industries: An Exploratory Study*, *Source: Journal of Marketing*.

Kelly, A. *et al.* (2009) *Modelling the Outcome of the UK Business and Management Studies RAE 2008 with reference to the ABS Journal Quality Guide Entrepreneurial Philanthropy View project Organizational History View project Modelling the Outcome of the UK Business and Management Studies RAE 2008 with reference to the ABS Journal Quality Guide Modelling the Outcome of the UK Business and Management Studies RAE 2008 with reference to the ABS Journal Quality Guide*. Available at: https://www.researchgate.net/publication/43251475.

Van Kenhove, P., De Wulf, K. and Van Waterschoot, W. (1999) ‘The impact of task definition on store-attribute saliences and store choice’, *Journal of Retailing*, 75(1), pp. 125–137. Available at: https://doi.org/10.1016/S0022-4359(99)80007-4.

Kenny, D.A. and McCoach, D.B. (2003) ‘Effect of the Number of Variables on Measures of Fit in Structural Equation Modeling’, *Structural Equation Modeling*, 10(3), pp. 333–351. Available at: https://doi.org/10.1207/S15328007SEM1003_1.

de Kervenoael, R. *et al.* (2020) ‘Leveraging human-robot interaction in hospitality services: Incorporating the role of perceived value, empathy, and information sharing into visitors’ intentions to use social robots’, *Tourism Management*, 78. Available at: https://doi.org/10.1016/j.tourman.2019.104042.

De Keyser, A. *et al.* (2021) ‘Opportunities and challenges of using biometrics for business: Developing a research agenda’, *Journal of Business Research*, 136, pp. 52–62. Available at: https://doi.org/10.1016/j.jbusres.2021.07.028.

Keyser, D. *et al.* (2015) *‘A Framework for Understanding and Managing the Customer Experience’ © 2015 Arne A Framework for Understanding and Managing the Customer Experience*.

Kim, D. *et al.* (2019) ‘Willingness to provide personal information: Perspective of privacy calculus in IoT services’, *Computers in Human Behavior*, 92, pp. 273–281. Available at: https://doi.org/10.1016/j.chb.2018.11.022.

Kim, D.J., Ferrin, D.L. and Rao, H.R. (2008) ‘A trust-based consumer decision-making model in electronic commerce: The role of trust, perceived risk, and their antecedents’, *Decision Support Systems*, 44(2), pp. 544–564. Available at: https://doi.org/10.1016/j.dss.2007.07.001.

Kim, D.J., Ferrin, D.L. and Rao, H.R. (2009) ‘Trust and Satisfaction, Two Stepping Stones for Successful E-Commerce Relationships: A Longitudinal Exploration’, *Research*, 20(2), pp. 237–257. Available at: https://doi.org/10.1287/isre.l080.0188.

Kim, H.Y. and Kim, Y.K. (2008) ‘Shopping enjoyment and store shopping modes: The moderating influence of chronic time pressure’, *Journal of Retailing and Consumer Services*, 15(5), pp. 410–419. Available at: https://doi.org/10.1016/j.jretconser.2007.10.003.

Kim, J., Bang, H. and Campbell, W.K. (2021) ‘Brand awe: A key concept for understanding consumer response to luxury and premium brands’, *Journal of Social Psychology*, 161(2), pp. 245–260. Available at: https://doi.org/10.1080/00224545.2020.1804313.

Kim, J., Jin, B. and Swinney, J.L. (2009) ‘The role of etail quality, e-satisfaction and e-trust in online loyalty development process’, *Journal of Retailing and Consumer Services*, 16(4), pp. 239–247. Available at: https://doi.org/10.1016/j.jretconser.2008.11.019.

Kim, N. *et al.* (2010) ‘An affordance-based formalism for modeling human-involvement in complex systems for prospective control’, in *Proceedings of the 2010 Winter Simulation Conference*. IEEE, pp. 811–823.

Kim, T., Barasz, K. and John, L.K. (2019) 'Why am i seeing this ad? The effect of ad transparency on ad effectiveness', *Journal of Consumer Research*, 45(5), pp. 906–932. Available at: https://doi.org/10.1093/jcr/ucy039.

Bin Kim, W. and Jung Choo, H. (2023) 'How virtual reality shopping experience enhances consumer creativity: The mediating role of perceptual curiosity', *Journal of Business Research*, 154. Available at: https://doi.org/10.1016/j.jbusres.2022.113378.

Kim, Y. *et al.* (2023) 'Privacy concern and its consequences: A meta-analysis', *Technological Forecasting and Social Change*, 196. Available at: https://doi.org/10.1016/j.techfore.2023.122789.

Kim, Y., Seok, J. and Roh, T. (2023) 'The linkage between quality of information systems and the impact of trust-based privacy on behavioral outcomes in unmanned convenience store: Moderating effect of gender and experience', *Technological Forecasting and Social Change*, 196. Available at: https://doi.org/10.1016/j.techfore.2023.122852.

Kim, Y., Wang, Q. and Roh, T. (2021) 'Do information and service quality affect perceived privacy protection, satisfaction, and loyalty? Evidence from a Chinese O2O-based mobile shopping application', *Telematics and Informatics*, 56. Available at: https://doi.org/10.1016/j.tele.2020.101483.

Kipnis, E. *et al.* (2019) 'Consumer Multicultural Identity Affiliation: Reassessing identity segmentation in multicultural markets', *Journal of Business Research*, 98, pp. 126–141. Available at: https://doi.org/10.1016/j.jbusres.2018.11.056.

Kleijnen, M., de Ruyter, K. and Wetzels, M. (2007) 'An assessment of value creation in mobile service delivery and the moderating role of time consciousness', *Journal of Retailing*, 83(1), pp. 33–46. Available at: https://doi.org/10.1016/J.JRETAI.2006.10.004.

Kline, R.B. (2011) *Principles and practice of structural equation modeling, 3rd ed.*, *Principles and practice of structural equation modeling, 3rd ed.* New York, NY, US: Guilford Press (Methodology in the Social Sciences.).

Knight, G.A. and Cavusgil, S.T. (2004) 'Innovation, organizational capabilities, and the born-global firm', *Journal of International Business Studies*, 35(2), pp. 124–141. Available at: https://doi.org/10.1057/palgrave.jibs.8400071.

Ko, E.-J., Kim, A.-H. and Kim, S.-S. (2021) 'Toward the understanding of the appropriation of ICT-based Smart-work and its impact on performance in organizations', *Technological Forecasting and Social Change*, 171, p. 120994. Available at: https://doi.org/10.1016/J.TECHFORE.2021.120994.

Kock, N. (2015) 'Common method bias in PLS-SEM: A full collinearity assessment approach', *International Journal of e-Collaboration*, 11(4), pp. 1–10. Available at: https://doi.org/10.4018/ijec.2015100101.

Kock, N. and Lynn, G.S. (2012) *Lateral Collinearity and Misleading Results in Variance-Based SEM: An Illustration and Recommendations*, *Journal of the Association for Information Systems*.

Koh, L.Y. *et al.* (2023) ‘Social media engagement in the maritime industry during the pandemic’, *Technological Forecasting and Social Change*, 192. Available at: https://doi.org/10.1016/j.techfore.2023.122553.

Kokolakis, S. (2017) ‘Privacy attitudes and privacy behaviour: A review of current research on the privacy paradox phenomenon’, *Computers and Security*. Elsevier Ltd, pp. 122–134. Available at: https://doi.org/10.1016/j.cose.2015.07.002.

König, T.M., Hein, N. and Nimsgern, V. (2022) ‘A value perspective on online review platforms: Profiling preference structures of online shops and traditional companies’, *Journal of Business Research*, 145, pp. 387–401. Available at: https://doi.org/10.1016/j.jbusres.2022.02.080.

Konstan, J.A. and Riedl, J. (2012) ‘Recommender systems: From algorithms to user experience’, *User Modeling and User-Adapted Interaction*, pp. 101–123. Available at: https://doi.org/10.1007/s11257-011-9112-x.

Kopalle, P.K. *et al.* (2021) ‘Examining artificial intelligence (AI) technologies in marketing via a global lens: Current trends and future research opportunities’, *International Journal of Research in Marketing* [Preprint]. Available at: https://doi.org/10.1016/j.ijresmar.2021.11.002.

Korneeva, E. *et al.* (2023) ‘Tracing the legitimacy of Artificial Intelligence: A longitudinal analysis of media discourse’, *Technological Forecasting and Social Change*, 192. Available at: https://doi.org/10.1016/j.techfore.2023.122467.

Kozinets, R. V (2008) *Technology/Ideology: How Ideological Fields Influence Consumers’ Technology Narratives*, *JOURNAL OF CONSUMER RESEARCH, Inc.* •. Available at: https://about.jstor.org/terms.

Krishen, A.S. *et al.* (2021) ‘The digital self and virtual satisfaction: A cross-cultural perspective’, *Journal of Business Research*, 124, pp. 254–263. Available at: https://doi.org/10.1016/j.jbusres.2020.11.056.

Kujur, F. and Singh, S. (2018) ‘Emotions as predictor for consumer engagement in YouTube advertisement’, *Journal of Advances in Management Research*, 15(2), pp. 184–197. Available at: https://doi.org/10.1108/JAMR-05-2017-0065.

Kumar, A. and Kashyap, A.K. (2018) ‘Leveraging utilitarian perspective of online shopping to motivate online shoppers’, *International Journal of Retail and Distribution Management*, 46(3), pp. 247–263. Available at: https://doi.org/10.1108/IJRDM-08-2017-0161.

Kumar, P. and Utkarsh (2023) ‘Effects of in-store information quality and store credibility on consumer engagement in green retailing’, *Journal of Retailing and Consumer Services*, 71. Available at: https://doi.org/10.1016/j.jretconser.2022.103195.

Kumar, V. (2008) *Customer Lifetime Value: The Path to Profitability*. Now Publishers (Foundations and trends in marketing). Available at: https://books.google.co.uk/books?id=k1KHFxS3gosC.

Kumar, V. *et al.* (2010) ‘Undervalued or overvalued customers: Capturing total customer engagement value’, *Journal of Service Research*, 13(3), pp. 297–310. Available at: https://doi.org/10.1177/1094670510375602.

Kumar, V. *et al.* (2013) 'Creating a measurable social media marketing strategy: Increasing the value and ROI of intangibles and tangibles for Hokey Pokey', *Marketing Science*, 32(2), pp. 194–212. Available at: https://doi.org/10.1287/mksc.1120.0768.

Kumar, V. *et al.* (2019) 'Customer engagement in service', *Journal of the Academy of Marketing Science*, 47(1), pp. 138–160. Available at: https://doi.org/10.1007/s11747-017-0565-2.

Kumar, V., Nim, N. and Agarwal, A. (2020) 'Platform-based mobile payments adoption in emerging and developed countries: Role of country-level heterogeneity and network effects', *Journal of International Business Studies*, 52. Available at: https://doi.org/10.1057/s41267-020-00346-6.

Kumar, V. and Pansari, A. (2016) 'Competitive Advantage through Engagement', *Journal of Marketing Research*, 53(4), pp. 497–514. Available at: https://doi.org/10.1509/jmr.15.0044.

Kumar, V., Ramachandran, D. and Kumar, B. (2021) 'Influence of new-age technologies on marketing: A research agenda', *Journal of Business Research*, 125, pp. 864–877. Available at: https://doi.org/10.1016/j.jbusres.2020.01.007.

Lam, S.Y. *et al.* (2004a) 'Customer value, satisfaction, loyalty, and switching costs: An illustration from a business-to-business service context', *Journal of the Academy of Marketing Science*, pp. 293–311. Available at: https://doi.org/10.1177/0092070304263330.

Lam, S.Y. *et al.* (2004b) 'Customer value, satisfaction, loyalty, and switching costs: An illustration from a business-to-business service context', *Journal of the Academy of Marketing Science*, pp. 293–311. Available at: https://doi.org/10.1177/0092070304263330.

Laradi, S. *et al.* (2024) 'Understanding factors affecting social commerce purchase behavior: A longitudinal perspective', *Journal of Retailing and Consumer Services*, 78. Available at: https://doi.org/10.1016/j.jretconser.2024.103751.

Larivière, B. *et al.* (2017) '"Service Encounter 2.0": An investigation into the roles of technology, employees and customers', *Journal of Business Research*, 79, pp. 238–246. Available at: https://doi.org/10.1016/j.jbusres.2017.03.008.

Laroche, M. *et al.* (2004) 'Exploring How Intangibility Affects Perceived Risk', *Journal of Service Research*, 6(4), pp. 373–389. Available at: https://doi.org/10.1177/1094670503262955.

Lattin, J.M., Carroll, J.D. and Green, P.E. (2003) *Analyzing Multivariate Data*. Thomson Brooks/Cole (Analyzing Multivariate Data). Available at: https://books.google.co.uk/books?id=VXxuQgAACAAJ.

Lavidge, R.J. and Steiner, G.A. (1961) *A Model for Predictive Measurements of Advertising Effectiveness*, *Source: Journal of Marketing*.

Lawson-Body, A. *et al.* (2018) 'Students' acceptance of E-books: An application of UTAUT', *https://doi.org/10.1080/08874417.2018.1463577*, 60(3), pp. 256–267. Available at: https://doi.org/10.1080/08874417.2018.1463577.

Lee, C. and Green, R.T. (1991) *Cross-Cultural Examination of the Fishbein Behavioral Intentions Model*, *Source: Journal of International Business Studies*. Available at: https://www.jstor.org/stable/155211?seq=1&cid=pdf-.

Lee, J. and Ko, G. (2021) 'In-store shopping hassles: Conceptualization and classification', *International Journal of Consumer Studies*, 45(1), pp. 119–130. Available at: https://doi.org/10.1111/ijcs.12607.

Lee, J.E. and Shin, E. (2020) 'The effects of apparel names and visual complexity of apparel design on consumers' apparel product attitudes: A mental imagery perspective', *Journal of Business Research*, 120, pp. 407–417. Available at: https://doi.org/10.1016/j.jbusres.2019.08.023.

Lee, J.H. *et al.* (2022) 'The role of residents' sustainable intelligence in agricultural heritage site management: Insights from PLS-SEM and Fs/QCA', *Journal of Hospitality and Tourism Management*, 52, pp. 65–74. Available at: https://doi.org/10.1016/j.jhtm.2022.06.004.

Lee, K.W. and Li, C.Y. (2023) 'It is not merely a chat: Transforming chatbot affordances into dual identification and loyalty', *Journal of Retailing and Consumer Services*, 74. Available at: https://doi.org/10.1016/j.jretconser.2023.103447.

Lee, M.K.O. *et al.* (2011) 'Consumer's decision to shop online: The moderating role of positive informational social influence', *Information and Management*, 48(6), pp. 185–191. Available at: https://doi.org/10.1016/j.im.2010.08.005.

Lee, S. (Ally) (2018) 'Enhancing customers' continued mobile app use in the service industry', *Journal of Services Marketing*, 32(6), pp. 680–691. Available at: https://doi.org/10.1108/JSM-01-2017-0015.

Lee, Y. *et al.* (2009) 'Tourists' attitudes towards textiles and apparel-related cultural products: A cross-cultural marketing study', *Tourism Management*, 30(5), pp. 724–732. Available at: https://doi.org/10.1016/j.tourman.2008.10.007.

Lemon, K.N. and Verhoef, P.C. (2016) 'Understanding customer experience throughout the customer journey', *Journal of Marketing*, 80(6), pp. 69–96. Available at: https://doi.org/10.1509/jm.15.0420.

Leonardi, P.M., Huysman, M. and Steinfield, C. (2013) 'Enterprise social media: Definition, history, and prospects for the study of social technologies in organizations', *Journal of Computer-Mediated Communication*, 19(1), pp. 1–19. Available at: https://doi.org/10.1111/jcc4.12029.

Lettinga, N and Lettinga, Niels (2011) *The effects of spatial constraints on choosing recommended products. The effects of spatial constraints on choosing recommended products*.

Leung, D. and Seah, C. (2022) 'The impact of crisis-induced changes in refund policy on consumers' brand trust and repurchase intention', *International Journal of Hospitality Management*, 105. Available at: https://doi.org/10.1016/j.ijhm.2022.103272.

Leung, X.Y. *et al.* (2023) 'Why do hotel frontline employees use service robots in the workplace? A technology affordance theory perspective', *International Journal of*

Hospitality Management, 108. Available at: https://doi.org/10.1016/j.ijhm.2022.103380.

Li, D., Browne, G.J. and Wetherbe, J.C. (2006) ‘Why do internet users stick with a specific web site? A relationship perspective’, *International Journal of Electronic Commerce*, pp. 105–141. Available at: https://doi.org/10.2753/JEC1086-4415100404.

Li, K.J. and Jain, S. (2016) ‘Behavior-based pricing: An analysis of the impact of peer-induced fairness’, *Management Science*, 62(9), pp. 2705–2721. Available at: https://doi.org/10.1287/mnsc.2015.2265.

Li, L.P., Juric, B. and Brodie, R.J. (2017) ‘Dynamic multi-actor engagement in networks: the case of United Breaks Guitars’, *Journal of Service Theory and Practice*, 27(4), pp. 738–760. Available at: https://doi.org/10.1108/JSTP-04-2016-0066.

Li, Y. *et al.* (2023) ‘The influence of relative popularity on negative fake reviews: A case study on restaurant reviews’, *Journal of Business Research*, 162. Available at: https://doi.org/10.1016/j.jbusres.2023.113895.

Liang, C.J. and Wang, W.H. (2007) ‘An insight into the impact of a retailer’s relationship efforts on customers’ attitudes and behavioral intentions’, *International Journal of Bank Marketing*, 25(5), pp. 336–366. Available at: https://doi.org/10.1108/02652320710772998.

