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AI insurance chatbots and phygital service engagement: the triadic impact of trust-anxiety-complexity- on aging consumers

Rajat Subhra Chatterjee[a], Bindu Singh[b], Ranjan Chaudhuri[c], Sheshadri Chatterjee[d], Demetris Vrontis[e,f] and Pantea Foroudi[g]

[a]Graduate Business School, University of Plymouth, Plymouth, UK; [b]Department of Management and Humanities, Indian Institute of Information Technology Lucknow, Lucknow, India; [c]De Vinci Research Center, EMLV Business School Paris, De Vinci Higher Education, Paris, France; [d]Department of Computer Science and Engineering, Indian Institute of Technology Kharagpur, India; [e]Gnosis: Mediterranean Institute for Management Science, School of Business, University of Nicosia, Nicosia, Cyprus; [f]S P Jain School of Global Management – Singapore Campus, Singapore, Singapore; [g]Brunel Business School, Brunel University London, UK

ABSTRACT

This study examines elderly consumers' perceptions of the design of AI insurance chatbot services in a phygital context. Drawing on the extended reality technology (ERT) framework and the stimulus – organism – response (SOR) model, it explores the cognitive – affective dynamics shaping chatbot adoption in a sensitive service setting. Data were collected from 396 elderly consumers of major insurance companies in Malaysia and analysed using structural equation modelling to assess mediating and moderating effects. Findings show that perceived trust critically mediates the relationship between cognitive factors and chatbot adoption. Technology anxiety and perceived complexity strongly moderate the trust – usage relationship, confirming a triadic interaction. The study advances theory by integrating the ERT – SOR framework to explain the physical – digital service dichotomy and the continuous use of chatbots. It also highlights the unique affective and psychosocial aspects of aging consumers and offers practical guidance for insurers to design trust-enhancing, user-friendly chatbot services for older users.

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Chatbot; ERT framework; SOR theory; technology complexity; service strategy; insurance industry

1. Introduction

In the dynamic world of the service industry, new paraphernalia of service delivery have emerged through technological development. The metamorphosis has been primarily driven by the advent of AI technology, which has enabled new service designs and customer interactions (Liu et al., 2024). This augmented, technology-driven service engagement has included chatbots that can emulate human interaction and manage consumer expectations, ranging from simple processes such as smart parking bills (Raj &

CONTACT Pantea Foroudi Pantea.Foroudi@brunel.ac.uk

Shetty, 2024) to complex information-oriented processes such as insurance claims, handled through highly customized bots (Patil et al., 2024). The key strategic aspect essential to the success of such endeavors lies in addressing the phygital nature of the service process, which demands a balanced approach to consumer interaction across service orientations (Gustafsson et al., 2025). The term 'phygital' in this context denotes the transcendence of a physical-to-digital approach in the service environment, which pertains to the experiential marketing mix leading to service performance transformation (Batat, 2024a). It involves integrating a service's physical and digital aspects to enable real-time solutions that satisfy the demand for better, more efficient service performance (Kumar et al., 2024). Although studies have observed the phygital alignment of the service domain in digital parlance, they have been limited to a multi-factor cognitive-affective dichotomy and its resonance in consumer decision-making. Several studies have inferred upon this aspect from varied research dimensions. To illustrate, a qualitative investigation in metaverse service design has revealed specific affective (sensory) alterations involving sight, sound, and taste as essential to phygital service orientation (Batat, 2024b). Similarly, studies involving AI-based portfolio management and AI-enabled (chatbot) customer services have stressed the differential adaptive ability based on cognitive and affective perceptivity of consumers that does not allow pervasiveness of such changes across every consumer group (Shaikh et al., 2024). However, the complex affective perceptuality that impacts strategic service design, especially in high-sensitivity services such as insurance, which closely align with anthropomorphic requirements (Patil et al., 2024), remains underexplored. Addressing such complexities mitigates digital vulnerabilities, thereby further strengthening the centrality of a physically informed, digitally enhanced phygital service orientation (Saragih, 2025). Hence, uncovering the relative impact of chatbot-based interactions in insurance services, which investigates the complexity of phygital affective components, is crucial. This would not only enhance understanding of phygital service orientation but also help optimize strategic maneuvering to deliver a better phygital experience.