Liao, C., Liu, C.C. and Chen, K. (2011) ‘Examining the impact of privacy, trust and risk perceptions beyond monetary transactions: An integrated model’, *Electronic Commerce Research and Applications*, 10(6), pp. 702–715. Available at: https://doi.org/10.1016/j.elerap.2011.07.003.

Lim, K.H. *et al.* (2006) ‘Do I trust you online, and if so, will I buy? An empirical study of two trust-building strategies’, *Journal of Management Information Systems*, 23(2), pp. 233–266. Available at: https://doi.org/10.2753/MIS0742-1222230210.

Lim, L.G., Tuli, K.R. and Grewal, R. (2020) ‘Customer Satisfaction and Its Impact on the Future Costs of Selling’, *Journal of Marketing*, 84(4), pp. 23–44. Available at: https://doi.org/10.1177/0022242920923307.

Lim, N. (2003) ‘Consumers’ perceived risk: Sources versus consequences’, in *Electronic Commerce Research and Applications*, pp. 216–228. Available at: https://doi.org/10.1016/S1567-4223(03)00025-5.

Lin, G.T.R. and Sun, C.C. (2009) ‘Factors influencing satisfaction and loyalty in online shopping: An integrated model’, *Online Information Review*, 33(3), pp. 458–475. Available at: https://doi.org/10.1108/14684520910969907.

Lin, J. *et al.* (2019) ‘Understanding the interplay of social commerce affordances and swift guanxi: An empirical study’, *Information and Management*, 56(2), pp. 213–224. Available at: https://doi.org/10.1016/j.im.2018.05.009.

Lin, J.S.C. and Hsieh, P.L. (2007) ‘The influence of technology readiness on satisfaction and behavioral intentions toward self-service technologies’, *Computers in Human Behavior*, 23(3), pp. 1597–1615. Available at: https://doi.org/10.1016/j.chb.2005.07.006.

Lindecrantz, E., Tjon Pian Gi, M. and Zerbi, S. (2020) *Personalizing the customer experience: Driving differentiation in retail*, *McKinsey & Company*. Available at: https://www.mckinsey.com/~/media/mckinsey/industries/retail/our%20insights/personalizing%20the%20customer%20experience%20driving%20differentiation%20in%20retail/personalizing-the-customer-experience-driving-differentiation-in-retail.pdf?shouldIndex=false (Accessed: 6 June 2021).

Liu, J. and Cong, Z. (2023) 'The Daily Me Versus the Daily Others: How Do Recommendation Algorithms Change User Interests? Evidence from a Knowledge-Sharing Platform', *Journal of Marketing Research* [Preprint]. Available at: https://doi.org/10.1177/00222437221134237.

Loehlin, J.C. (2004) *Latent Variable Models: An Introduction to Factor, Path, and Structural Equation Analysis*. Taylor & Francis. Available at: https://books.google.co.uk/books?id=6MleqQnT0Q4C.

Longoni, C., Bonezzi, A. and Morewedge, C.K. (2019) 'Resistance to Medical Artificial Intelligence', *Journal of Consumer Research*, 46(4), pp. 629–650. Available at: https://doi.org/10.1093/jcr/ucz013.

Lopes, M. and Reis, J. (2021) 'The Influence of COVID-19 in Retail: A Systematic Literature Review', in *Advances in Intelligent Systems and Computing*. Springer Science and Business Media Deutschland GmbH, pp. 171–181. Available at: https://doi.org/10.1007/978-3-030-72651-5_17.

Lorente-Martínez, J., Navío-Marco, J. and Rodrigo-Moya, B. (2020) 'Analysis of the adoption of customer facing InStore technologies in retail SMEs', *Journal of Retailing and Consumer Services*, 57. Available at: https://doi.org/10.1016/j.jretconser.2020.102225.

Loureiro, S.M.C., Guerreiro, J. and Tussyadiah, I. (2021) 'Artificial intelligence in business: State of the art and future research agenda', *Journal of Business Research*, 129, pp. 911–926. Available at: https://doi.org/10.1016/j.jbusres.2020.11.001.

Louro, M.J., Pieters, R. and Zeelenberg, M. (2007) 'Dynamics of Multiple-Goal Pursuit', *Journal of Personality and Social Psychology*, 93(2), pp. 174–193. Available at: https://doi.org/10.1037/0022-3514.93.2.174.

Lu, B. and Yi, X. (2023) 'Institutional trust and repurchase intention in the sharing economy: The moderating roles of information privacy concerns and security concerns', *Journal of Retailing and Consumer Services*, 73. Available at: https://doi.org/10.1016/j.jretconser.2023.103327.

Lu, Y., He, Y. and Ke, Y. (2023) 'The influence of e-commerce live streaming affordance on consumer's gift-giving and purchase intention', *Data Science and Management*, 6(1), pp. 13–20. Available at: https://doi.org/10.1016/j.dsm.2022.10.002.

Lugosi, P. and Quinton, S. (2018) 'More-than-human netnography', *Journal of Marketing Management*, 34(3–4), pp. 287–313. Available at: https://doi.org/10.1080/0267257X.2018.1431303.

Lundin, L. and Kindström, D. (2023) 'Digitalizing customer journeys in B2B markets', *Journal of Business Research*, 157. Available at: https://doi.org/10.1016/j.jbusres.2022.113639.

Lutz, C. and Newlands, G. (2018) ‘Consumer segmentation within the sharing economy: The case of Airbnb’, *Journal of Business Research*, 88, pp. 187–196. Available at: https://doi.org/10.1016/j.jbusres.2018.03.019.

Luyat, M. and Regia-Corte, T. (2009) ‘Les affordances : de James Jerome Gibson aux formalisations récentes du concept’, *L’Année psychologique*, Vol. 109(2), pp. 297–332. Available at: https://doi.org/10.3917/anpsy.092.0297.

Lwin, M., Stanaland, A. and Miyazaki, A. (2008) ‘Protecting children’s privacy online: How parental mediation strategies affect website safeguard effectiveness’, *Journal of Retailing*, 84(2), pp. 205–217. Available at: https://doi.org/10.1016/j.jretai.2008.04.004.

Lwin, M.O., Wirtz, J. and Stanaland, A.J.S. (2016) ‘The privacy dyad: Antecedents of promotion- and prevention-focused online privacy behaviors and the mediating role of trust and privacy concern’, *Internet Research*, 26(4), pp. 919–941. Available at: https://doi.org/10.1108/IntR-05-2014-0134.

Lynch, J.G. and Ariely, D. (2000) *Wine Online: Search Costs Affect Competition on Price, Quality, and Distribution*, *Source: Marketing Science*. Winter. Available at: www.bizrate.com,.

Lyngdoh, T. *et al.* (2021) ‘A systematic literature review of negative psychological states and behaviors in sales’, *Journal of Business Research*, 122, pp. 518–533. Available at: https://doi.org/10.1016/j.jbusres.2020.09.031.

MacCallum, R.C., Browne, M.W. and Sugawara, H.M. (1996) ‘Power analysis and determination of sample size for covariance structure modeling.’, *Psychological Methods*, 1(2), pp. 130–149. Available at: https://doi.org/10.1037/1082-989X.1.2.130.

Mackenzie, S.B., Podsakoff, P.M. and Podsakoff, N.P. (2011) *Construct Measurement and Validation Procedures in MIS and Behavioral Research: Integrating New and Existing Techniques*, *Source: MIS Quarterly*.

Macpherson, A. and Jones, O. (2010) ‘Editorial: Strategies for the development of International Journal of Management reviews’, *International Journal of Management Reviews*, pp. 107–113. Available at: https://doi.org/10.1111/j.1468-2370.2010.00282.x.

Maduku, D.K. and Thusi, P. (2023) ‘Understanding consumers’ mobile shopping continuance intention: New perspectives from South Africa’, *Journal of Retailing and Consumer Services*, 70. Available at: https://doi.org/10.1016/j.jretconser.2022.103185.

Mägi, A.W. (2003) ‘Share of wallet in retailing: the effects of customer satisfaction, loyalty cards and shopper characteristics’, *Journal of Retailing*, 79(2), pp. 97–106. Available at: https://doi.org/10.1016/S0022-4359(03)00008-3.

Mahliza, F. (2020) ‘CONSUMER TRUST IN ONLINE PURCHASE DECISION’, *EPRA International Journal of Multidisciplinary Research (IJMR)-Peer Reviewed Journal* [Preprint], (2). Available at: https://doi.org/10.36713/epra2013.

Mainardes, E.W., Coutinho, A.R.S. and Alves, H.M.B. (2023) ‘The influence of the ethics of E-retailers on online customer experience and customer satisfaction’, *Journal of Retailing and Consumer Services*, 70. Available at: https://doi.org/10.1016/j.jretconser.2022.103171.

Malhotra, G. and Ramalingam, M. (2023) ‘Perceived anthropomorphism and purchase intention using artificial intelligence technology: examining the moderated effect of trust’, *Journal of Enterprise Information Management* [Preprint]. Available at: https://doi.org/10.1108/JEIM-09-2022-0316.

Malhotra, N.K. (1984) *Reflections on the Information Overload Paradigm in Consumer Decision Making*, *Source: Journal of Consumer Research*. Available at: https://about.jstor.org/terms.

Malhotra, N.K. (2004) *Marketing Research: An Applied Orientation*. Prentice-Hall International (Pearson International edition). Available at: https://books.google.co.uk/books?id=Il58kQEACAAJ.

Malhotra, N.K., Kim, S.S. and Agarwal, J. (2004) ‘Internet Users’ Information Privacy Concerns (IUIPC): The Construct, the Scale, and a Causal Model and a Causal Model’, *Information Systems Research*, 15(4), pp. 336–355. Available at: https://doi.org/10.1287/isre.l040.0032.

Man Hong, L. *et al.* (2018) *The Chronology of Perceived Risk INVESTIGATING THE PRODUCT QUALITY AND E-SERVICE QUALITY ATTRIBUTES THAT INFLUENCE CUSTOMERS SATISFACTION OF ONLINE APPARELS. View project The Chronology of Perceived Risk*. Available at: https://www.researchgate.net/publication/346968091.

Mancuso, I., Messeni Petruzzelli, A. and Panniello, U. (2023) ‘Innovating agri-food business models after the Covid-19 pandemic: The impact of digital technologies on the value creation and value capture mechanisms’, *Technological Forecasting and Social Change*, 190. Available at: https://doi.org/10.1016/j.techfore.2023.122404.

Mani, Z. and Chouk, I. (2018) ‘Consumer Resistance to Innovation in Services: Challenges and Barriers in the Internet of Things Era’, *Journal of Product Innovation Management*, 35(5), pp. 780–807. Available at: https://doi.org/10.1111/jpim.12463.

Manis, K.T. and Madhavaram, S. (2023) ‘AI-Enabled marketing capabilities and the hierarchy of capabilities: Conceptualization, proposition development, and research avenues’, *Journal of Business Research*, 157. Available at: https://doi.org/10.1016/j.jbusres.2022.113485.

Mano, H. and Elliott, M.T. (1997) ‘Smart shopping: the origins and consequences of price savings’, *ACR North American Advances* [Preprint].

Mansoori, K.A. Al, Sarabdeen, J. and Tchantchane, A.L. (2018) ‘Investigating Emirati citizens’ adoption of e-government services in Abu Dhabi using modified UTAUT model’, *Information Technology & People*, 31(2), pp. 455–481. Available at: https://doi.org/10.1108/ITP-12-2016-0290.

Marangunić, N. and Granić, A. (2015) ‘Technology acceptance model: a literature review from 1986 to 2013’, *Universal Access in the Information Society*, 14(1), pp. 81–95. Available at: https://doi.org/10.1007/s10209-014-0348-1.

Marder, B., Angell, R. and Boyd, E. (2023) ‘How and why (imagined) online reviews impact frontline retail encounters’, *Journal of Retailing*, 99(2), pp. 265–279. Available at: https://doi.org/10.1016/j.jretai.2023.03.004.

María, E. *et al.* (2014) ‘SUMA PSICOLÓGICA SUMA PSICOLÓGICA Structural Equations Model (SEM) of a questionnaire on the evaluation of intercultural secondary education classrooms’, 21(2), pp. 107–115. Available at: www.elsevier.es/sumapsicolwww.elsevier.es/sumapsicol.

Marino, V. and Lo Presti, L. (2018) ‘Engagement, satisfaction and customer behavior-based CRM performance: An empirical study of mobile instant messaging’, *Journal of Service Theory and Practice*, 28(5), pp. 682–707. Available at: https://doi.org/10.1108/JSTP-11-2017-0222.

Markus, M.L. and Silver, M. (2008) ‘A Foundation for the Study of IT Effects: A New Look at DeSanctis and Poole’s Concepts of Structural Features and Spirit’, *Journal of the Association for Information Systems*, 9(10), pp. 609–632. Available at: https://doi.org/10.17705/1jais.00176.

Maroufkhani, P. *et al.* (2022) ‘How do interactive voice assistants build brands’ loyalty?’, *Technological Forecasting and Social Change*, 183. Available at: https://doi.org/10.1016/j.techfore.2022.121870.

Marsh, H.W. and Balla, J. (1994) *Goodness of fit in confirmatory factor analysis: the effects of sample size and model parsimony*, *Quality & Quantity*. Kluwer Academic Publishers.

Marshall, C. and Rossman, G.B. (1998) *Designing Qualitative Research*. SAGE Publications. Available at: https://books.google.co.uk/books?id=vxN-xwEACAAJ.

Marshall, C. and Rossman, G.B. (2014) *Designing Qualitative Research*. SAGE Publications. Available at: https://books.google.co.uk/books?id=qTByBgAAQBAJ.

Martin, J., Mortimer, G. and Andrews, L. (2015) ‘Re-examining online customer experience to include purchase frequency and perceived risk’, *Journal of Retailing and Consumer Services*, 25, pp. 81–95. Available at: https://doi.org/10.1016/j.jretconser.2015.03.008.

Martin, K. (2018) ‘The penalty for privacy violations: How privacy violations impact trust online’, *Journal of Business Research*, 82, pp. 103–116. Available at: https://doi.org/10.1016/j.jbusres.2017.08.034.

Martin, K. and Nissenbaum, H. (2020) ‘WHAT IS IT ABOUT LOCATION?’ Available at: https://doi.org/10.15779/Z382F7JR6F.

Martin, K.D. *et al.* (2020) ‘Data Privacy in Retail’, *Journal of Retailing*, 96(4), pp. 474–489. Available at: https://doi.org/10.1016/j.jretai.2020.08.003.

Martin, K.D., Borah, A. and Palmatier, R.W. (2017) ‘Data Privacy: Effects on Customer and Firm Performance’:, *https://doi.org/10.1509/jm.15.0497*, 81(1), pp. 36–58. Available at: https://doi.org/10.1509/JM.15.0497.

Martin, K.D. and Murphy, P.E. (2017) ‘The role of data privacy in marketing’, *Journal of the Academy of Marketing Science*, 45(2), pp. 135–155. Available at: https://doi.org/10.1007/s11747-016-0495-4.

Martin, K.D. and Palmatier, R.W. (2020) ‘Data Privacy in Retail: Navigating Tensions and Directing Future Research’, *Journal of Retailing*. Elsevier Ltd, pp. 449–457. Available at: https://doi.org/10.1016/j.jretai.2020.10.002.

Martin, K.E. (2017) *Measuring Privacy: An Empirical Test Using Context to Expose Confounding Variables*. Available at: https://www.researchgate.net/publication/315643368.

Martínez-Córcoles, M., Teichmann, M. and Murdvee, M. (2017) ‘Assessing technophobia and technophilia: Development and validation of a questionnaire’, *Technology in Society*, 51, pp. 183–188. Available at: https://doi.org/10.1016/j.techsoc.2017.09.007.

Martins, J. *et al.* (2019) ‘How smartphone advertising influences consumers’ purchase intention’, *Journal of Business Research*, 94, pp. 378–387. Available at: https://doi.org/10.1016/j.jbusres.2017.12.047.

Masur, P.K. and Trepte, S. (2021) ‘Transformative or Not? How Privacy Violation Experiences Influence Online Privacy Concerns and Online Information Disclosure’, *Human Communication Research*, 47(1), pp. 49–74. Available at: https://doi.org/10.1093/hcr/hqaa012.

Mauri, M. *et al.* (2024) ‘Comparing the effects of immersive and non-immersive real estate experience on behavioral intentions’, *Computers in Human Behavior*, 150. Available at: https://doi.org/10.1016/j.chb.2023.107996.

Maxham, J.G. and Netemeyer, R.G. (2003) ‘Firms Reap what they Sow: The Effects of Shared Values and Perceived Organizational Justice on Customers’ Evaluations of Complaint Handling’, *Journal of Marketing*, 67(1), pp. 46–62. Available at: https://doi.org/10.1509/jmkg.67.1.46.18591.

Mayer, R.C., Davis, J.H. and Schoorman, F.D. (1995) ‘An Integrative Model Of Organizational Trust’, *Academy of Management Review*, 20(3), pp. 709–734. Available at: https://doi.org/10.5465/amr.1995.9508080335.

McDaniel, C. and Gates, R. (2016) *Marketing Research Essentials*. Wiley. Available at: https://books.google.co.uk/books?id=DcE7CwAAQBAJ.

McKinsey & Company (2020) *Rebooting retail: How technology will shape the future of retail*. Available at: https://www.mckinsey.com/~/media/mckinsey/industries/retail/our%20insights/rebooting%20retail%20how%20technology%20will%20shape%20the%20future%20of%20 retail/rebooting-retail-how-technology-will-shape-the-future-of-retail.pdf (Accessed: 18 June 2021).

McKnight, D.H. and Chervany, N.L. (2001) ‘What trust means in e-commerce customer relationships: An interdisciplinary conceptual typology’, *International Journal of Electronic Commerce*, 6(2), pp. 35–59. Available at: https://doi.org/10.1080/10864415.2001.11044235.

McLean, G. (2018) ‘Examining the determinants and outcomes of mobile app engagement - A longitudinal perspective’, *Computers in Human Behavior*, 84, pp. 392–403. Available at: https://doi.org/10.1016/j.chb.2018.03.015.

McLean, G. and Osei-Frimpong, K. (2019) ‘Hey Alexa … examine the variables influencing the use of artificial intelligent in-home voice assistants’, *Computers in Human Behavior*, 99, pp. 28–37. Available at: https://doi.org/10.1016/j.chb.2019.05.009.

McLean, G., Osei-Frimpong, K. and Barhorst, J. (2021) ‘Alexa, do voice assistants influence consumer brand engagement? – Examining the role of AI powered voice assistants in influencing consumer brand engagement’, *Journal of Business Research*, 124, pp. 312–328. Available at: https://doi.org/10.1016/j.jbusres.2020.11.045.

McLean, G. and Wilson, A. (2019) ‘Shopping in the digital world: Examining customer engagement through augmented reality mobile applications’, *Computers in Human Behavior*, 101, pp. 210–224. Available at: https://doi.org/10.1016/j.chb.2019.07.002.

McQuitty, S. (2004) ‘Statistical power and structural equation models in business research’, *Journal of Business Research*, 57(2), pp. 175–183. Available at: https://doi.org/10.1016/S0148-2963(01)00301-0.

Meißner, M. *et al.* (2020) ‘How virtual reality affects consumer choice’, *Journal of Business Research*, 117, pp. 219–231. Available at: https://doi.org/10.1016/j.jbusres.2020.06.004.

Mele, C. *et al.* (2021) ‘Smart nudging: How cognitive technologies enable choice architectures for value co-creation’, *Journal of Business Research*, 129, pp. 949–960. Available at: https://doi.org/10.1016/J.JBUSRES.2020.09.004.

Melis, K. *et al.* (2015) ‘The Impact of the Multi-channel Retail Mix on Online Store Choice: Does Online Experience Matter?’, *Journal of Retailing*, 91(2), pp. 272–288. Available at: https://doi.org/10.1016/j.jretai.2014.12.004.

Meuter, M.L. *et al.* (2000) ‘Self-Service Technologies: Understanding Customer Satisfaction with Technology-Based Service Encounters’, *Journal of Marketing*, 64(3), pp. 50–64. Available at: https://doi.org/10.1509/jmkg.64.3.50.18024.

Miles, M.B. and Huberman, A.M. (1994) *Qualitative Data Analysis: An Expanded Sourcebook*. SAGE Publications. Available at: https://books.google.co.uk/books?id=U4lU_-wJ5QEC.

Miller, A.P. and Hosanagar, K. (2019) *How Targeted Ads and Dynamic Pricing Can Perpetuate Bias*, *Harvard Business Review* . Available at: https://hbr.org/2019/11/how-targeted-ads-and-dynamic-pricing-can-perpetuate-bias (Accessed: 17 May 2021).

Milne, G.R. and Boza, M.E. (1999) ‘Trust and concern in consumers’ perception of marketing information management practices’, *Journal of Interactive Marketing*, 13(1), pp. 5–24. Available at: https://doi.org/10.1002/(SICI)1520-6653(199924)13:1<5::AID-DIR2>3.0.CO;2-9.

Milne, G.R. and Gordon, M.E. (1993) *Direct Mail Privacy-Efficiency Trade-offs within an Implied Social Contract Framework*, *Source: Journal of Public Policy & Marketing*.

Mitchell, V.-W. (1999) *Consumer perceived risk: conceptualisations and models*.

Mitchell, V.W. *et al.* (1999) ‘Using neural networks to understand service risk in the holiday product’, *Journal of Business Research*, 46(2), pp. 167–180. Available at: https://doi.org/10.1016/S0148-2963(98)00020-4.

Mittelstadt, B.D. *et al.* (2016) ‘The ethics of algorithms: Mapping the debate’, *Big Data and Society*, 3(2). Available at: https://doi.org/10.1177/2053951716679679.

Mofokeng, T.E. (2023) ‘Antecedents of trust and customer loyalty in online shopping: The moderating effects of online shopping experience and e-shopping spending’, *Heliyon*, 9(5). Available at: https://doi.org/10.1016/j.heliyon.2023.e16182.

Mora Cortez, R., Højbjerg Clarke, A. and Freytag, P.V. (2021) ‘B2B market segmentation: A systematic review and research agenda’, *Journal of Business Research*. Elsevier Inc., pp. 415–428. Available at: https://doi.org/10.1016/j.jbusres.2020.12.070.

Mora, L., Kummitha, R.K.R. and Esposito, G. (2021) ‘Not everything is as it seems: Digital technology affordance, pandemic control, and the mediating role of sociomaterial arrangements’, *Government Information Quarterly*, 38(4), p. 101599. Available at: https://doi.org/https://doi.org/10.1016/j.giq.2021.101599.

Morey, T., Forbath, T. and Schoop, A. (2015) *Customer Data: Designing for Transparency and Trust*, *Harvard Business Review*. Available at: https://hbr.org/2015/05/customer-data-designing-for-transparency-and-trust (Accessed: 6 July 2021).

Morgan, R.M. and Hunt, S.D. (1994) ‘The Commitment-Trust Theory of Relationship Marketing’, *Journal of Marketing*, 58(3), pp. 20–38. Available at: https://doi.org/10.1177/002224299405800302.

Morgan-Thomas, A., Dessart, L. and Veloutsou, C. (2020) ‘Digital ecosystem and consumer engagement: A socio-technical perspective’, *Journal of Business Research*, 121, pp. 713–723. Available at: https://doi.org/10.1016/j.jbusres.2020.03.042.

Moriuchi, E. and Murdy, S. (2024) ‘The role of robots in the service industry: Factors affecting human-robot interactions’, *International Journal of Hospitality Management*, 118. Available at: https://doi.org/10.1016/j.ijhm.2023.103682.

Morrison, M.A., Cheong, H.J. and McMillan, S.J. (2013) ‘Posting, Lurking, and Networking: Behaviors and Characteristics of Consumers in the Context of User-Generated Content’, *Journal of Interactive Advertising*, 13(2), pp. 97–108. Available at: https://doi.org/10.1080/15252019.2013.826552.

Mostaghel, R. and Chirumalla, K. (2021) ‘Role of customers in circular business models’, *Journal of Business Research*, 127, pp. 35–44. Available at: https://doi.org/10.1016/j.jbusres.2020.12.053.

Muhammad, S.S., Dey, B.L. and Weerakkody, V. (2018) ‘Analysis of Factors that Influence Customers’ Willingness to Leave Big Data Digital Footprints on Social Media: A Systematic Review of Literature’, *Information Systems Frontiers*, 20(3), pp. 559–576. Available at: https://doi.org/10.1007/s10796-017-9802-y.

Mulgund, P. *et al.* (2021) ‘The implications of the California Consumer Privacy Act (CCPA) on healthcare organizations: Lessons learned from early compliance experiences', *Health Policy and Technology*, 10(3). Available at: https://doi.org/10.1016/j.hlpt.2021.100543.

Mullainathan, S. and Obermeyer, Z. (2017) 'Does Machine Learning Automate Moral Hazard and Error?', *American Economic Review*, 107(5), pp. 476–80. Available at: https://doi.org/10.1257/AER.P20171084.

Müller-Seitz, G. *et al.* (2009) 'Customer acceptance of RFID technology: Evidence from the German electronic retail sector', *Journal of Retailing and Consumer Services*, 16(1), pp. 31–39. Available at: https://doi.org/10.1016/j.jretconser.2008.08.002.

Mwesiumo, D. *et al.* (2021) 'An exploratory and confirmatory composite analysis of a scale for measuring privacy concerns', *Journal of Business Research*, 136, pp. 63–75. Available at: https://doi.org/10.1016/j.jbusres.2021.07.027.

Narang, U. and Shankar, V. (2019) 'Mobile app introduction and online and offline purchases and product returns', *Marketing Science*, 38(5), pp. 756–772. Available at: https://doi.org/10.1287/mksc.2019.1169.

Nasiri, J. (2022) 'The Illinois Biometric Privacy Act Post-Rosenbach: Disposing of The Illinois Biometric Privacy Act Post-Rosenbach: Disposing of Actual Harm Inflicts Limitless Harm Onto Businesses Actual Harm Inflicts Limitless Harm Onto Businesses Recommended Citation Recommended Citation THE ILLINOIS BIOMETRIC PRIVACY ACT POST-ROSENBACH: DISPOSING OF ACTUAL HARM INFLICTS LIMITLESS HARM ONTO BUSINESSES', *DePaul L. Review*, 71. Available at: https://www.workplaceclassaction.com/2019/07/copy.

Nataraajan, R. and Angur, M.G. (2014) 'Innovative ability and entrepreneurial activity: Two factors to enhance "quality of life"', *Journal of Business and Industrial Marketing*, 29(6), pp. 469–475. Available at: https://doi.org/10.1108/JBIM-09-2013-0205.

Nawres, D. *et al.* (2024) 'The role of augmented reality in shaping purchase intentions and WOM for luxury products', *Journal of Business Research*, 171. Available at: https://doi.org/10.1016/j.jbusres.2023.114368.

Naylor, R.W., Lamberton, P. and West, P.M. (2012) 'Beyond the "Like" Button: The Impact of Mere Virtual Presence on Brand Evaluations and Purchase Intentions in Social Media Settings', *Journal of Marketing*, 76, pp. 105–120. Available at: www.Groupon.com.

Neff, G. *et al.* (2012) 'Affordances, Technical Agency, and the Politics of Technologies of Cultural Production', *Journal of Broadcasting and Electronic Media*, 56(2), pp. 299–313. Available at: https://doi.org/10.1080/08838151.2012.678520.

Neslin, S.A. *et al.* (2006) 'Challenges and Opportunities in Multichannel Customer Management', *Journal of Service Research*, 9(2), pp. 95–112. Available at: https://doi.org/10.1177/1094670506293559.

Neuman, L.W. (2007) *Social research methods, 6/E*. Pearson Education India.

Nguyen, D.H., de Leeuw, S. and Dullaert, W.E.H. (2018) 'Consumer Behaviour and Order Fulfilment in Online Retailing: A Systematic Review', *International Journal of Management Reviews*. Blackwell Publishing Ltd, pp. 255–276. Available at: https://doi.org/10.1111/ijmr.12129.

Nguyen, S. and Llosa, S. (2023) ‘When users decide to bypass collaborative consumption platforms: The interplay of economic benefit, perceived risk, and perceived enjoyment’, *Tourism Management*, 96. Available at: https://doi.org/10.1016/j.tourman.2022.104713.

Nichols, M.R. (2018) *Amazon Wants to Use Predictive Analytics to Offer Anticipatory Shipping*, *Smart Data Collective*. Available at: https://www.smartdatacollective.com/amazon-wants-predictive-analytics-offer-anticipatory-shipping/ (Accessed: 17 June 2023).

Nicosia, F.M. and Mayer, R.N. (1976) *Toward a Sociology of Consumption*, *Source: Journal of Consumer Research*. Available at: https://www.jstor.org/stable/2489112.

Nikhashemi, S.R. *et al.* (2021) ‘Augmented reality in smart retailing: A (n) (A) Symmetric Approach to continuous intention to use retail brands’ mobile AR apps’, *Journal of Retailing and Consumer Services*, 60. Available at: https://doi.org/10.1016/j.jretconser.2021.102464.

Norberg, P.A., Horne, D.R. and Horne, D.A. (2007) ‘The privacy paradox: Personal information disclosure intentions versus behaviors’, *Journal of Consumer Affairs*, 41(1), pp. 100–126. Available at: https://doi.org/10.1111/j.1745-6606.2006.00070.x.

Norman, D. (2013) ‘The DESIGN of EVERYDAY THINGS’. Available at: www.basickbooks.com (Accessed: 2 January 2022).

Norman, D.A. (1988) *The Psychology of Everyday Things*. United States: Basic Books.

Norman, D.A. (1999) *A FFORDANCE, C ONVENTIONS, AND D ESIGN*. Available at: http://www.jnd.org.

Norman, D.A. (2016) ‘Affordance, conventions, and design’, in *Security and Privacy: Volume III*. Taylor and Francis, pp. 469–473. Available at: https://doi.org/10.1145/301153.301168.

Nunnally, J.C. and Bernstein, I.H. (1994) *Psychometric Theory*. McGraw-Hill Companies,Incorporated (McGraw-Hill series in psychology). Available at: https://books.google.co.uk/books?id=r0fuAAAAMAAJ.

Ofcom (2024) *Connected Nations 2023 - Ofcom*. Available at: https://www.ofcom.org.uk/phones-and-broadband/coverage-and-speeds/connected-nations-2023/?utm_source=chatgpt.com (Accessed: 10 January 2025).

Office for National Statistics (2024) *Internet sales as a percentage of total retail sales (ratio) (%) - Office for National Statistics*. Available at: https://www.ons.gov.uk/businessindustryandtrade/retailindustry/timeseries/j4mc/drsi (Accessed: 10 January 2025).

Ofir, C. and Simonson, I. (2007) ‘The Effect of Stating Expectations on Customer Satisfaction and Shopping Experience’, *Journal of Marketing Research* [Preprint].

O’Flaherty, K. (2019) *Marriott CEO Reveals New Details About Mega Breach*, *Forbes*. Available at: https://www.forbes.com/sites/kateoflahertyuk/2019/03/11/marriott-ceo-reveals-new-details-about-mega-breach/?sh=6810c91e155c (Accessed: 8 July 2021).

Oghazi, P. *et al.* (2020) ‘User self-disclosure on social network sites: A cross-cultural study on Facebook’s privacy concepts’, *Journal of Business Research*, 112, pp. 531–540. Available at: https://doi.org/10.1016/J.JBUSRES.2019.12.006.

Okazaki, S. *et al.* (2020) ‘Understanding the Strategic Consequences of Customer Privacy Concerns: A Meta-Analytic Review’, *Journal of Retailing*, 96(4), pp. 458–473. Available at: https://doi.org/10.1016/J.JRETAI.2020.05.007.

Okazaki, S., Li, H. and Hirose, M. (2009) ‘Consumer privacy concerns and preference for degree of regulatory control: A study of mobile advertising in Japan’, *Journal of Advertising*, 38(4), pp. 63–77. Available at: https://doi.org/10.2753/JOA0091-3367380405.

de Oliveira Santini, F. *et al.* (2018) ‘The brand experience extended model: a meta-analysis’, *Journal of Brand Management*, 25(6), pp. 519–535. Available at: https://doi.org/10.1057/s41262-018-0104-6.

Oliver, M. (2005) ‘The Problem with Affordance’, *E-Learning and Digital Media*, 2(4), pp. 402–413. Available at: https://doi.org/10.2304/elea.2005.2.4.402.

Oliver, R.L. (1980) *A Cognitive Model of the Antecedents and Consequences of Satisfaction Decisions*, *Source: Journal of Marketing Research*.

Oliver, R.L. (2013) *Satisfaction: A Behavioral Perspective on the Consumer*. M.E. Sharpe. Available at: https://books.google.co.uk/books?id=OKIXnQAACAAJ.

Oliver, R.L. (2014) *Satisfaction: A Behavioral Perspective on the Consumer: A Behavioral Perspective on the Consumer*. Taylor & Francis. Available at: https://books.google.co.uk/books?id=TzrfBQAAQBAJ.

ONS (2021a) *Census - Office for National Statistics*. Available at: https://www.ons.gov.uk/census (Accessed: 10 January 2025).

ONS (2021b) *CT21_0360_Census 2021 - Office for National Statistics*. Available at: https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/adhocs/2556ct210360census2021 (Accessed: 10 January 2025).

Oosthuizen, K. (2021) *ARTIFICIAL INTELLIGENCE IN RETAIL: THE AI-ENABLED VALUE CHAIN*. Available at: https://scholar.sun.ac.za.

Orben, A. and Przybylski, A. (2019) ‘The association between adolescent well-being and digital technology use’, *Nature-Human-Behaviour* [Preprint].

Osborne, J.W. (2015) ‘What is rotating in exploratory factor analysis?’, *Practical Assessment, Research and Evaluation*, 20(2), pp. 1–7. Available at: https://www.scopus.com/inward/record.uri?eid=2-s2.0-84930409254&partnerID=40&md5=bd76bbaa953272f462401ed2f1ec07b1.

Ostrom, A.L. *et al.* (2021) ‘Service Research Priorities: Managing and Delivering Service in Turbulent Times’, *Journal of Service Research*, 24(3), pp. 329–353. Available at: https://doi.org/10.1177/10946705211021915.

Ostrom, A.L., Fotheringham, D. and Bitner, M.J. (2019) ‘Customer Acceptance of AI in Service Encounters: Understanding Antecedents and Consequences’, in P.P. Maglio et al. (eds) *Handbook of Service Science, Volume II*. Cham: Springer

International Publishing, pp. 77–103. Available at: https://doi.org/10.1007/978-3-319-98512-1_5.

Ovani, D.J. and Windasari, N.A. (2022) 'The Impact of Electronic Shelf Label on Customer Well-Being in the Omnichannel Smart Retail', in R. Qiu et al. (eds) *City, Society, and Digital Transformation*. Cham: Springer International Publishing, pp. 31–46.

Pagani, M., Racat, M. and Hofacker, C.F. (2019) 'Adding Voice to the Omnichannel and How that Affects Brand Trust', *Journal of Interactive Marketing*, 48, pp. 89–105. Available at: https://doi.org/10.1016/j.intmar.2019.05.002.

Palmatier, R.W. and Martin, K.D. (2019) *The intelligent marketer's guide to data privacy: The impact of big data on customer trust*. Springer.

Pan, Y. and Zinkhan, G.M. (2006) 'Exploring the impact of online privacy disclosures on consumer trust', *Journal of Retailing*, 82(4), pp. 331–338. Available at: https://doi.org/10.1016/j.jretai.2006.08.006.