Chatbots have proliferated across various service industries, including hospitality, tourism, retail, banking, and insurance, offering enhanced efficiency and effectiveness. Although highly regulated, insurance organizations have rapidly adopted chatbots, which add substantial value by managing multiple processes, such as premium calculation, grievance handling, routine policy inquiries, and even drafting complex policy plans (Jafar et al., 2023). The elderly population, who typically have little inclination for, and in some instances are not adept at, adopting such technology-enabled interactions (Leite et al., 2024), is likely to be affected by these service initiatives. One significant factor, alongside a lack of trust, is customers' perceived anxiety about new technology (Sun & Ye, 2024). It is not that older adults have a phobia of adopting new technology; rather, it reflects a state of resistance stemming from concerns about safety, privacy, and cognitive limitations (Sixsmith & Cosco, 2024). Reverting to phygital service orientation, a definitive strategy for connecting customers with the brand requires strong cognitive and affective proximity, which is a crucial service design challenge (Batat, 2022). This is another strength of phygital service orientation, which is based on the transition from a one-dimensional thought process, whether subject- or object-centric, to a liquid ontology (Batat, 2024). The transition gives rise to a service ecosystem that enables value co-creation across cognitive-affective dichotomies (Mele & Russo-Spena, 2025). Though studies have been undertaken to gauge affective components such as anxiety and depression and their contextual impact through chatbot implementation in the medical field (Pergantis et al., 2025), the triadic influence involving phygital transcendence has not yet been explored. Therefore, a deeper investigation of the mediating roles of trust and anxiety in observing chatbot-based service interactions toward phygital attribution is necessary.

In the insurance domain, the criticality of such observations is heightened, as the aging population constitutes the bulk of insurers' customer base and requires health insurance to cover their care (Purwar & Chawla, 2024). This is further supported by recent studies that have identified the limitations of chatbots in complex service environments. In such environments, human interaction is considered critical to completing the process. Although the above is contrary, other technologies, such as virtual reality, are supportive of cognitive and physical engagement among older adults (Mahmoud, 2024); similar outcomes for chatbots are not evident, as critical observations regarding perceived psycho-technical barriers persist. These barriers emanate from cognitive (i.e. AI-based knowledge/competency of human versus machine) (M. Huang & Ki, 2024) and affective (i.e. lack of trust in chatbot service interaction/fear of and anxiety about technology) factors that inhibit the transition from rejection to adoption (Chaudhuri et al., 2023; Zhang et al., 2024). This is critical to assess, as a lackadaisical approach typically fails to consider the social and personal coping mechanisms of aging consumers (Meng et al., 2022), thereby affecting phygital service design. However, ironically, this is absent from current chatbot intervention studies, which have either focused on the new generations (Magni et al., 2024) or have limited findings that can be construed as effective to gauge the socialization impact of phygital transition. Furthermore, the dichotomy of anxiety and complexity, including its impact on service flow, needs better interpretation. To further justify this, cognitive chatbot features may have different attributions from affective ones when the elderly population is considered, as evidenced by similar technological interventions in the medical field (Mishra et al., 2024). It has also been asserted that such attributions might be strongly influenced by the pure technical side of the phygital context, such as enhanced app features (Chatterjee et al., 2025) or a dominant psychology factor such as resistance to innovation (Hameed et al., 2025) However, the reasons for the varied affective perceptivity within this consumer group, and its cognitive underpinning in the service chatbot context, remain unclear. Therefore, in considering the relevant gaps, the current study strives to address the following pertinent questions:

RQ1: Would there be a differential impact of the cognitive-affective dichotomy that further supports age and service orientation complexity in AI service design?

RQ2: Would the psycho-social affective components significantly contribute to phygital aging consumers' behavioral ambiguity when encountering AI-oriented services?

Building on these research questions, the primary aim of this study is to theoretically extend and empirically validate the applicability of the extended reality technology (ERT) and stimulus-organism-response (SOR) frameworks in the context of chatbot services, with a specific focus on elderly consumers' phygital engagement. Accordingly, the study seeks to: (1) examine the influence of chatbot service orientation as a stimulus within socially interactive phygital environments; (2) investigate perceived trust as a core organismic mechanism that mediates the effects of perceived technology anxiety and complexity on user responsiveness; and (3) assess the strategic implications of affective trust in shaping elderly consumers' behavioural and psychological responses to chatbot services. Through these objectives, the research aims to generate theoretically grounded and practically relevant insights into how socially oriented chatbot interactions can enhance trust formation and improve technology adoption among ageing user groups in digitally mediated service ecosystems.

Several pivotal contributions of this study lie in its integration of rigorous empirical examination with theoretical advancement, thereby generating novel insights for chatbot service applications. First, it advances the extant phygital engagement literature by foregrounding the socialization interaction dimension, consequently reinforcing the extended reality technology (ERT) framework as a comprehensive representation of phygital experience (Batat & Hammedi, 2023). While prior research has substantiated the influence of technological interventions via ERT within virtual environments, particularly the metaverse (Batat, 2024; Mladenović et al., 2024), their applicability to the context of chatbot services remains insufficiently theorized. By operationalizing the stimulus-organism-response (SOR) model, this study systematically evaluates both the theoretical relevance and strategic implications of chatbot service orientation in shaping elderly consumer responsiveness.

Secondly, the study conceptualizes perceived trust (PT) as a central organismic construct, validating its role as a mediating bridge and psychologically contingent response to usage-related factors, namely perceived technology anxiety and complexity. Although contemporary scholarship has confirmed the antecedent influence of trust on chatbot usage behavior in financial service contexts, these effects have predominantly been examined as direct or moderating relationships. This perspective extends the sensory and affective scope of ERT by substantiating affective trust as an integral component of the triadic emotive relationship that fundamentally shapes the phygital experience perceived by the targeted elderly user cohort.

The structure of this paper is outlined as follows. The next section presents the theoretical foundations of this paper, including a review of pertinent literature and a theoretical model that explains the relationships among key variables identified within the trichotomic (stimulus, organism, and response) framework, integrating the two theories. The hypothesis is presented accordingly within this discussion. A succinct presentation of the applied methodology and sampling framework follows this. The subsequent section presents the comprehensive analysis undertaken, including structural and hypothesis testing using structural equation modelling (SEM). Lastly, the paper presents the findings and outlines the novel theoretical and practical implications, with a note on limitations and future research directions.

2. Background and review

2.1. Conceptual review

2.1.1. Stimulus: cognitive construct(s)

Subjective norms (SN) are identified as an 'individual's perception of whether significant others think that he/she should undertake a definite behaviour' (Park, 2000-pp-3). Age and subjective norms are observed to correlate in technology adoption and use. Earlier studies focusing on the effect of SN have found that they persuade aging workers to adopt technology. SN involving technological adoption may come from peers or superiors who influence others to follow their lead. In the SOR context, Wang et al. (2023) observed a direct cognitive impact of SN on citizens' sense of responsibility to participate in a smart-city project. This study interprets SN as a stimulus component derived from social knowledge and awareness about insurance chatbots. Similarly, a recent study on chatbot applications in the beauty industry found that SN strongly influenced consumer attitudes (Dassouli et al., 2025).

Facilitating conditions (FC) have been defined as 'objective factors in the environment that observers agree to make, including the provision of computer support' (Teo et al., 2008, p. 132). Past studies on AI adoption have identified FC's applicability from organizational and consumer perspectives. The presence of AI-based infrastructure, such as databases and data warehouses, and also cognitive factors, such as staff training and resource allocation, are considered critical when implementing organizational AI (Grover et al., 2022; Shams et al., 2024). Recent studies have found that FC cognitive strength is an indicator of consumer use of WhatsApp-based chatbot recommendations (Romero-Charneco et al., 2025). Though the impact of FC on AI-based adoption has been observed, its relative influence on perceived affective chatbot trust as an antecedent cognitive stimulus requires further exploration.