Pansari, A. and Kumar, V. (2017) 'Customer engagement: the construct, antecedents, and consequences', *Journal of the Academy of Marketing Science*, 45(3), pp. 294–311. Available at: https://doi.org/10.1007/s11747-016-0485-6.

Pantano, E. *et al.* (2021) 'Enhancing store layout decision with agent-based simulations of consumers' density', *Expert Systems with Applications*, 182. Available at: https://doi.org/10.1016/j.eswa.2021.115231.

Pantano, E. and Dennis, C. (2019) *Smart Retailing Technologies and Strategies*.

Pantano, E. and Pizzi, G. (2020) 'Forecasting artificial intelligence on online customer assistance: Evidence from chatbot patents analysis', *Journal of Retailing and Consumer Services*, 55. Available at: https://doi.org/10.1016/j.jretconser.2020.102096.

Pantano, E. and Priporas, C.V. (2016) 'The effect of mobile retailing on consumers' purchasing experiences: A dynamic perspective', *Computers in Human Behavior*, 61, pp. 548–555. Available at: https://doi.org/10.1016/j.chb.2016.03.071.

Pantano, E. and Timmermans, H. (2014) 'What is Smart for Retailing?', *Procedia Environmental Sciences*, 22, pp. 101–107. Available at: https://doi.org/10.1016/j.proenv.2014.11.010.

Pappas, I.O. *et al.* (2017) 'The interplay of online shopping motivations and experiential factors on personalized e-commerce: A complexity theory approach', *Telematics and Informatics*, 34(5), pp. 730–742. Available at: https://doi.org/10.1016/j.tele.2016.08.021.

Parchoma, G. (2014) 'The contested ontology of affordances: Implications for researching technological affordances for collaborative knowledge production', *Computers in Human Behavior*, 37, pp. 360–368. Available at: https://doi.org/10.1016/j.chb.2012.05.028.

Park, C.W., Mothersbaugh, D.L. and Feick, L. (1994) *Consumer Knowledge Assessment*, *Source: Journal of Consumer Research*. Available at: https://www.jstor.org/stable/2489741.

Park, H. and Hur, W.M. (2023) 'Customer showrooming behavior, customer orientation, and emotional labor: Sales control as a moderator', *Journal of Retailing and Consumer Services*, 72. Available at: https://doi.org/10.1016/j.jretconser.2023.103268.

Park, H.S., Dailey, R. and Lemus, D. (2002) 'The Use of Exploratory Factor Analysis and Principal Components Analysis in Communication Research', *Human Communication Research*, 28(4), pp. 562–577. Available at: https://doi.org/10.1093/hcr/28.4.562.

Park, S. and Tussyadiah, I.P. (2017) 'Multidimensional Facets of Perceived Risk in Mobile Travel Booking', *Journal of Travel Research*, 56(7), pp. 854–867. Available at: https://doi.org/10.1177/0047287516675062.

Patel, A.K. *et al.* (2023) 'Assessing customers' attitude towards online apparel shopping: A three-way interaction model', *Journal of Business Research*, 164. Available at: https://doi.org/10.1016/j.jbusres.2023.113917.

Patel, P.C., Oghazi, P. and Arunachalam, S. (2023) 'Does consumer privacy act influence firm performance in the retail industry? Evidence from a US state-level law change', *Journal of Business Research*, 162. Available at: https://doi.org/10.1016/j.jbusres.2023.113881.

Pavlou, P.A. (2003) 'Consumer Acceptance of Electronic Commerce: Integrating Trust and Risk with the Technology Acceptance Model', *International Journal of Electronic Commerce*, 7(3), pp. 101–134. Available at: https://doi.org/10.1080/10864415.2003.11044275.

Pavlou, P.A. and Fygenson, M. (2006) *Understanding and Predicting Electronic Commerce Adoption: An Extension of the Theory of Planned Behavior*, *Source: MIS Quarterly*.

Pavlou, P.A. and Gefen, D. (2004) 'Building Effective Online Marketplaces with Institution-Based Trust', *Information Systems Research*, 15(1), pp. 37–59. Available at: https://doi.org/10.1287/isre.

Pavlović-Höck, Dr.N. (2022) 'Herd behaviour along the consumer buying decision process - experimental study in the mobile communications industry', *Digital Business*, 2(1), p. 100018. Available at: https://doi.org/10.1016/j.digbus.2021.100018.

Payne, J., Bettman, J.R. and Johnson, E.J. (1991) 'Consumer decision making', *Handbook of consumer behaviour*, pp. 50–84.

Pazzanese, C. (2020) *Ethical concerns mount as AI takes bigger decision-making role – Harvard Gazette*, *The Harvard Gazette*. Available at: https://news.harvard.edu/gazette/story/2020/10/ethical-concerns-mount-as-ai-takes-bigger-decision-making-role/ (Accessed: 31 May 2021).

Pea, R.D. (1993) 'Practices of distributed intelligence and designs for education', *Distributed cognitions: Psychological and educational considerations*, 11, pp. 47–87.

Pei, X.L. *et al.* (2020) 'Does the effect of customer experience on customer satisfaction create a sustainable competitive advantage? A comparative study of different shopping situations', *Sustainability (Switzerland)*, 12(18). Available at: https://doi.org/10.3390/SU12187436.

Pennanen, K. (2006) ‘How consumers build trust in e-commerce: towards a trust formation model’, *ACR Latin American Advances* [Preprint].

Pentz, C.D., du Preez, R. and Swiegers, L. (2020) ‘To bu(Y) or not to bu(Y): Perceived risk barriers to online shopping among South African generation Y consumers’, *Cogent Business and Management*, 7(1). Available at: https://doi.org/10.1080/23311975.2020.1827813.

Pérez, J. *et al.* (2015) ‘A Data Preparation Methodology in Data Mining Applied to Mortality Population Databases’, *Journal of Medical Systems*, 39(11). Available at: https://doi.org/10.1007/s10916-015-0312-5.

Peter, J.P. and Ryan, M.J. (1976) ‘An investigation of perceived risk at the brand level’, *Journal of marketing research*, 13(2), pp. 184–188.

Petit, O., Velasco, C. and Spence, C. (2019) ‘Digital Sensory Marketing: Integrating New Technologies Into Multisensory Online Experience’, *Journal of Interactive Marketing*, 45, pp. 42–61. Available at: https://doi.org/10.1016/j.intmar.2018.07.004.

Petrosyan, A. (2023) *Internet usage in the United Kingdom (UK) - Statistics & Facts | Statista*. Available at: https://www.statista.com/topics/3246/internet-usage-in-the-uk/#topicOverview (Accessed: 10 January 2025).

Phelps, J., Nowak, G. and Ferrell, E. (2000) ‘Privacy concerns and consumer willingness to provide personal information’, *Journal of Public Policy and Marketing*, 19(1), pp. 27–41. Available at: https://doi.org/10.1509/jppm.19.1.27.16941.

Pickard, T. (2020) *What is Amazon Go Grocery?*, *Linkedin*. Available at: https://www.linkedin.com/pulse/what-amazon-go-grocery-toby-pickard (Accessed: 2 October 2023).

Pieters, R., Baumgartner, H. and Alien, D. (1995) *A means-end chain approach to consumer goal structures*, *Intern. J. of Research in Marketing*.

Pillai, R., Sivathanu, B. and Dwivedi, Y.K. (2020) ‘Shopping intention at AI-powered automated retail stores (AIPARS)’, *Journal of Retailing and Consumer Services*, 57. Available at: https://doi.org/10.1016/j.jretconser.2020.102207.

Pizzi, G. *et al.* (2022) ‘Privacy concerns and justice perceptions with the disclosure of biometric versus behavioral data for personalized pricing tell me who you are, I’ll tell you how much you pay. Consumers’ fairness and privacy perceptions with personalized pricing’, *Journal of Business Research*, 148, pp. 420–432. Available at: https://doi.org/10.1016/j.jbusres.2022.04.072.

Pizzi, G. and Scarpi, D. (2020) ‘Privacy threats with retail technologies: A consumer perspective’, *Journal of Retailing and Consumer Services*, 56, p. 102160. Available at: https://doi.org/10.1016/j.jretconser.2020.102160.

Pizzutti, C., Gonçalves, R. and Ferreira, M. (2022) ‘Information search behavior at the post-purchase stage of the customer journey’, *Journal of the Academy of Marketing Science*, 50(5), pp. 981–1010. Available at: https://doi.org/10.1007/s11747-022-00864-9.

Plangger, K. *et al.* (2022) 'The future of digital technologies in marketing: A conceptual framework and an overview', *Journal of the Academy of Marketing Science* [Preprint]. Springer. Available at: https://doi.org/10.1007/s11747-022-00906-2.

Podsakoff, P.M. *et al.* (2003) 'Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies', *Journal of Applied Psychology*, pp. 879–903. Available at: https://doi.org/10.1037/0021-9010.88.5.879.

Polacco, A. and Backes, K. (2018) *THE AMAZON GO CONCEPT: IMPLICATIONS, APPLICATIONS, AND SUSTAINABILITY*.

Poncin, I. *et al.* (2017) 'Smart technologies and shopping experience: Are gamification interfaces effective? The case of the Smartstore', *Technological Forecasting and Social Change*, 124, pp. 320–331. Available at: https://doi.org/10.1016/j.techfore.2017.01.025.

Pongpaew, W., Speece, M. and Tiangsoongnern, L. (2017) 'Social presence and customer brand engagement on Facebook brand pages', *Journal of Product and Brand Management*, 26(3), pp. 262–281. Available at: https://doi.org/10.1108/JPBM-08-2015-0956.

Porter, M.E. and Heppelmann, J.E. (2015) 'How smart, connected products are transforming competition', *Harvard Business Review* [Preprint].

Pozzi, G., Pigni, F. and Vitari, C. (2014) 'Affordance Theory in the IS Discipline: a Review and Synthesis of the Literature', *AMCIS* [Preprint]. Available at: https://aisel.aisnet.org/amcis2014/ResearchMethods (Accessed: 6 January 2022).

Prentice, C., Dominique Lopes, S. and Wang, X. (2020) 'The impact of artificial intelligence and employee service quality on customer satisfaction and loyalty', *Journal of Hospitality Marketing and Management*, 29(7), pp. 739–756. Available at: https://doi.org/10.1080/19368623.2020.1722304.

Priester, J.R. (2010) 'The use of structural equation models in Consumer Psychology: A methodological dialogue on its contributions, cautions, and concerns', *Journal of Consumer Psychology*, 20(2), pp. 205–207. Available at: https://doi.org/10.1016/j.jcps.2010.03.005.

Priporas, C.V., Stylos, N. and Fotiadis, A.K. (2017) 'Generation Z consumers' expectations of interactions in smart retailing: A future agenda', *Computers in Human Behavior*, 77, pp. 374–381. Available at: https://doi.org/10.1016/j.chb.2017.01.058.

Puccinelli, N.M. *et al.* (2009) 'Customer Experience Management in Retailing: Understanding the Buying Process', *Journal of Retailing*, 85(1), pp. 15–30. Available at: https://doi.org/10.1016/j.jretai.2008.11.003.

Puntoni, S. *et al.* (2021) 'Consumers and Artificial Intelligence: An Experiential Perspective', *Journal of Marketing*, 85(1), pp. 131–151. Available at: https://doi.org/10.1177/0022242920953847.

Qalati, S.A. *et al.* (2021) 'Effects of perceived service quality, website quality, and reputation on purchase intention: The mediating and moderating roles of trust and perceived risk in online shopping', *Cogent Business and Management*, 8(1). Available at: https://doi.org/10.1080/23311975.2020.1869363.

Rainie, L. and Duggan, M. (2016) *Americans' opinions on privacy and information sharing | Pew Research Center*, *PEW RESEARCH CENTER*. Available at: https://www.pewresearch.org/internet/2016/01/14/privacy-and-information-sharing/ (Accessed: 8 July 2021).

Rajavi, K., Kushwaha, T. and Steenkamp, J.B.E.M. (2019) 'In Brands We Trust? A Multicategory, Multicountry Investigation of Sensitivity of Consumers' Trust in Brands to Marketing-Mix Activities', *Journal of Consumer Research*, 46(4), pp. 651–670. Available at: https://doi.org/10.1093/jcr/ucz026.

Raji, I.D. *et al.* (2020) 'Closing the AI accountability gap: Defining an end-to-end framework for internal algorithmic auditing', in *FAT* 2020 - Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency*. Association for Computing Machinery, Inc, pp. 33–44. Available at: https://doi.org/10.1145/3351095.3372873.

Ranaweera, C., McDougall, G. and Bansal, H. (2005) 'A model of online customer behavior during the initial transaction: Moderating effects of customer characteristics', *Marketing Theory*, 5(1), pp. 51–74. Available at: https://doi.org/10.1177/1470593105049601.

Rapp, A. *et al.* (2015) 'Perceived customer showrooming behavior and the effect on retail salesperson self-efficacy and performance', *Journal of Retailing*, 91(2), pp. 358–369. Available at: https://doi.org/10.1016/j.jretai.2014.12.007.

Ratchford, B. *et al.* (2022a) 'Online and offline retailing: What we know and directions for future research', *Journal of Retailing*, 98(1), pp. 152–177. Available at: https://doi.org/10.1016/j.jretai.2022.02.007.

Ratchford, B. *et al.* (2022b) 'Online and offline retailing: What we know and directions for future research', *Journal of Retailing*, 98(1), pp. 152–177. Available at: https://doi.org/10.1016/j.jretai.2022.02.007.

Rauschnabel, P.A., He, J. and Ro, Y.K. (2018) 'Antecedents to the adoption of augmented reality smart glasses: A closer look at privacy risks', *Journal of Business Research*, 92, pp. 374–384. Available at: https://doi.org/10.1016/j.jbusres.2018.08.008.

Recalde, D., Jai, T.C. and Jones, R.P. (2024) 'I can find the right product with AR! The mediation effects of shopper engagement on intent to purchase beauty products', *Journal of Retailing and Consumer Services*, 78. Available at: https://doi.org/10.1016/j.jretconser.2024.103764.

Rehman, Z.U., Baharun, R. and Salleh, N.Z.M. (2020) 'Antecedents, consequences, and reducers of perceived risk in social media: A systematic literature review and directions for further research', *Psychology and Marketing*. Wiley-Liss Inc., pp. 74–86. Available at: https://doi.org/10.1002/mar.21281.

Reimers, V. and Chao, F. (2014) 'The role of convenience in a recreational shopping trip', *European Journal of Marketing*, 48(11–12), pp. 2213–2236. Available at: https://doi.org/10.1108/EJM-12-2012-0734.

Reinartz, W., Wiegand, N. and Imschloss, M. (2019) 'The impact of digital transformation on the retailing value chain', *International Journal of Research in*

Marketing, 36(3), pp. 350–366. Available at: https://doi.org/10.1016/j.ijresmar.2018.12.002.

Rese, A., Ganster, L. and Baier, D. (2020) ‘Chatbots in retailers’ customer communication: How to measure their acceptance?’, *Journal of Retailing and Consumer Services*, 56. Available at: https://doi.org/10.1016/j.jretconser.2020.102176.

Resnick, P. and Varian, H.R. (1997) *Recommender Systems*, *COMMUNICATIONS OF THE ACM*. Available at: http://www.firefly.com.

Ribeiro-Navarrete, S., Saura, J.R. and Palacios-Marqués, D. (2021) ‘Towards a new era of mass data collection: Assessing pandemic surveillance technologies to preserve user privacy’, *Technological Forecasting and Social Change*, 167, p. 120681. Available at: https://doi.org/10.1016/j.techfore.2021.120681.

Riegger, A.S. *et al.* (2021) ‘Technology-enabled personalization in retail stores: Understanding drivers and barriers’, *Journal of Business Research*, 123, pp. 140–155. Available at: https://doi.org/10.1016/j.jbusres.2020.09.039.

Riegger, A.S. *et al.* (2022) ‘Technology-enabled personalization: Impact of smart technology choice on consumer shopping behavior’, *Technological Forecasting and Social Change*, 181. Available at: https://doi.org/10.1016/j.techfore.2022.121752.

Ringle, Sarstedt and Straub (2012) ‘Editor’s Comments: A Critical Look at the Use of PLS-SEM in “MIS Quarterly”’, *MIS Quarterly*, 36(1), p. iii. Available at: https://doi.org/10.2307/41410402.

Rita, P., Oliveira, T. and Farisa, A. (2019) ‘The impact of e-service quality and customer satisfaction on customer behavior in online shopping’, *Heliyon*, 5(10). Available at: https://doi.org/10.1016/j.heliyon.2019.e02690.

Ritter, T. and Pedersen, C.L. (2020) ‘Digitization capability and the digitalization of business models in business-to-business firms: Past, present, and future’, *Industrial Marketing Management*. Elsevier Inc., pp. 180–190. Available at: https://doi.org/10.1016/j.indmarman.2019.11.019.

Rizomyliotis, I. *et al.* (2022) ‘“How mAy I help you today?” The use of AI chatbots in small family businesses and the moderating role of customer affective commitment’, *Journal of Business Research*, 153, pp. 329–340. Available at: https://doi.org/10.1016/j.jbusres.2022.08.035.

Roberts, J. (2005) *Poll: Privacy Rights Under Attack - CBS News*, *CBS News*. Available at: https://www.cbsnews.com/news/poll-privacy-rights-under-attack/ (Accessed: 8 July 2021).

Robertson, N. *et al.* (2016) ‘Examining customer evaluations across different self-service technologies’, *Journal of Services Marketing*, 30(1), pp. 88–102. Available at: https://doi.org/10.1108/JSM-07-2014-0263.

Robeyns, I. (2020) ‘Wellbeing, place and technology’, *Wellbeing, Space and Society*, 1, p. 100013. Available at: https://doi.org/10.1016/j.wss.2020.100013.

Robson, C. (1993) *Real World Research: A Resource for Social Scientists and Practitioner-Researchers*. Blackwell Publishing. Available at: https://books.google.co.uk/books?id=gNO6QgAACAAJ.