Since their inception, chatbots have been replacing human interaction by mimicking human communication patterns to interact with people (Satu & Parvez, 2015). A critical aspect of any chatbot interaction is its inability to consider the social and personal characteristics of the individual with whom it interacts, often highlighted as the anthropomorphic component of AI (Kumar et al., 2025). However, it is worth noting that social presence is a differentiated chatbot characteristic, which in a psycho-social manner aims to augment human-AI interactive acknowledgement (Lee et al., 2024). In the context of interactivity, the presence of a strong socialization characteristic in a chatbot fosters greater trust and flexibility in accommodating varied needs and user groups (Wang & Qiu, 2024). Hence, a more in-depth investigation of this chatbot characteristic in a specific service environment is necessary to improve understanding of the socializing intervention further.

2.1.2. Organism: affective construct(s)

As an affective intervention, trust is interpreted as the emotion that emanates from the belief in and/or experiences about the object (brand/service/product); trust makes it possible to create a better affinity towards brands, and simultaneously, strengthens the antecedent cognitive association towards behavior (Jeon, 2024). The construct of affective trust has been altered to fit various domains. Research on sustainable, green behavior has utilized 'green trust' as the affective mediating component to behavior (Chatterjee et al., 2017; Huang et al., 2024), while in AI-based behavior, trust is considered a strong cognitive as well as emotive intervening construct to gauge the human psyche (Riley & Dixon, 2024; Sheshadri, 2015; Vrontis et al., 2022). The strength of perceived trust as a direct and mediating factor transcends the contextual boundaries of applicability, whereby it extends from a behavioral influencer in an educational context (Chatterjee et al., 2023;

Polyportis & Pahos, 2025) to intervening in the emotional dimension in product and service descriptions (Cicek et al., 2025).

An integral attribute of product innovativeness, perceived complexity (PC) measures users' relative difficulty when using a new product. The degree of PC in a new technology product is associated with trust, as the latter helps to alleviate the fear of the former (Chatterjee & Mariani, 2022; De Kimpe et al., 2022). The level of complexity in adopting new technology might be perceived differently depending on the tasks it will perform. It has also been observed that the higher the perceived difficulty of operating a new technology, the lower the level of trust in the effectiveness of that technology (Chaudhuri et al., 2022; Choung et al., 2023). Although the direct effects of this construct as a cognitive antecedent in the context of machine intelligence have been tested (Adapa et al., 2020; Sheshadri, 2020), its affective impact on human–AI interaction remains to be explored.

In reference to interactions between humans and machines, technology anxiety represents an individual's fear or apprehension that can be triggered when using a new technology-oriented product or service (Morris &;. Studies examining AI phenomena have repeatedly focused on this construct and emphasized its influence on the individual's propensity to use AI-based applications, coining it 'AI anxiety' in certain respects (Kim et al., 2025). It is an effective response that mitigates the perceived negativity towards complex technology applications, which can limit the scope of technology use (Koechling et al., 2023; Ranjan et al., 2023). Therefore, in technology or AI parlance, measuring the extent to which technology-oriented anxiety impacts trust and inhibits AI-favored decision-making is essential.

2.2. Theoretical underpinning

2.2.1. Stimulus Organism Response (SOR) model

The SOR model represents the progressive impact of perceived external stimuli (FC) in the physical setting (stimulus) on the components influencing the individual's (organism's) affective dimension, resulting in a definitive action (response) towards that object (Bagozzi & Yi, 1988; Mehrabian & Russell, 1974). In the context of AI chatbots, stimuli refer to factors that contribute to engagement, such as the chatbot's specific characteristics, its popularity within the known community (subjective norm), and external environmental conditions that facilitate its use. The component of trust reflects the organism, as it is a perceived stimulus (psychological state) that can lead to an intention (response) towards the specific chatbot (Chen, 2023). In a service context such as e-commerce, the impact of the affective trust (organism) on the customer's specific service adoption (response) is significant. Similarly, SOR adaptation to assess the influence of chatbot service quality dimensions across varied service delivery environments, such as fast food (Elayat & Elalfy, 2025) and online luxury brands (Shahzad et al., 2024), demonstrates the model's viability for measuring chatbot service implementation. Recent studies employing similar theories, such as UTAUT, to investigate the impact of chatbots on phygital consumers have identified chatbot interactivity (performance expectancy), social influence (subjective norm), and consumer trust as key antecedent factors influencing engagement and behavior (Nyagadza et al., 2022). An extended TAM-based observation of perceived utility and service appropriateness has also been undertaken (Liu et al., 2024). However, the scope of such models is more focused on the attitudinal manifestations of technology adaptation. It does not involve observing the cognitive-affective interplay, which is equally important, as such interactions differ across specific user groups; hence, acceptance cannot be generalized.

2.2.2. Extended Reality Technology (ERT) and SOR

As the current study explores the engagement dimension of a chatbot, it draws from the socialization dimension of the extended reality technology framework, which considers such technologies as virtual socialistic agents that bridge the physical-digital divide, which is an integral aspect of a successful phygital experience (Batat, 2024a). Enhanced phygital customer experience (CX) is a multidimensional construct that involves gauging the cognitive and affective components and their relative interaction in a social setting that connects (engages) the consumer to the brand (Alexander & Varley, 2025). It is worth noting that the current research aims to examine both direct and moderating influences that vary according to older people's actual experiences interacting with a chatbot, both on-site (at the insurance company premises) and online (via mobile or laptop). This pertains to experiential research examining phygital experiences that are challenging to observe due to their hybrid nature, eliciting complex, interrelated cognitive and affective responses (Batat, 2023). The integration further helps ascertain the technological attribution to the user's perceptivity dimension. Recent studies, albeit in the tourism context, have adopted an integrated approach to examine the complex interplay between media type and its relative impact on virtual tourism perceptivity (Dutta & Dixit, 2025). Hence, it is evident that integrating SOR acts as an equilibrium that facilitates canvassing the phygital engagement of chatbot service tasks to user perceptivity. Further, the SOR-based service determinants and the adaptability of the SOT framework enable concurrent alignment of variables to assess physical and digital engagements effectively.

3. Hypothesis development

3.1. Subjective norm

Subjective norms (SN) in technology and social parlance are perceived pressure from one's social network that directly or indirectly (as a mediator or moderator) influences the user's technology attitude and acceptance (Islam et al., 2024). Although SN was introduced to attitude research through the technology acceptance model, its applicability in technology-oriented judgments and its connection to the socialization process of elderly consumers are evident in recent studies (Subhra Chatterjee et al., 2025). This phenomenon has been observed across different technology-based products; however, the results have been mixed. As an example, in online shopping behavior, SN was not found to impact older adults' decision to continue such behavior (Wu & Song, 2021). However, utilizing the SOR framework, Irimia-Diéguez et al. (2023) found the individual's SN to be a strong cognitive stimulus that impacts the perceived use of peer-to-peer mobile payment systems. It is worth noting that, as an extensively researched construct, the associative outcomes would differ across industries or domains of observation. For example, its influence on perceived trust has differed significantly depending on the theoretical positioning of these two variables, although the outcomes were significant. To further substantiate, the antecedent SN impact on e-banking adoption behavior has been significant, with perceived trust as a social factor (Jermsittiparsert et al., 2023). In contrast, the consequential impact of SN on the aging population is evident when individuals agree to use household-based Internet of Things applications (Jaspers & Pearson, 2022). Hence, as a cognitive stimulus of a chatbot, its impact on affective perceptivity is inferred to be significant. Based on these findings, the following hypothesis is formed regarding the impact of subjective norm.

H1: Subjective norm (stimulus) impacts the insurance chatbot's perceived trust (organism).