Rodríguez, P.G. *et al.* (2020) 'A PLS-SEM approach to understanding E-SQ, E-Satisfaction and E-Loyalty for fashion E-Retailers in Spain', *Journal of Retailing and Consumer Services*, 57. Available at: https://doi.org/10.1016/j.jretconser.2020.102201.

Rodríguez-Entrena, M., Schuberth, F. and Gelhard, C. (2018) 'Assessing statistical differences between parameters estimates in Partial Least Squares path modeling', *Quality and Quantity*, 52(1), pp. 57–69. Available at: https://doi.org/10.1007/s11135-016-0400-8.

Rodríguez-Priego, N. *et al.* (2023) 'Perceived customer care and privacy protection behavior: The mediating role of trust in self-disclosure', *Journal of Retailing and Consumer Services*, 72. Available at: https://doi.org/10.1016/j.jretconser.2023.103284.

Roe, M. *et al.* (2022) 'Drivers and challenges of internet of things diffusion in smart stores: A field exploration', *Technological Forecasting and Social Change*, 178. Available at: https://doi.org/10.1016/j.techfore.2022.121593.

Roggeveen, A.L. and Sethuraman, R. (2020) 'Customer-Interfacing Retail Technologies in 2020 & Beyond: An Integrative Framework and Research Directions', *Journal of Retailing*. Elsevier Ltd, pp. 299–309. Available at: https://doi.org/10.1016/j.jretai.2020.08.001.

Roldán, J.L. and Sánchez-Franco, M.J. (2012) 'Variance-based structural equation modeling: Guidelines for using partial least squares in information systems research', in *Research Methodologies, Innovations and Philosophies in Software Systems Engineering and Information Systems*. IGI Global, pp. 193–221. Available at: https://doi.org/10.4018/978-1-4666-0179-6.ch010.

Roman, S. (2007) 'The ethics of online retailing: A scale development and validation from the consumers' perspective', *Journal of Business Ethics*, 72(2), pp. 131–148. Available at: https://doi.org/10.1007/s10551-006-9161-y.

Roscoe, J.T. (1975) *Fundamental Research Statistics for the Behavioral Sciences*. Holt, Rinehart and Winston (Editors' Series in Marketing). Available at: https://books.google.co.uk/books?id=Fe8vAAAAMAAJ.

Rose, S. *et al.* (2012) 'Online Customer Experience in e-Retailing: An empirical model of Antecedents and Outcomes', *Journal of Retailing*, 88(2), pp. 308–322. Available at: https://doi.org/10.1016/j.jretai.2012.03.001.

Rotenberg, M. (1991) *In Support of a Data Protection Board in the United States*.

Roy, R. and Naidoo, V. (2021) 'Enhancing chatbot effectiveness: The role of anthropomorphic conversational styles and time orientation', *Journal of Business Research*, 126, pp. 23–34. Available at: https://doi.org/https://doi.org/10.1016/j.jbusres.2020.12.051.

Roy, S.K. *et al.* (2017) ‘Constituents and consequences of smart customer experience in retailing’, *Technological Forecasting and Social Change*, 124, pp. 257–270. Available at: https://doi.org/10.1016/J.TECHFORE.2016.09.022.

Roy, S.K. *et al.* (2018) ‘Predictors of customer acceptance of and resistance to smart technologies in the retail sector’, *Journal of Retailing and Consumer Services*, 42, pp. 147–160. Available at: https://doi.org/10.1016/j.jretconser.2018.02.005.

Roy, S.K., Balaji, M.S. and Nguyen, B. (2020) ‘Consumer-computer interaction and in-store smart technology (IST) in the retail industry: the role of motivation, opportunity, and ability’, *Journal of Marketing Management*, 36(3–4), pp. 299–333. Available at: https://doi.org/10.1080/0267257X.2020.1736130.

Rust, R.T. and Chung, T.S. (2006) ‘Marketing models of service and relationships’, *Marketing Science*, 25(6), pp. 560–580. Available at: https://doi.org/10.1287/mksc.1050.0139.

Ryff, C.D. (1989) ‘Happiness is everything, or is it? Explorations on the meaning of psychological well-being.’, *Journal of Personality and Social Psychology*, 57, pp. 1069–1081. Available at: https://doi.org/10.1037/0022-3514.57.6.1069.

Ryu, S. and Park, Y. na (2020) ‘How consumers cope with location-based advertising (LBA) and personal information disclosure: The mediating role of persuasion knowledge, perceived benefits and harms, and attitudes toward LBA’, *Computers in Human Behavior*, 112, p. 106450. Available at: https://doi.org/10.1016/j.chb.2020.106450.

Salibian-Barrera, M. (2005) ‘Estimating the p-values of robust tests for the linear model’, *Journal of Statistical Planning and Inference*, 128(1), pp. 241–257. Available at: https://doi.org/10.1016/j.jspi.2003.09.033.

Salo, J. (2017) ‘Social media research in the industrial marketing field: Review of literature and future research directions’, *Industrial Marketing Management*. Elsevier Inc., pp. 115–129. Available at: https://doi.org/10.1016/j.indmarman.2017.07.013.

Sarstedt, M. *et al.* (2014) ‘Partial Least Squares Structural Equation Modeling (PLS-SEM): A Useful Tool for Family Business Researchers’, *Journal of Family Business Strategy*, 5, pp. 105–115. Available at: https://doi.org/10.1016/j.jfbs.2014.01.002.

Sarstedt, M., Ringle, C.M. and Hair, J.F. (2021) ‘Partial Least Squares Structural Equation Modeling’, in *Handbook of Market Research*. Springer International Publishing, pp. 1–47. Available at: https://doi.org/10.1007/978-3-319-05542-8_15-2.

Sarstedt, M., Ringle, C.M. and Hair, J.F. (2022) ‘Partial Least Squares Structural Equation Modeling’, in C. Homburg, M. Klarmann, and A. Vomberg (eds) *Handbook of Market Research*. Cham: Springer International Publishing, pp. 587–632. Available at: https://doi.org/10.1007/978-3-319-57413-4_15.

Saunders, M., Lewis, P. and Thornhill, A. (2009) *Research Methods for Business Students*. Prentice Hall (Always learning). Available at: https://books.google.co.uk/books?id=u-txtfaCFiEC.

Saunders, M.N.K., Lewis, P. and Thornhill, A. (2019) *Research methods for business students*. Eighth. Harlow, England: Pearson. Available at: https://go.exlibris.link/TBQtK9zs.

Scarpi, D., Pizzi, G. and Visentin, M. (2014) ‘Shopping for fun or shopping to buy: Is it different online and offline?’, *Journal of Retailing and Consumer Services*, 21(3), pp. 258–267. Available at: https://doi.org/10.1016/j.jretconser.2014.02.007.

Schamberger, T. *et al.* (2020) ‘Robust partial least squares path modeling’, *Behaviormetrika*, 47(1), pp. 307–334. Available at: https://doi.org/10.1007/s41237-019-00088-2.

Schau, H.J., Muñiz, A.M. and Arnould, E.J. (2009) ‘How Brand Community Practices Create Value’, *Journal of Marketing*, 73, pp. 1547–7185.

Schlosser, A.E., White, T.B. and Lloyd, S.M. (2006) ‘Converting Web Site Visitors into Buyers: How Web Site Investment Increases Consumer Trusting Beliefs and Online Purchase Intentions "I’, *Journal of Marketing*, 70, pp. 133–148.

Schmitt, B.H. (2010) *Customer experience management: A revolutionary approach to connecting with your customers*. John Wiley & Sons.

Schmitz, A., Díaz-Martín, A.M. and Yagüe Guillén, M.J. (2022) ‘Modifying UTAUT2 for a cross-country comparison of telemedicine adoption’, *Computers in Human Behavior*, 130. Available at: https://doi.org/10.1016/j.chb.2022.107183.

Schreiber, J.B. *et al.* (2006) ‘Reporting Structural Equation Modeling and Confirmatory Factor Analysis Results: A Review’, *The Journal of Educational Research*, 99(6), pp. 323–338. Available at: https://doi.org/10.3200/JOER.99.6.323-338.

Schultz, D.E. and Peltier, J.J. (2013) ‘Social media’s slippery slope: challenges, opportunities and future research directions’, *Journal of Research in Interactive Marketing*, 7(2), pp. 86–99. Available at: https://doi.org/10.1108/JRIM-12-2012-0054.

Schumacker, R.E. and Lomax, R.G. (2004) *A Beginner’s Guide to Structural Equation Modeling*. Taylor & Francis. Available at: https://books.google.co.uk/books?id=RVF4AgAAQBAJ.

Schwartz, B. *et al.* (2002) ‘Maximizing versus satisficing: Happiness is a matter of choice’, *Journal of Personality and Social Psychology*, 83(5), pp. 1178–1197. Available at: https://doi.org/10.1037/0022-3514.83.5.1178.

Seiders, K. *et al.* (2007) ‘SERVCON: Development and validation of a multidimensional service convenience scale’, *Journal of the Academy of Marketing Science*, 35(1), pp. 144–156. Available at: https://doi.org/10.1007/s11747-006-0001-5.

Seiders, K., Berry, L.L. and Gresham, L.G. (2000) ‘Attention, Retailers! How Convenient Is Your Convenience Strategy?’, *Sloan Management Review*, 41(3), pp. 79–89. Available at: https://search.ebscohost.com/login.aspx?direct=true&AuthType=ip,shib&db=buh&AN=3060855&site=ehost-live&scope=site&custid=s1123049.

Sembada, A.Y. and Koay, K.Y. (2021) ‘How perceived behavioral control affects trust to purchase in social media stores’, *Journal of Business Research*, 130, pp. 574–582. Available at: https://doi.org/10.1016/j.jbusres.2019.09.028.

Senecal, S. and Nantel, J. (2004) ‘The influence of online product recommendations on consumers’ online choices’, *Journal of Retailing*, 80(2), pp. 159–169. Available at: https://doi.org/10.1016/j.jretai.2004.04.001.

Septianto, F., Kemper, J.A. and Choi, J. (Jane) (2020) ‘The power of beauty? The interactive effects of awe and online reviews on purchase intentions’, *Journal of Retailing and Consumer Services*, 54. Available at: https://doi.org/10.1016/j.jretconser.2020.102066.

Sestino, A. *et al.* (2020) ‘Internet of Things and Big Data as enablers for business digitalization strategies’, *Technovation*. Elsevier Ltd. Available at: https://doi.org/10.1016/j.technovation.2020.102173.

Sevignani, S. (2016) *Privacy and Capitalism in the Age of Social Media*. Routledge (Routledge research in information technology and society). Available at: https://books.google.co.uk/books?id=Mr1jAQAACAAJ.

Shaheed, A. (2004) ‘How convenience has changed the nation’, *Brand Strategy May (182)*, pp. 44–46.

Shankar, V. *et al.* (2010) ‘Mobile marketing in the retailing environment: Current insights and future research avenues’, *Journal of Interactive Marketing*, 24(2), pp. 111–120. Available at: https://doi.org/10.1016/j.intmar.2010.02.006.

Shankar, V. *et al.* (2016) ‘Mobile Shopper Marketing: Key Issues, Current Insights, and Future Research Avenues’, *Journal of Interactive Marketing*, 34, pp. 37–48. Available at: https://doi.org/10.1016/j.intmar.2016.03.002.

Shankar, V. (2018) ‘How Artificial Intelligence (AI) is Reshaping Retailing’, *Journal of Retailing*, 94(4), pp. vi–xi. Available at: https://doi.org/10.1016/s0022-4359(18)30076-9.

Shankar, V. (2019) *Amazon is 25 – here’s a look back at how it changed the world | World Economic Forum*, *World Economic Forum*. Available at: https://www.weforum.org/agenda/2019/07/amazon-is-turning-25-here-s-a-look-back-at-how-it-changed-the-world/ (Accessed: 17 June 2023).

Shankar, V. *et al.* (2021) ‘How Technology is Changing Retail’, *Journal of Retailing*, 97(1), pp. 13–27. Available at: https://doi.org/10.1016/j.jretai.2020.10.006.

Shankar, V. and Balasubramanian, S. (2009) ‘Mobile Marketing: A Synthesis and Prognosis’, *Journal of Interactive Marketing*, 23(2), pp. 118–129. Available at: https://doi.org/10.1016/j.intmar.2009.02.002.

Shankar, V., Smith, A.K. and Rangaswamy, A. (2003a) ‘Customer satisfaction and loyalty in online and offline environments’, *International Journal of Research in Marketing*, 20(2), pp. 153–175. Available at: https://doi.org/10.1016/S0167-8116(03)00016-8.

Shankar, V., Smith, A.K. and Rangaswamy, A. (2003b) ‘Customer satisfaction and loyalty in online and offline environments’, *International Journal of Research in Marketing*, 20(2), pp. 153–175. Available at: https://doi.org/10.1016/S0167-8116(03)00016-8.

Sharma, P. *et al.* (2023) 'Emerging digital technologies and consumer decision-making in retail sector: Towards an integrative conceptual framework', *Computers in Human Behavior*, 148. Available at: https://doi.org/10.1016/j.chb.2023.107913.

Sharma, V. *et al.* (2020) 'Security, privacy and trust for smart mobile-Internet of Things (M-IoT): A survey', *IEEE Access*, 8, pp. 167123–167163. Available at: https://doi.org/10.1109/ACCESS.2020.3022661.

Shaw, D. and Shiu, E. (2002) 'The role of ethical obligation and self-identity in ethical consumer choice', *International Journal of Consumer Studies*, 26(2), pp. 109–116. Available at: https://doi.org/10.1046/j.1470-6431.2002.00214.x.

Shen, X.L., Zhang, K.Z.K. and Zhao, S.J. (2016) 'Herd behavior in consumers' adoption of online reviews', *Journal of the Association for Information Science and Technology*, 67(11), pp. 2754–2765. Available at: https://doi.org/10.1002/asi.23602.

Sheth, J.N., Jain, V. and Ambika, A. (2023) 'The growing importance of customer-centric support services for improving customer experience', *Journal of Business Research*, 164, p. 113943. Available at: https://doi.org/10.1016/j.jbusres.2023.113943.

Shiau, W.L. and Luo, M.M. (2012) 'Factors affecting online group buying intention and satisfaction: A social exchange theory perspective', *Computers in Human Behavior*, 28(6), pp. 2431–2444. Available at: https://doi.org/10.1016/j.chb.2012.07.030.

Shin, S., Shin, H.H. and Gim, J. (2023) 'How positive do testimonials on a restaurant website need to be? Impact of positivity of testimonial reviews on customers' decision-making', *International Journal of Hospitality Management*, 108. Available at: https://doi.org/10.1016/j.ijhm.2022.103382.

Shmueli, G. *et al.* (2019) 'Predictive model assessment in PLS-SEM: guidelines for using PLSpredict', *European Journal of Marketing* [Preprint]. Available at: https://doi.org/10.1108/EJM-02-2019-0189.

Siddaway, A.P., Wood, A.M. and Hedges, L. V (2019) 'How to Do a Systematic Review: A Best Practice Guide for Conducting and Reporting Narrative Reviews, Meta-Analyses, and Meta-Syntheses', *Annu. Rev. Psychol*, 70, pp. 747–770. Available at: https://doi.org/10.1146/annurev-psych-010418.

Simons, D.J. and Chabris, C.F. (1999) 'simons-chabris-1999-gorillas-in-our-midst-sustained-inattentional-blindness-for-dynamic-events'.

Smith, A.D. and Rupp, W.T. (2003) 'Strategic online customer decision making: Leveraging the transformational power of the Internet', *Online Information Review*, 27(6), pp. 418–432. Available at: https://doi.org/10.1108/14684520310510055.

Smith, H.J. *et al.* (1996) *Information Privacy: Measuring Individuals' Concerns about Organizational Practices About Organizational Practices1 About Organizational Practices1*, *Quarterly*.

Soegaard, M. (2010) *Affordances | The Glossary of Human Computer Interaction*, *Interaction Design Foundation*. Available at: https://www.interaction-design.org/literature/book/the-glossary-of-human-computer-interaction/affordances (Accessed: 2 January 2022).

Sohn, S. (2024) ‘Consumer perceived risk of using autonomous retail technology’, *Journal of Business Research*, 171, p. 114389. Available at: https://doi.org/10.1016/j.jbusres.2023.114389.

Song, C.S. and Kim, Y.K. (2022) ‘The role of the human-robot interaction in consumers’ acceptance of humanoid retail service robots’, *Journal of Business Research*, 146, pp. 489–503. Available at: https://doi.org/10.1016/j.jbusres.2022.03.087.

Souka, M., Bilstein, N. and Decker, R. (2024) ‘Give me your data and I’ll dress you: A two-sided messaging approach to address privacy concerns surrounding in-store technologies’, *Journal of Business Research*, 172. Available at: https://doi.org/10.1016/j.jbusres.2023.114396.

Stahl, B.C. *et al.* (2021) ‘Artificial intelligence for human flourishing – Beyond principles for machine learning’, *Journal of Business Research*, 124, pp. 374–388. Available at: https://doi.org/10.1016/J.JBUSRES.2020.11.030.

Stanciu, V. and Rîndaşu, S.M. (2021) ‘Artificial Intelligence in Retail: Benefits and Risks Associated With Mobile Shopping Applications’, *Amfiteatru Economic*, 23(56), pp. 46–46. Available at: https://doi.org/10.24818/EA/2021/56/46.

Statista (2021) • *Annual number of mobile app downloads worldwide 2020 | Statista*, *App Annie; TechCrunch*. Available at: https://www.statista.com/statistics/271644/worldwide-free-and-paid-mobile-app-store-downloads/ (Accessed: 20 June 2021).

Steenkamp, J.-B.E.M., Batra, R. and Alden, D.L. (2003) *How Perceived Brand Globalness Creates Brand Value*, *Source: Journal of International Business Studies*. Available at: www.jibs.net.