3.2. Chatbot characteristics

According to social constructivism theory, the characteristics of a chatbot are essential for effective interaction, underscoring the importance of a chatbot having cognitive, intellectual, and motor skills (Bialkova, 2024). This is critical in the current study context, as the specific alignment of chatbot characteristics (CC) as a cognitive link establishes its role in the SOR context. In a study on chatbot interaction, Chaves and Gerosa (2020) explored the social aspect of the CC when used in service contexts. They implied that it can be domain-specific or general. This signifies the dimensionality of CC's impact on the consumer's behavioral aspect as a knowledge component. Subsequently, efforts have been made to improve chatbots' personality characteristics to leverage their influence on users' perceived trust (PT). The impact of such distinctive characteristics on generating trust and interactivity is also observed to differ by age, prior experience with chatbots, and social setting. For example, intervention studies have found a negative association between certain social factors, such as identity consistency among citizens, and interactions with government-allocated chatbots (Ju et al., 2023). To summarize, the findings indicate that the effective attribution of CC in a service setting may have differential impacts on the affective and behavioral components, depending mainly on the user's characteristics. To further elicit, though CC has been firmly attributed as a functional (cognitive) characteristic, it is also considered to exhibit anthropomorphic traits, such as warmth and empathy, in handling service inquiries (Sestino et al., 2025). Hence, the following hypothesis on the impact of chatbot characteristics is proposed.

H2: Chatbot characteristics (stimulus) impact insurance chatbots' perceived trust (organism).

3.3. Facilitating conditions

Facilitating conditions (FC) are the factors that help individuals better understand technology. In a service interaction setting, this construct is interpreted as the signifying factor that facilitates system adoption through augmented trust and has been observed in specific AI-oriented studies utilizing UTAUT (Strzelecki & ElArabawy, 2024). The applicability of FC within an enterprise as a cognitive factor is well evident. Earlier studies on chatbot applications found FC to be a deliberative rationalization factor that helps reduce the perceived complexity of this new technology for users (Brachten et al., 2021). The ambivalent role of this construct in technology parlance can be seen in its differing cognitive impact across contexts. As an example, in a study conducted on the adoption of mobile payment systems, the quality of information provided to users to facilitate their decision-making was found to impact their adoption of this technology (Gao & Waechter, 2017). However, its impact on students' motivation to adopt and use voice-over assistants was found to be negligible (Al Shamsi et al., 2022). Furthermore, FC has been linked to ChatGPT AI technology and the trust issues associated with it. As an example, the impact of FC as a direct influencer of behavioral intention was examined in a meta-UTAUT-based study (Polyportis & Pahos, 2025). Still, the associative strength of FC as a cognitive stimulus within a cognitive affective AI-enabled service orientation is not definitive. This substantiates the need to explore the facet of FC further to gauge its effectiveness as an antecedent cognitive factor of perceived trust.

H3: Facilitating conditions (FC) impact the insurance chatbots' perceived trust (PT).

3.4. Perceived trust

Perceived trust (PT) has been observed to facilitate decision-making processes that directly influence individuals' BIs. Organizational factors, such as vendor reputation and expertise, and environmental factors, such as sustainability impact, have significantly affected people's perceived benefits and perceived use intentions for electric vehicles (Featherman et al., 2021). In a study on the effect of chatbot disclosure, Mozafari et al. (2022) observed that PT is an antecedent of cognitive identification of a chatbot and has varied impacts across different service-related contexts. The study found that, depending on the importance of the service delivered by the chatbot (high versus low), disclosing the chatbot's identity affects consumer retention rate (negative/positive), with this effect mediated by the trust component. Recent observations, which have deepened the psychological trust mechanism, have also shown its significance across varied demographics. According to Küper and Krämer (2025), the propensity to trust in an AI-oriented environment can vary across user groups, which, in turn, can be influenced by their technological affinity and expertise. However, the interrelationship between affective psychological comfort, experienced anxiety, and perceived complexity, and its direct effect on aging consumers' behavior within fully AI-mediated service encounters, remains largely underexplored. It is also evident that PT has strong demographic allegiance, with its impact on initiating and continuing AI-enabled services varying across countries. Hence, based on the above discussion, this study takes the following hypothesis on the influence of perceived trust.