Stevenson, S., Hack-Polay, D. and Tehseen, S. (2022) ‘Social Media Influencers, the New Advertising Agency?’, *International Journal of Public Sociology and Sociotherapy*, 2(1), pp. 1–21. Available at: https://doi.org/10.4018/ijpss.297201.

Stone, R.N. and Grønhaug, K. (1993) ‘Perceived Risk: Further Considerations for the Marketing Discipline’, *European Journal of Marketing*, 27(3), pp. 39–50. Available at: https://doi.org/10.1108/03090569310026637.

Straub, D.W. (1986) *Instrument Validation in the MIS Research Process*. Available at: https://about.jstor.org/terms.

Strutton, D., Vitell, S.J. and Pelton, L.E. (1994) *How Consumers May Justify Inappropriate Behavior in Market Settings: An. Application on the Techniques of Neutra .lization*.

Su, L. *et al.* (2022) ‘Effects of tourism experiences on tourists’ subjective well-being through recollection and storytelling’, *Journal of Vacation Marketing* [Preprint]. Available at: https://doi.org/10.1177/13567667221101414.

Suh, T. and Moradi, M. (2023) ‘Transferring in-store experience to online: An omnichannel strategy for DIY customers’ enhanced brand resonance and co-creative actions’, *Journal of Business Research*, 168. Available at: https://doi.org/10.1016/j.jbusres.2023.114237.

Sun, C. *et al.* (2022) ‘Influence of augmented reality product display on consumers’ product attitudes: A product uncertainty reduction perspective’, *Journal of Retailing and Consumer Services*, 64. Available at: https://doi.org/10.1016/j.jretconser.2021.102828.

Sun, Y. *et al.* (2015) ‘Location information disclosure in location-based social network services: Privacy calculus, benefit structure, and gender differences’, *Computers in Human Behavior*, 52, pp. 278–292. Available at: https://doi.org/10.1016/j.chb.2015.06.006.

Sun, Y. *et al.* (2019) ‘How live streaming influences purchase intentions in social commerce: An IT affordance perspective’, *Electronic Commerce Research and Applications*, 37. Available at: https://doi.org/10.1016/j.elerap.2019.100886.

Swani, K., Milne, G.R. and Slepchuk, A.N. (2021) ‘Revisiting Trust and Privacy Concern in Consumers’ Perceptions of Marketing Information Management Practices: Replication and Extension’, *Journal of Interactive Marketing*, 56, pp. 137–158. Available at: https://doi.org/10.1016/j.intmar.2021.03.001.

Sweeney, L. (2013) ‘Discrimination in Online Ad Delivery: Google Ads, Black Names and White Names, Racial Discrimination, and Click Advertising’, *Queue*, 11(3), pp. 10–29. Available at: https://doi.org/10.1145/2460276.2460278.

Tabachnick, B.G. and Fidell, L.S. (2007) *Using Multivariate Statistics*.

Tabaghdehi, A. (2022) ‘COVID-19 and Digital Economy: The Journey Towards a Digital Transformation in New Normal: How to Prepare for the Future’, in. Emerald Publishing Limited, pp. 95–104. Available at: https://doi.org/10.1108/S0573-855520220000296008.

Takyi-Annan, G.E. and Zhang, H. (2023) ‘Assessing the impact of overcoming BIM implementation barriers on BIM usage frequency and circular economy in the project lifecycle using Partial least Squares structural Equation modelling (PLS-SEM) analysis’, *Energy and Buildings*, 295. Available at: https://doi.org/10.1016/j.enbuild.2023.113329.

Tamilmani, K. *et al.* (2021) ‘The extended Unified Theory of Acceptance and Use of Technology (UTAUT2): A systematic literature review and theory evaluation’, *International Journal of Information Management*, 57. Available at: https://doi.org/10.1016/j.ijinfomgt.2020.102269.

Taylor, J.W. (1974) *The Role of Risk in Consumer Behavior*, *Source: Journal of Marketing*.

Tech, J.L., Scherer, U. and Matthew, U. (2016) *Regulating artificial intelligence systems: risks, challenges, competencies, and strategies*, *Copyright Information Harvard Journal ofLaw & Technology*. Available at: http://www.theguardian.com/technology/2014/sep/12/artificial-intelligence-data-.

Thaichon, P., Phau, I. and Weaven, S. (2022) ‘Moving from multi-channel to Omni-channel retailing: Special issue introduction’, *Journal of Retailing and Consumer Services*, 65. Available at: https://doi.org/10.1016/j.jretconser.2020.102311.

Thatcher, B.J. *et al.* (2013) ‘A classification and investigation of trustees in B-to-C e-commerce: General vs. specific trust’, *Communications of the Association for*

Information Systems, 32(1), pp. 107–134. Available at: https://doi.org/10.17705/1cais.03204.

Thill, S. *et al.* (2013) 'Theories and computational models of affordance and mirror systems: An integrative review', *Neuroscience and Biobehavioral Reviews*, pp. 491–521. Available at: https://doi.org/10.1016/j.neubiorev.2013.01.012.

Thompson, C.J., Locander, W.B. and Pollio, H.R. (1989) *Putting Consumer Experience Back into Consumer Research: The Philosophy and Method of Existential-Phenomenology*, *Source: Journal of Consumer Research*. Available at: https://www.jstor.org/stable/2489313.

Trade Commission, F. (2013) *.com Disclosures: How to Make Effective Disclosures in Digital Advertising*.

Tranfield, D., Denyer, D. and Smart, P. (2003) 'Towards a Methodology for Developing Evidence-Informed Management Knowledge by Means of Systematic Review', *British Journal of Management*, 14(3), pp. 207–222. Available at: https://doi.org/https://doi.org/10.1111/1467-8551.00375.

Treem, J.W. and Leonardi, P.M. (2013) 'Social Media Use in Organizations: Exploring the Affordances of Visibility, Editability, Persistence, and Association', *Annals of the International Communication Association*, 36(1), pp. 143–189. Available at: https://doi.org/10.1080/23808985.2013.11679130.

Trepte, S. and Reinecke, L. (2011) *Privacy online: Perspectives on privacy and self-disclosure in the social web*. Springer.

Trepte, S., Scharkow, M. and Dienlin, T. (2020) 'The privacy calculus contextualized: The influence of affordances', *Computers in Human Behavior*, 104. Available at: https://doi.org/10.1016/j.chb.2019.08.022.

Trivedi, S.K. and Yadav, M. (2018) 'Predicting online repurchase intentions with e-satisfaction as mediator: a study on Gen Y', *VINE Journal of Information and Knowledge Management Systems*, 48(3), pp. 427–447. Available at: https://doi.org/10.1108/VJIKMS-10-2017-0066.

Trochim, W., Donnelly, J.P. and Arora, K. (2015) *Research Methods: The Essential Knowledge Base*. Cengage Learning. Available at: https://books.google.co.uk/books?id=IRNvjwEACAAJ.

Trochim, W.M.K. (2005) *Research Methods: The Concise Knowledge Base*. Atomic Dog Pub. Available at: https://books.google.co.uk/books?id=cx9FPwAACAAJ.

Tseng, S.M. (2015) 'Exploring the intention to continue using web-based self-service', *Journal of Retailing and Consumer Services*, 24(C), pp. 85–93. Available at: https://doi.org/10.1016/j.jretconser.2015.02.001.

Tucker, L. and Lewis, C. (1973) 'A reliability coefficient for maximum likelihood factor analysis', *Psychometrika*, 38(1), pp. 1–10. Available at: https://EconPapers.repec.org/RePEc:spr:psycho:v:38:y:1973:i:1:p:1-10.

Tull, D.S. and Hawkins, D.I. (1993) *Marketing Research: Measurement and Method : a Text with Cases*. Macmillan (Business & economics). Available at: https://books.google.co.uk/books?id=Z46CQgAACAAJ.

Tuncer, I. (2021) ‘The relationship between IT affordance, flow experience, trust, and social commerce intention: An exploration using the S-O-R paradigm’, *Technology in Society*, 65. Available at: https://doi.org/10.1016/j.techsoc.2021.101567.

Turel, O. and Serenko, A. (2020) ‘Cognitive biases and excessive use of social media: The facebook implicit associations test (FIAT)’, *Addictive Behaviors*, 105. Available at: https://doi.org/10.1016/j.addbeh.2020.106328.

Turkle, S. (2011) *Alone Together: Why We Expect More from Technology and Less from Each Other*. ReadHowYouWant.com, Limited. Available at: https://books.google.co.uk/books?id=hc7SYAPVIXwC.

Tussyadiah, I. (2020) ‘A review of research into automation in tourism: Launching the Annals of Tourism Research Curated Collection on Artificial Intelligence and Robotics in Tourism’, *Annals of Tourism Research*, 81. Available at: https://doi.org/10.1016/j.annals.2020.102883.

Vadakkepatt, G.G. *et al.* (2021) ‘Sustainable Retailing’, *Journal of Retailing*, 97(1), pp. 62–80. Available at: https://doi.org/10.1016/J.JRETAI.2020.10.008.

Vakulenko, Y. *et al.* (2019) ‘Online retail experience and customer satisfaction: the mediating role of last mile delivery’, *International Review of Retail, Distribution and Consumer Research*, 29(3), pp. 306–320. Available at: https://doi.org/10.1080/09593969.2019.1598466.

Varadarajan, R. *et al.* (2010) ‘Interactive technologies and retailing strategy: A review, conceptual framework and future research directions’, *Journal of Interactive Marketing*, 24(2), pp. 96–110. Available at: https://doi.org/10.1016/j.intmar.2010.02.004.

Varmuza, K. and Filzmoser, P. (2016) *Introduction to Multivariate Statistical Analysis in Chemometrics*. Available at: https://doi.org/10.1201/9781420059496.

Vazquez, D., Dennis, C. and Zhang, Y. (2017) ‘Understanding the effect of smart retail brand – Consumer communications via mobile instant messaging (MIM) – An empirical study in the Chinese context’, *Computers in Human Behavior*, 77, pp. 425–436. Available at: https://doi.org/10.1016/j.chb.2017.08.018.

Del Vecchio, P., Secundo, G. and Garzoni, A. (2023) ‘Phygital technologies and environments for breakthrough innovation in customers’ and citizens’ journey. A critical literature review and future agenda’, *Technological Forecasting and Social Change*, 189. Available at: https://doi.org/10.1016/j.techfore.2023.122342.

Veloutsou, C. and Ruiz Mafe, C. (2020) ‘Brands as relationship builders in the virtual world: A bibliometric analysis’, *Electronic Commerce Research and Applications*, 39. Available at: https://doi.org/10.1016/j.elerap.2019.100901.

Venkatesan, R. (2017) ‘Executing on a customer engagement strategy’, *Journal of the Academy of Marketing Science*. Springer New York LLC, pp. 289–293. Available at: https://doi.org/10.1007/s11747-016-0513-6.

Venkatesh, V. *et al.* (2003a) *User Acceptance of Information Technology: Toward a Unified View*, *Quarterly*.

Venkatesh, V. *et al.* (2003b) *User Acceptance of Information Technology: Toward a Unified View*, *Quarterly*.

Venkatesh, V., Thong, James Y. L. and Xu, X. (2012) 'Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology', *MIS Quarterly*, 36(1), pp. 157–178. Available at: https://www-jstor-org.ezproxy.brunel.ac.uk/stable/pdf/41410412.pdf?refreqid=excelsior%3A72d52dbadf663719f42940d916061754 (Accessed: 19 November 2021).

Venkatesh, V., Thong, James Y L and Xu, X. (2012) *Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology*, *Source: MIS Quarterly*.

Verhoef, P.C. *et al.* (2009) 'Customer Experience Creation: Determinants, Dynamics and Management Strategies', *Journal of Retailing*, 85(1), pp. 31–41. Available at: https://doi.org/10.1016/j.jretai.2008.11.001.

Verhoef, P.C., Kannan, P.K. and Inman, J.J. (2015) 'From Multi-Channel Retailing to Omni-Channel Retailing. Introduction to the Special Issue on Multi-Channel Retailing.', *Journal of Retailing*, 91(2), pp. 174–181. Available at: https://doi.org/10.1016/j.jretai.2015.02.005.

Verleye, K., Gemmel, P. and Rangarajan, D. (2014) 'Managing Engagement Behaviors in a Network of Customers and Stakeholders: Evidence From the Nursing Home Sector', *Journal of Service Research*, 17(1), pp. 68–84. Available at: https://doi.org/10.1177/1094670513494015.

Viglia, G. *et al.* (2023) 'Engagement and value cocreation within a multi-stakeholder service ecosystem', *Journal of Business Research*, 157. Available at: https://doi.org/10.1016/j.jbusres.2022.113584.

Vimalkumar, M. *et al.* (2021) '"Okay google, what about my privacy?": User's privacy perceptions and acceptance of voice based digital assistants', *Computers in Human Behavior*, 120. Available at: https://doi.org/10.1016/j.chb.2021.106763.

Vinzi, V.E. *et al.* (2010) *Handbook of partial least squares*. Springer.

Vishwanath, V. and Rigby, D. (2006) *The era of standardization is ending. Consumer communities are growing more diverse-in ethnicity, wealth, lifestyle, and values*.

Viswanathan, V. *et al.* (2017) 'The dynamics of consumer engagement with mobile technologies', *Service Science*, 9(1), pp. 36–49. Available at: https://doi.org/10.1287/serv.2016.0161.

Vivek, S.D. *et al.* (2014) 'A generalized multidimensional scale for measuring customer engagement', *Journal of Marketing Theory and Practice*, 22(4), pp. 401–420. Available at: https://doi.org/10.2753/MTP1069-6679220404.

Vivek, S.D., Beatty, S.E. and Morgan, R.M. (2012) 'Customer engagement: Exploring customer relationships beyond purchase', *Journal of Marketing Theory and Practice*, 20(2), pp. 122–146. Available at: https://doi.org/10.2753/MTP1069-6679200201.

Vlačić, B. *et al.* (2021) 'The evolving role of artificial intelligence in marketing: A review and research agenda', *Journal of Business Research*. Elsevier Inc., pp. 187–203. Available at: https://doi.org/10.1016/j.jbusres.2021.01.055.

VO, N.T., Chovancová, M. and Tri, H.T. (2020) 'The Impact of E-service Quality on the Customer Satisfaction and Consumer Engagement Behaviors Toward Luxury Hotels', *Journal of Quality Assurance in Hospitality and Tourism*, 21(5), pp. 499–523. Available at: https://doi.org/10.1080/1528008X.2019.1695701.

Volkoff, O. and Strong, D. (2017) *Affordance Theory and How to Use it in IS Research*.

Volkoff, O. and Strong, D.M. (2013) *Critical Realism and Affordances: Theorizing It-Associated Organizational Change Processes Quarterly-_ Change Processes1*, *Source: MIS Quarterly*.

Volpert, J. and Michel, G. (2022) 'Brand resurrections: How past and present narrations impact consumer reactions towards resurrected utilitarian brands', *Journal of Business Research*, 153, pp. 479–493. Available at: https://doi.org/10.1016/j.jbusres.2022.08.016.

Vrontis, D., Thrassou, A. and Amirkhanpour, M. (2017) 'B2C smart retailing: A consumer-focused value-based analysis of interactions and synergies', *Technological Forecasting and Social Change*, 124, pp. 271–282. Available at: https://doi.org/10.1016/j.techfore.2016.10.064.

Wajid, A. *et al.* (2019) 'Value co-creation through actor embeddedness and actor engagement', *Marketing Intelligence and Planning*, 37(3), pp. 271–283. Available at: https://doi.org/10.1108/MIP-07-2018-0241.

Walker, K.L. (2016a) 'Surrendering information through the looking glass: Transparency, trust, and protection', *Journal of Public Policy and Marketing*, 35(1), pp. 144–158. Available at: https://doi.org/10.1509/jppm.15.020.

Walker, K.L. (2016b) 'Surrendering information through the looking glass: Transparency, trust, and protection', *Journal of Public Policy and Marketing*, 35(1), pp. 144–158. Available at: https://doi.org/10.1509/jppm.15.020.

Wallace, M. and Sheldon, N. (2015) 'Business Research Ethics: Participant Observer Perspectives', *Journal of Business Ethics*, 128(2), pp. 267–277. Available at: https://doi.org/10.1007/s10551-014-2102-2.

Wang, C.L. and Chugh, H. (2014) *Entrepreneurial Learning: Past Research and Future Challenges*.

Wang, D. *et al.* (2023) 'Customers' help-seeking propensity and decisions in brands' self-built live streaming E-Commerce: A mixed-methods and fsQCA investigation from a dual-process perspective', *Journal of Business Research*, 156. Available at: https://doi.org/10.1016/j.jbusres.2022.113540.

Wang, L.C. *et al.* (2007) 'Can a retail Web Site be social?', *Journal of Marketing*. SAGE PublicationsSage CA: Los Angeles, CA, pp. 143–157. Available at: https://doi.org/10.1509/jmkg.71.3.143.

Wang, N. *et al.* (2022) 'From knowledge seeking to knowledge contribution: A social capital perspective on knowledge sharing behaviors in online Q&A communities', *Technological Forecasting and Social Change*, 182. Available at: https://doi.org/10.1016/j.techfore.2022.121864.

Wang, R. *et al.* (2023) 'Transparency in persuasive technology, immersive technology, and online marketing: Facilitating users' informed decision making and practical implications', *Computers in Human Behavior*. Elsevier Ltd. Available at: https://doi.org/10.1016/j.chb.2022.107545.

Wang, X. *et al.* (2021) 'Adoption of shopper-facing technologies under social distancing: A conceptualisation and an interplay between task-technology fit and technology trust', *Computers in Human Behavior*, 124, p. 106900. Available at: https://doi.org/10.1016/j.chb.2021.106900.