H4: Perceived trust (PT) impacts customers' behavioral intention (BI) towards insurance chatbots.

3.5. Perceived technology anxiety and perceived complexity

3.5.1. Direct effect

Though technology anxiety is well documented, with the advent of AI-based technologies, perceived technology anxiety has gained greater prominence, especially in relation to user orientation (Kim et al., 2025). The source of such anxiety lies in the consumer, though the manifestation may differ. For example, the impact of anxiety on the adoption of new information system-based devices directly influences perceived usefulness and relative ease of use (Huang et al., 2024). At the same juncture, motivation and acquired skill set might render this anxiety insignificant in behavioral manifestation, as observed among AI teachers in schools (Ayanwale et al., 2022). Hence, the following hypotheses are proposed for the above constructs and their relative influence on trust and BI towards chatbots.

$H5_a$: Perceived technology anxiety (PTA) impacts the perceived trust (PT) of insurance chatbots.

The role of perceived complexity (PC) in technology adoption and transference is well documented. Earlier studies in similar service industries, such as insurance, have asserted the relevance of PC in the context of product trust, both as a direct and mediating factor (Wang & Lu, 2014). Furthermore, the system complexity associated with new technologies and products has also been observed. The direct impact of PC is evident among consumers with a higher degree of innovativeness. using intelligent retail technologies (Adapa et al., 2020), and in the case of business-to-business AI adoption and use intention (Polisetty et al., 2024). Hence, the following hypothesis based on the impact of PC is being taken.

$H5_b$: Perceived complexity (PC) impacts perceived trust (PT) of insurance chatbots.

3.5.2. Moderating effect

Several studies have highlighted the mediating role of technology-oriented anxiety in technology adaptation and decision-making across different technological stances. Perceived Technology Anxiety (PTA) in the context of mobile health services has been shown to act as a significant moderator of both the cognitive and affective components of these services (Meng et al., 2022). Also, technology anxiety was observed to moderate the relationship between attitude and continuous intention to use mobile learning among students (Huang et al., 2022). Similarly, the moderating effect of perceived complexity (PC) in mobile learning on organizational task performance is found to influence employers' attitudes towards such learning (R. T. Huang, 2024). This was further refined by observing specific task-related complexity. It was found that the perceived enjoyment of undertaking the task, along with the employees' frequency of performing that task and the task's complexity, are intrinsically linked (Li et al., 2024). It is also perceived that this warrants further exploration due to the enhanced complexity of AI-enabled chatbots, which exhibit greater capabilities and emulate human interaction more effectively than their predecessors (Xiao et al., 2025). Hence, the following hypotheses are taken:

$H6_a$: Perceived technology anxiety (PTA) moderates the relative impact of perceived trust (PT) on customers' behavioral intention (BI) towards the insurance chatbot.

$H6_b$: Perceived complexity (PC) moderates the relative impact of perceived trust (PT) on the customers' behavioral intention (BI) of the insurance chatbot.

3.6. Subjective norms, chatbot characteristics, and facilitating conditions

The role of perceived trust (PT) in chatbot-based applications has been of relative importance, both as a direct and an indirect construct. In e-retailing-based chatbot applications, trust impacts the perceived risk and the flow. These effects have been demonstrated in both quantitative and qualitative inquiry. As an example in experimental research on uncanny valley effects in e-commerce chatbots, trust mediated the effects of purchase intention and the customer's willingness to reuse the same chatbot (Song & Shin, 2024). Similarly, another recent experimental design exploring multiple trust dimensions and the dispositional trust of the chatbot service provider found that dispositional trust of the chatbot service provider mediated the user's learned trust. It is also evident that, as an affective (emotional) factor, the consequential impact of PT is augmented by stronger facilitating conditions, such as stronger app grounding and ensuing app characteristics that enhance perceived control and data privacy (Shabankareh et al., 2025). Hence, the following hypothesis on the mediating effect of PT is proposed:

$H7_a$: Perceived trust (PT) mediates the impact of the subjective norm (SN) on the behavioral intention (BI) of aging consumers.