Wang, Y. *et al.* (2022) 'How Live Streaming Changes Shopping Decisions in E-commerce: A Study of Live Streaming Commerce', *Computer Supported Cooperative Work: CSCW: An International Journal*, 31(4), pp. 701–729. Available at: https://doi.org/10.1007/s10606-022-09439-2.

Wang, Y. *et al.* (2023) 'Who pays buyers for not disclosing supplier lists? Unlocking the relationship between supply chain transparency and trade credit', *Journal of Business Research*, 155, p. 113404. Available at: https://doi.org/https://doi.org/10.1016/j.jbusres.2022.113404.

Ward, A.F. *et al.* (2017) 'Brain drain: The mere presence of one's own smartphone reduces available cognitive capacity', *Journal of the Association for Consumer Research*, 2(2), pp. 140–154. Available at: https://doi.org/10.1086/691462.

Warren, W.H. (1984) 'Perceiving affordances: Visual guidance of stair climbing', *Journal of Experimental Psychology: Human Perception and Performance*, 10(5), pp. 683–703. Available at: https://doi.org/10.1037/0096-1523.10.5.683.

Wasko, M.M. and Faraj, S. (2005) *Why Should I Share? Examining Social Capital and Knowledge Contribution in Electronic Networks of Practice*, *Source: MIS Quarterly*.

Wasserman, T. (2012) *Facebook Now Has 901 Million Users | Mashable*, *Mashable*. Available at: https://mashable.com/archive/facebook-now-has-901-million-users#ZM.bMfVz_8qL (Accessed: 17 November 2022).

Watkins, M.W. (2018) 'Exploratory Factor Analysis: A Guide to Best Practice', *Journal of Black Psychology*, 44(3), pp. 219–246. Available at: https://doi.org/10.1177/0095798418771807.

Waziri, A.Y., Yakubu, M. and Sa'adiya Ilyasu, M. (2017) *STRUCTURAL EQUATION MODELLING ANALYTICAL APPROACH: MODEL FIT, RELIABILITY AND VALIDITY 1*, *Journal of Physical Science and Innovation*.

Wedel, M. and Kannan, P.K. (2016) 'Marketing analytics for data-rich environments', *Journal of Marketing*, 80(6), pp. 97–121. Available at: https://doi.org/10.1509/jm.15.0413.

Whittaker, Z. (2019) *Marriott to face $123 million fine by UK authorities over data breach | TechCrunch*, *TechCrunch*. Available at: https://techcrunch.com/2019/07/09/marriott-data-breach-uk-fine/ (Accessed: 8 July 2021).

Wiederhold, B.K. (2018) 'Stop Scrolling, Start Living: The Growing Reality of Internet Addiction Disorder', *Cyberpsychology, Behavior, and Social Networking*. Mary Ann

Liebert Inc., pp. 279–280. Available at: https://doi.org/10.1089/cyber.2018.29111.bkw.

Wieringa, J. *et al.* (2021) ‘Data analytics in a privacy-concerned world’, *Journal of Business Research*, 122, pp. 915–925. Available at: https://doi.org/10.1016/J.JBUSRES.2019.05.005.

Wirtz, B.W. and Lihotzky, N. (2003) ‘Customer retention management in the B2C electronic business’, *Long Range Planning*, 36(6), pp. 517–532. Available at: https://doi.org/10.1016/j.lrp.2003.08.010.

Wirtz, J. *et al.* (2013) ‘Managing brands and customer engagement in online brand communities’, *Journal of Service Management*. Edited by L. Aksoy, A. van Riel, and J. Kandampully, 24(3), pp. 223–244. Available at: https://doi.org/10.1108/09564231311326978.

Wirtz, J. *et al.* (2019) ‘Platforms in the peer-to-peer sharing economy’, *Journal of Service Management*, 30(4), pp. 452–483. Available at: https://doi.org/10.1108/JOSM-11-2018-0369.

Wirtz, J. and Lwin, M.O. (2009) ‘Regulatory focus theory, trust, and privacy concern’, *Journal of Service Research*, 12(2), pp. 190–207. Available at: https://doi.org/10.1177/1094670509335772.

Wold, H. (2004) ‘Partial Least Squares’, in *Encyclopedia Statistical Sci*. Available at: https://doi.org/10.1002/0471667196.ess1914.

Wolfinbarger, M. and Gilly, M.C. (2003) ‘eTailQ: Dimensionalizing, measuring and predicting etail quality’, *Journal of Retailing*, 79(3), pp. 183–198. Available at: https://doi.org/10.1016/S0022-4359(03)00034-4.

Wong, K.K. (2019) *Mastering Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS in 38 Hours*. Available at: https://www.researchgate.net/publication/332031150.

Wu, W. *et al.* (2023) ‘Elucidating trust-building sources in social shopping: A consumer cognitive and emotional trust perspective’, *Journal of Retailing and Consumer Services*, 71. Available at: https://doi.org/10.1016/j.jretconser.2022.103217.

Wünderlich, N. V., Wangenheim, F. V. and Bitner, M.J. (2013) ‘High Tech and High Touch: A Framework for Understanding User Attitudes and Behaviors Related to Smart Interactive Services’, *Journal of Service Research*. SAGE Publications Inc., pp. 3–20. Available at: https://doi.org/10.1177/1094670512448413.

Xiao, B. and Benbasat, I. (2007) *E-Commerce Product Recommendation Agents: Use, Characteristics, and Impact*, *Source: MIS Quarterly*. Available at: http://www.forrester.com/Research/Document/Excerpt/0,7211,34576,00.

Xiong, J., Wang, Y. and Li, Z. (2023) ‘Understanding the Relationship between IT Affordance and Consumers’ Purchase Intention in E-Commerce Live Streaming: The Moderating Effect of Gender’, *International Journal of Human-Computer Interaction* [Preprint]. Available at: https://doi.org/10.1080/10447318.2023.2250607.

Xu, G. *et al.* (2021) ‘TT-SVD: An Efficient Sparse Decision-Making Model with Two-Way Trust Recommendation in the AI-Enabled IoT Systems’, *IEEE Internet of Things*

Journal, 8(12), pp. 9559–9567. Available at: https://doi.org/10.1109/JIOT.2020.3006066.

Xu, H. *et al.* (2008) *Association for Information Systems AIS Electronic Library (AISeL) Examining the Formation of Individual' s Privacy Concerns: Toward an Integrative View Recommended Citation*. Available at: http://aisel.aisnet.org/icis2008/6.

Xu, X. *et al.* (2017a) 'The impact of informational incentives and social influence on consumer behavior during Alibaba's online shopping carnival', *Computers in Human Behavior*, 76, pp. 245–254. Available at: https://doi.org/10.1016/j.chb.2017.07.018.

Xu, X. *et al.* (2017b) 'The impact of informational incentives and social influence on consumer behavior during Alibaba's online shopping carnival', *Computers in Human Behavior*, 76, pp. 245–254. Available at: https://doi.org/10.1016/j.chb.2017.07.018.

Xu, X. (2020) 'Examining consumer emotion and behavior in online reviews of hotels when expecting managerial response', *International Journal of Hospitality Management*, 89. Available at: https://doi.org/10.1016/j.ijhm.2020.102559.

Xu, X., Jia, Q. and Tayyab, S.M.U. (2023) 'The exploration of customization in augmented reality from the affordance lens: A three-stage hybrid approach', *Technological Forecasting and Social Change*, 194, p. 122729. Available at: https://doi.org/10.1016/j.techfore.2023.122729.

Yale, L. and Venkatesh, A. (1986) 'Toward the construct of convenience in consumer research', *ACR North American Advances* [Preprint].

Yan, Y. *et al.* (2023) 'How IT affordances influence customer engagement in live streaming commerce? A dual-stage analysis of PLS-SEM and fsQCA', *Journal of Retailing and Consumer Services*, 74. Available at: https://doi.org/10.1016/j.jretconser.2023.103390.

Yang, S. *et al.* (2023) 'EXPRESS: Virtual Fitting Room Effect: Moderating Role of Body Mass Index', *Journal of Marketing Research*, p. 002224372311548. Available at: https://doi.org/10.1177/00222437231154871.

Yang, Z. *et al.* (2019) 'Does Ethics Perception Foster Consumer Repurchase Intention? Role of Trust, Perceived Uncertainty, and Shopping Habit', *SAGE Open*, 9(2). Available at: https://doi.org/10.1177/2158244019848844.

Yeomans, M. *et al.* (2019) 'Making sense of recommendations', *Journal of Behavioral Decision Making*, 32(4), pp. 403–414. Available at: https://doi.org/10.1002/bdm.2118.

Yi, Z. *et al.* (2018) 'The Impact of Consumer Fairness Seeking on Distribution Channel Selection: Direct Selling vs. Agent Selling', *Production and Operations Management*, 27(6), pp. 1148–1167. Available at: https://doi.org/10.1111/poms.12861.

Yin, R.K. (2003) *Case Study Research: Design and Methods*. SAGE Publications (Applied Social Research Methods). Available at: https://books.google.co.uk/books?id=BWea_9ZGQMwC.

Yin, R.K. (2008) *Case Study Research: Design and Methods*. SAGE Publications (Applied Social Research Methods). Available at: https://books.google.co.uk/books?id=fpx1AwAAQBAJ.

Ying, S. *et al.* (2023) ‘Privacy paradox for location tracking in mobile social networking apps: The perspectives of behavioral reasoning and regulatory focus’, *Technological Forecasting and Social Change*, 190. Available at: https://doi.org/10.1016/j.techfore.2023.122412.

Ying, T. *et al.* (2021) ‘“I have to watch my back”: Exploring Chinese hotel guests’ generalized distrust and coping behavior’, *Tourism Management*, 86. Available at: https://doi.org/10.1016/j.tourman.2021.104355.

Yoo, K. *et al.* (2023) ‘The merchants of meta: A research agenda to understand the future of retailing in the metaverse’, *Journal of Retailing* [Preprint]. Available at: https://doi.org/10.1016/j.jretai.2023.02.002.

Yu, H., Zhang, R. and Liu, B. (2018) ‘Analysis on Consumers’ Purchase and Shopping Well-Being in Online Shopping Carnivals with Two Motivational Dimensions’, *Sustainability*, 10(12). Available at: https://doi.org/10.3390/su10124603.

Yu, N., Wang, S. and Liu, Z. (2022) ‘Managing brand competition with consumer fairness concern via manufacturer incentive’, *European Journal of Operational Research*, 300(2), pp. 661–675. Available at: https://doi.org/10.1016/j.ejor.2021.08.026.

Yuan, K.H. and Bentler, P.M. (1998) ‘Structural equation modeling with robust covariances’, *Sociological Methodology*, 28(1), pp. 363–396. Available at: https://doi.org/10.1111/0081-1750.00052.

Zegwaard, K.E., Campbell, M. and Pretti, T.J. (2017) ‘Professional Identities and Ethics: The Role of Work-Integrated Learning in Developing Agentic Professionals’, in *Work-Integrated Learning in the 21st Century*. Emerald Publishing Limited (International Perspectives on Education and Society), pp. 145–160. Available at: https://doi.org/10.1108/S1479-367920170000032009.

Zeithaml, V.A. (1988) *Consumer Perceptions of Price, Quality, and Value: A Means-End Model and Synthesis of Evidence*, *Source: Journal of Marketing*.

Zeithaml, V.A., Berry, L.L. and Parasuraman, A. (1996) ‘The behavioral consequences of service quality’, *Journal of marketing*, 60(2), pp. 31–46.

Zhang, J. *et al.* (2024) ‘Emotional expression by artificial intelligence chatbots to improve customer satisfaction: Underlying mechanism and boundary conditions’, *Tourism Management*, 100. Available at: https://doi.org/10.1016/j.tourman.2023.104835.

Zhang, J.Z. and Watson IV, G.F. (2020) ‘Marketing ecosystem: An outside-in view for sustainable advantage’, *Industrial Marketing Management*, 88, pp. 287–304. Available at: https://doi.org/10.1016/j.indmarman.2020.04.023.

Zhang, M. *et al.* (2018) ‘The impact of channel integration on consumer responses in omni-channel retailing: The mediating effect of consumer empowerment’, *Electronic Commerce Research and Applications*, 28, pp. 181–193. Available at: https://doi.org/10.1016/j.elerap.2018.02.002.

Zhang, N. (Andy) *et al.* (2022) ‘Peer Privacy Concerns: Conceptualization and Measurement’, *MIS Quarterly*, 46(1), pp. 491–530. Available at: https://doi.org/10.25300/MISQ/2022/14861.

Zhang, Y. *et al.* (2024) ‘Examining the moderating effects of shopping orientation, product knowledge and involvement on the effectiveness of Virtual Reality (VR) retail environment’, *Journal of Retailing and Consumer Services*, 78. Available at: https://doi.org/10.1016/j.jretconser.2024.103713.

Zhani, N., Mouri, N. and Ahmed, T. (2022) ‘The role of mobile value and trust as drivers of purchase intentions in m-servicescape’, *Journal of Retailing and Consumer Services*, 68. Available at: https://doi.org/10.1016/j.jretconser.2022.103060.

Zhao, Y., Guan, Z. min and Zhang, J. (2023) ‘Return freight strategies and selling formats in e-commerce supply chain: The perspective of consumer fairness concerns and online shopping returns’, *Journal of Retailing and Consumer Services*, 75. Available at: https://doi.org/10.1016/j.jretconser.2023.103493.

Zhu, H., Vigren, O. and Söderberg, I.L. (2024) ‘Implementing artificial intelligence empowered financial advisory services: A literature review and critical research agenda’, *Journal of Business Research*, 174. Available at: https://doi.org/10.1016/j.jbusres.2023.114494.

Zhu, W., Mou, J. and Benyoucef, M. (2019) ‘Exploring purchase intention in cross-border E-commerce: A three stage model’, *Journal of Retailing and Consumer Services*, 51, pp. 320–330. Available at: https://doi.org/10.1016/j.jretconser.2019.07.004.

Zikmund, W.G. (2003) *Business Research Methods*. Thomson/South-Western. Available at: https://books.google.co.uk/books?id=kPQJAQAAMAAJ.

Zou, Y. *et al.* (2023) ‘Wanted! Investigating how elements from the personal usage context affect Gen Z consumers’ value-in-use experience and engagement with mobile service’, *Journal of Business Research*, 160. Available at: https://doi.org/10.1016/j.jbusres.2023.113824.

Žukauskas, P., Vveinhardt, J. and Andriukaitienė, R. (2018) ‘Philosophy and Paradigm of Scientific Research’, *Management Culture and Corporate Social Responsibility* [Preprint]. Available at: https://doi.org/10.5772/INTECHOPEN.70628.

Chapter 9: Appendix

This chapter contains conclusions, limitations, and recommendations – so what is the theory? Where to from here? What are the practical implications? Discussion of where the study may be extended.

9.1.1 Participant Information Sheet

PARTICIPANT INFORMATION SHEET

Study title: Smart Retailing and the Challenges and Opportunities of the AI Ethics”

Dear participant, you are being asked to take part in a research study. Before you decide, it is important for you to understand why the research is being done and what it will involve. Take time to read the following information carefully and discuss it with others if you wish. Ask me/us if there is anything that is not clear or if you would like more information. Take time to decide whether or not you wish to take part. Thank you for reading this.

What is the purpose of the study?

Retailing is experiencing a remarkable transformation inspired by the advent of Artificial Intelligence (AI) themed technologies (Martin et al., 2020). Although convenient, they indicated that AI-themed products present some concerns such as AI-adoption, AI-based decision-making bias, digital-wellbeing, and ethical challenges including consumer trust, AI-bias, privacy-concerns, and adoption (Martin et al., 2020). This study will investigate and better the understanding of the impact of smart retailing and artificial intelligence's use in retail on consumer behaviours and digital wellbeing.

Why have I been invited to participate?

You have been invited because you are a person aged over 18 and it is inevitable you may need to engage with smart retailing soon if you are not already. Your attitude towards ethical and unethical smart retail activities will add value to the results of the current research.

Do I have to take part?

As participation is entirely voluntary, it is up to you to decide whether or not to take part. If you do decide to take part you will be given this information sheet to keep and you may be asked to sign a consent form. If you decide to take part you are still free to withdraw at any time up until 30 -09-2024 and without having to give a reason.

What will happen to me if I take part?

If you accept to participate in the study, you will be asked to sign a permission/consent form. Then you will be asked questions regarding your engagement and experience with smart retailing. The questionnaire will be administered electronically, and your answers stored on a secure Brunel university server. All the information you provide will be treated as entirely private and confidential, and no one will be able to identify the information you submit, neither will your name appear anywhere on the survey. The information gathered from this study is to allow the researcher to collect all your responses, analyse them and then present the findings as part of the PhD thesis and may lead to the development of policies to improve smart consumer experience. The questionnaire will only take you around 20 - 30 minutes to complete. Your co-operation is much appreciated and will contribute to the success of this research.

Are there any lifestyle restrictions?

there are no lifestyle restrictions.

What are the possible disadvantages and risks of taking part?

As far as the researcher is aware, no hazards are associated with doing this research.

What are the possible benefits of taking part?

The information gathered from this study is to allow the researcher to collect all your responses, analyse them and then present the findings as part of the PhD thesis and may lead to the development of policies to improve smart consumer experience.

What if something goes wrong?

If you have a complaint about your involvement as a participant, please contact the Chair of the College of Business School, Art, and Social Science (CBASS) Research Ethics Committee.

Will my taking part in this study be kept confidential?

All information which is collected about you during the course of the research will be kept strictly confidential. Any information about you which leaves the University will have all your identifying information removed. With your permission, anonymised data will be stored and may be used in future research (please note that you can indicate whether or not you give permission for this by way of the Consent Form).

Will I be recorded, and how will the recording be used?

You will not be recorded. The study is solely a survey based online.

What will happen to the results of the research study?

Textual data and data analysis shall be used exclusively in academic works, such as the PhD thesis and publication that emerge from this study.

Who is organising and funding the research?

This research is being organised by Edem Boni in conjunction with Brunel University London.

What are the indemnity arrangements?

Brunel University London provides appropriate insurance cover for research which has received ethical approval.'

Who has reviewed the study?

The College of Business, Art, and Social Science's Research Ethics Committee has evaluated and approved this study. Brunel University is dedicated to adhering to the Universities UK Concordat on Research Integrity. You have a right to expect our researchers to act with the utmost honesty throughout their study.

Research Integrity

Brunel University London is committed to compliance with the Universities UK Research Integrity Concordat. You are entitled to expect the highest level of integrity from the researchers during the course of this research.

Contact for further information and complaints.

Researcher name and details:

Principal Researcher Details Name:

Edem Boni (Doctoral Researcher)

Email: edem.boni@brunel.ac.uk

Address: Brunel University London College Business, Arts & Social Sciences Business School, UK Eastern Gateway Building, Brunel University London, Uxbridge, UB8 3PH, United Kingdom.

Principal Supervisor Details Name:

Dr Asieh Tabaghdehi BA, MSc, PhD, PGCHE, FHEA, FCMI, MEI Lecturer in Strategy and Business Economics | Programme Lead in BSc International Business

Email: asieh.Tabaghdehi@brunel.ac.uk Address: Brunel University London College Business, Arts & Social Sciences Business School, UK Eastern Gateway Building, Brunel University London, Uxbridge, UB8 3PH, United Kingdom

For complaints, Chair of the Research Ethics Committee: The Ethics Committee is chaired by Dr Derek Healy; They can be contacted by College of Business, Arts and Social Sciences Research Ethics Committee Chair – Professor David Gallear (David.Gallear@brunel.ac.uk)

9.1.2 Questionnaire

Draft Questionnaire

Consumer Awareness			**REFRENCE**
Knowledge		**KNW**	
	When shopping online, I have good level of information about the product.	KNW1	(Fang, 2019)
	When shopping online, I have good level of information about the product availability.	KNW2	
	When shopping online, I can save a lot of time by being able to access my shopping history available in my past-shopping cart .	KNW3	
Intentions		**INT**	
	I intend to use online shopping more frequently in the future.	INT1	(Pavlou, 2003; Roy et al., 2017)
	I am willing to use online shopping in the near future.	INT2	
	I will continue to use online shopping in the future.	INT3	
Attitude		**ATT**	
	I enjoy online shopping experience.	ATT1	
	I will be happy, if I shop online.	ATT2	
	I like online shopping	ATT3	
	I will be delighted, if I shop online.	ATT4	
Consumer Digital Ethical Perception			
Fairness		**FRI**	
	I believe that online businesses access my information in a fair way.	FR1	(Martin et al., 2017)
	I believe that online businesses are honest when using my information.	FR2	
	I believe that online businesses manage my information in a reasonable way.	FR3	
Privacy Protection		**PP**	
	When shopping online, I am sensitive to the way that online retailer handles my personal information.	**PP1**	(Martin et al., 2017, 2020)

	When shopping online, it is important to keep my privacy safe from online retailers.	**PP2**	
	When shopping online, personal privacy is very important to me, compared to other ethical factors.	**PP3**	
Brand Trust		**TR**	
	I believe that online businesses are trustworthy.	TR1	(Gefen, Karahanna and Straub, 2003)
	I believe that online businesses care about their consumers.	TR2	
	I believe that online businesses keep their promises.	TR3	
Expectation			
Perceived ease of use		**PEU**	
	Online shopping is more convenient than in-store shopping.	PEU 1	(Glover & Benbasat, 2010; Roy et al., 2017)
	Online shopping gives me a better purchasing experience.	PEU 2	
	Online shopping is more transparent and straightforward than in-store shopping.	PEU 3	
	Online shopping platforms are easy to use .	PEU 4	
Perceived usefulness		**PU**	
	Shopping online improves my ability to make good purchasing decisions.	PU 1	(Davis, 1989)
	Shopping online allows me to get my shopping done more quickly.	PU 2	
	Shopping online allows me to find the most suitable products for my needs.	PU 3	
Personalisation			
	Online shopping provides me with personalised services.	PER 1	(Glover & Benbasat, 2010; Roy et al., 2017)
	Online shopping understands my particular request.	PER 2	
	Online shopping gives me recommendations that suit my situation and needs.	PER 3	
Perceived Smart Retail Risk			
Perceived Financial risk		**PFR**	
	When shopping online, I am concerned that my financial information might be misused.	PFR1	(Stone & Grønhaug, 1993; Hassan et al., 2006; Glover & Benbasat, 2010)
	When shopping online, I am concerned that my financial information might be insecurely safeguarded.	PFR2	
	When shopping online, I am concerned that my transaction might include some hidden cost that will be shown at final stage.	PFR3	
Perceived Psychological Risk			
	When shopping online, I feel concern that it may lead to social isolation.	PPR1	(Stone & Grønhaug, 1993; Hassan et al.,

			2006; Mortimer, 2018)
	When shopping online, I feel concern that it might misrepresent the quality, size, colour, and style of the actual product.	PPR2	
	When shopping online, I feel concern that it might be difficult to feel, test, or experience a product prior to purchase.	PPR3	
	When shopping online, I feel concern that online retailer might not be a real merchant.	PPR4	
Personal information Misuse		**PIM**	
	When shopping online, I am concerned that my personal information might be misused.	PIM1	(Glover & Benbasat, 2010; Roy et al., 2017)
	When shopping online, I am concerned that my personal information might be insecurely safeguarded.	PIM2	
	When shopping online, I am concerned about being a victim of data breach.	PIM3	
Perceived Safety Risk		**PSR**	
	When shopping online, I feel concern that the online retailer may misinform me about their business, products and reputation.	PSR1	(Glover & Benbasat, 2010; N. K. Malhotra et al., 2004).
	When shopping online, I feel worried.	PSR2	
	When shopping online, I am concerned that my personal privacy might be misused.	PSR3	
Product Return Risk		**PRR**	
	I am concerned that I may not be able to return the product because the retailer no longer exists online.	PRR1	(Glover & Benbasat, 2010)
	I am concerned that the online retailer might provide misleading information on where to return the product.	PRR2	
	I am concerned that I might not be able to change my mind once the transaction is final.	PRR3	
	I am concerned that there might be no way to return a product if it was a download.	PRR4	
EXPERIENCE			
Smart Consumer experience			
	My shopping experience is more efficient when I purchase online.	CE1	(Roy et al., 2017)
	My shopping experience is more productive when I purchase online.	CE2	
	My shopping experience is smoother when I purchase online.	CE3	
	My shopping experience is easier when I purchase online.	CE4	
Smart Satisfaction			
Consumer Satisfaction			

	The product received through online shopping is closed to my expectation.	CS1	(Roy et al., 2017)
	The product received through online shopping exceed my expectation.	CS2	
	I am satisfied with the product purchased through online shopping.	CS3	
Hedonic Motivation		**HM**	
	Shopping online is fun.	HM1	(Roy et al., 2017)
	Shopping online is enjoyable.	HM2	
	Shopping online is entertaining.	HM3	
Consumer Digital Well-being			
	Online shopping platforms have benefited my overall digital skills.	WELL1	
	Online shopping helps me improve the quality of life.	WELL 2	
	Online shopping helps me improve my social well-being.	WELL 3	
Affordability		**AF**	
	Online products are reasonably priced.	AF1	(Venkatesh et al., 2012)
	Online products are good value for money.	AF2	
	Online products are more economical.	AF3	
(RE) Purchasing Behaviour			
Consumer Decision Making			
	Online shopping platforms to help me make better decisions in my shopping selection.	CPB1	(Rippé et al., 2017)
	Online shopping platforms propose the best products to purchase.	CPB 2	
	Online shopping platforms offer good recommendations.	CPB 3	
	The customer reviews on the online shopping platform helped me with my online purchase.	CPB 4	
Brand Loyalty		**LOY**	
	I have a sense of belonging to my favourite online retailer.	LOY1	(Fang, 2019; Glover & Benbasat, 2010)
	I experience an emotional connection with my favourite online retailer.	LOY2	
	I have strong emotions towards my favourite online retailer.	LOY3	

9.1.3 Descriptive Statistics

Table 60:Descriptive Statistics for all Items

Descriptive Statistics

	N	Minimum	Maximum	Mean		Std. Deviation
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic

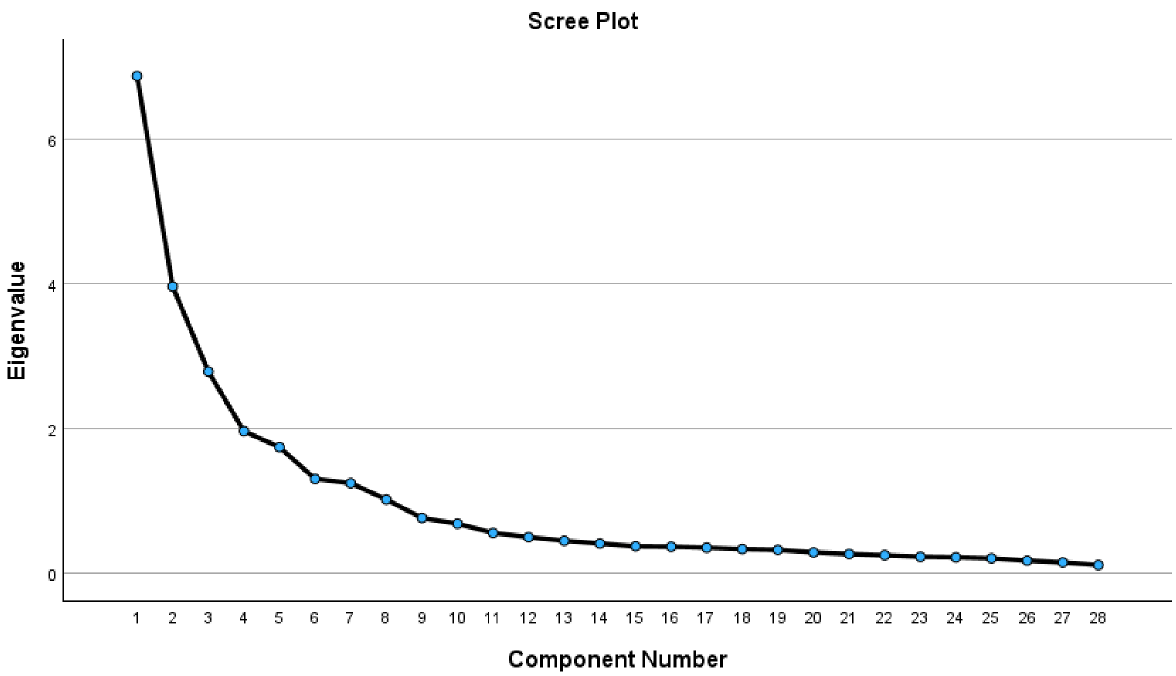
PRIV1	510	1.00	7.00	5.4235	.06446	1.45564
PRIV2	510	1.00	7.00	5.8137	.05787	1.30685
PRIV3	510	1.00	7.00	5.6176	.06517	1.47170
FAIR1	510	1.00	7.00	3.8176	.06754	1.52519
FAIR2	510	1.00	7.00	3.5804	.06546	1.47820
FAIR3	510	1.00	7.00	3.6569	.06453	1.45728
PSR1	510	1.00	7.00	5.0667	.06787	1.53270
PSR2	510	1.00	7.00	3.9412	.07546	1.70417
PSR3	510	1.00	7.00	5.0824	.07324	1.65404
TRUST1	510	1.00	7.00	4.1235	.05604	1.26555
TRUST2	510	1.00	7.00	4.2569	.05591	1.26254
TRUST3	510	1.00	7.00	4.2549	.05181	1.17008
CE1	510	1.00	7.00	5.0078	.06509	1.47005
CE2	510	1.00	7.00	4.9804	.06317	1.42653
CE3	510	1.00	7.00	4.9333	.06106	1.37886
CE4	510	1.00	7.00	5.2725	.05944	1.34231
CS1	510	1.00	7.00	4.8941	.04752	1.07323
CS2	510	1.00	7.00	4.0824	.05327	1.20293
CS3	510	1.00	7.00	4.9647	.04749	1.07239
INT1	510	1.00	7.00	5.2588	.05722	1.29214
INT2	510	1.00	7.00	5.7059	.05049	1.14033
INT3	510	1.00	7.00	5.8098	.05082	1.14778
LOY1	510	1.00	7.00	3.9255	.07383	1.66742
LOY2	510	1.00	7.00	3.4922	.07167	1.61857
LOY3	510	1.00	7.00	3.4020	.07240	1.63496
WELL1	510	1.00	7.00	4.6333	.06343	1.43246
WELL2	510	1.00	7.00	4.4784	.06291	1.42063
WELL3	510	1.00	7.00	3.8333	.06699	1.51277
Valid N (listwise)	510					

9.1.4 Exploratory Factor Analysis

Communalities

	Initial	Extraction
PRIV1	1.000	.740
PRIV2	1.000	.790
PRIV3	1.000	.763
FAIR1	1.000	.805
FAIR2	1.000	.839
FAIR3	1.000	.827
PSR1	1.000	.643
PSR2	1.000	.737
PSR3	1.000	.670
TRUST1	1.000	.637
TRUST2	1.000	.605
TRUST3	1.000	.631
CE1	1.000	.745
CE2	1.000	.794
CE3	1.000	.812
CE4	1.000	.727
CS1	1.000	.741
CS2	1.000	.648
CS3	1.000	.773
INT1	1.000	.700
INT2	1.000	.868
INT3	1.000	.822
LOY1	1.000	.789
LOY2	1.000	.895
LOY3	1.000	.850
WELL1	1.000	.655
WELL2	1.000	.736
WELL3	1.000	.697

Extraction Method: Principal Component Analysis.



Pattern Matrix[a]

	Component							
	1	2	3	4	5	6	7	8
CE3	.894							
CE2	.878							
CE1	.842							
CE4	.797							
PRIV2		.887						
PRIV3		.848						
PRIV1		.829						
LOY2			.934					
LOY3			.912					
LOY1			.873					
FAIR2				.902				
FAIR1				.899				
FAIR3				.890				
INT2					.931			
INT3					.888			
INT1					.808			
PSR1						.762		
PSR2						.757		
PSR3		.387				.572		

TRUST3						-.562		
TRUST2				.349		-.474		
TRUST1				.437		-.440		
WELL2							-.811	
WELL3							-.802	
WELL1							-.775	
CS1								.817
CS2								.793
CS3								.781

Extraction Method: Principal Component Analysis.
Rotation Method: Oblimin with Kaiser Normalization.
a. Rotation converged in 14 iterations.

Component Matrix[a]

	Component							
	1	2	3	4	5	6	7	8
PRIV1		.634		.513				
PRIV2		.622		.522				
PRIV3		.638		.518				
FAIR1	.555	-.441						
FAIR2	.585	-.441						
FAIR3	.622							
PSR1		.522						
PSR2	-.459	.428						
PSR3		.657						
TRUST1	.603							
TRUST2	.618							
TRUST3	.578							
CE1	.590							
CE2	.616							
CE3	.605							
CE4	.604		-.406					
CS1	.543							
CS2	.432				-.410			

CS3	.603							
INT1	.480				.537			
INT2	.513				.608			
INT3	.510				.547			
LOY1	.436		.550					
LOY2			.629					
LOY3			.632					
WELL1	.449						-.474	
WELL2	.546						-.485	
WELL3							-.522	

Extraction Method: Principal Component Analysis.
a. 8 components extracted.

Structure Matrix

	Component							
	1	2	3	4	5	6	7	8
PRIV1		.851						
PRIV2		.874						
PRIV3		.868						
FAIR1				.885				
FAIR2				.907				
FAIR3				.904				
PSR1						.779		
PSR2						.773		
PSR3		.545				.704		
TRUST1				.660		-.606		
TRUST2				.595		-.610		
TRUST3				.539		-.652		
CE1	.861							
CE2	.885							
CE3	.899							
CE4	.844				.405			
CS1	.401							.848
CS2								.776
CS3	.479							.850
INT1					.812			
INT2					.930			

INT3					.902			
LOY1			.879					
LOY2			.945					
LOY3			.920					
WELL1							-.802	
WELL2							-.839	
WELL3							-.805	

Extraction Method: Principal Component Analysis.
Rotation Method: Oblimin with Kaiser Normalization.

Component Correlation Matrix

Component	1	2	3	4	5	6	7	8
1	1.000	.025	.112	.115	.393	-.129	-.243	.405
2	.025	1.000	.062	-.112	-.009	.230	-.166	.037
3	.112	.062	1.000	.141	.074	.005	-.349	.166
4	.115	-.112	.141	1.000	.124	-.405	-.226	.197
5	.393	-.009	.074	.124	1.000	-.175	-.216	.177
6	-.129	.230	.005	-.405	-.175	1.000	.064	-.221
7	-.243	-.166	-.349	-.226	-.216	.064	1.000	-.233
8	.405	.037	.166	.197	.177	-.221	-.233	1.000

Extraction Method: Principal Component Analysis.
Rotation Method: Oblimin with Kaiser Normalization.

Table 61:Discriminant validity: Fornell-Larcker criterion

	LOY	FAIR	PRIV	PSR	INT	CS	CE	TRUST	WELL
LOY	0.878								
FAIR	0.184	0.878							
PRIV	0.041	-0.271	0.825						
PSR	0.019	-0.475	0.543	0.745					
INT	0.160	0.192	-0.009	-0.224	0.823				
CS	0.412	0.230	0.033	-0.129	0.374	0.900			
CE	0.198	0.215	0.062	-0.179	0.464	0.395	0.831		
TRUST	0.267	0.682	-0.106	-0.533	0.286	0.300	0.276	0.769	
WELL	0.472	0.235	0.123	0.023	0.350	0.576	0.409	0.418	0.733