$H7_b$: Perceived trust (PT) mediates the impact of chatbot characteristics (CC)on the behavioral intention (BI) of aging consumers.

$H7_c$: Perceived trust (PT) mediates the impact of facilitating conditions (FC) on the behavioral intention (BI) of aging consumers.

With all these inputs, a conceptual model is developed and is shown in Figure 1.

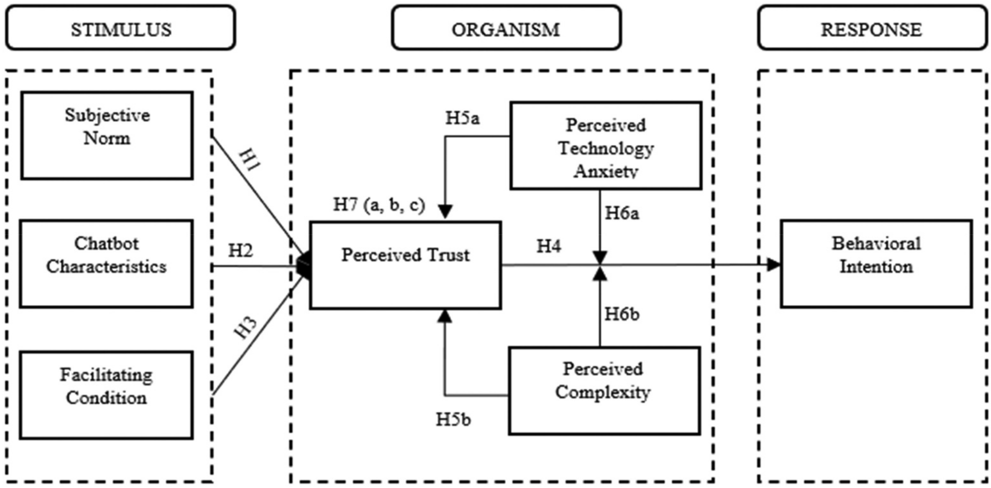


Figure 1. Conceptual framework.

4. Research methodology

4.1. Sampling and data collection

The survey was conducted in four major cities in Malaysia: Kuala Lumpur, Penang, Johor Bahru, and Kuching. The justification for this approach was to include the diverse aging population from different regions in Malaysia. Furthermore, considering the study's objective, which required a quantitative investigation of the construct relationships with a larger sample size representing the Malaysian insurance service sector, the survey method was deemed more appropriate than other methods, such as interviews. The choice of metropolitan cities was also relevant since all major insurance service organizations had established service networks in these cities. Purposive sampling was utilized to identify a representative sample from major insurance service providers. The choice of sampling method was based on the scope, objective, and the study's demographic location, with previous studies emphasizing this sampling design for better statistical accuracy within the study context (Hameed et al., 2024). The survey questionnaire was self-administered by the researcher during visits to the office service premises, and an online link to the questionnaire was also made available to participants. The research instrument was designed in English, and all respondents in the study had a minimum graduate-level qualification in English. This filter ensured the respondents understood the instrument clearly, as English is not Malaysia's native language. Participants were also filtered by age to ensure the sample represented people aged 60 or older.

All the participants were asked about their recent insurance-based chatbot interactions to indicate which insurance organization's chatbot-based service they used. Furthermore, as most insurance companies in Malaysia use standardized chatbot facilities for customer service inquiries, this was used as the main inquiry component (i.e. have you had any AI/chatbot customer service interaction with any insurance company in the last 6 months?). This negated the effect of different insurance products, which might differ in their interactions. It is hypothesized that, regardless of the product's nature, chatbot-based

Table 1. Demographic profile of respondents.

Characteristic	Particular	Frequency	Percentage
Gender	Female	154	38.9
	Male	242	61.1
	Not Specified	0	0
Age	60 to 65	267	67.4
	66 to 70	106	26.8
	71 and above	23	5.8
Income	Below RM 2000	86	21.7
	RM2001-RM3999	193	48.7
	RM4000-RM5999	110	27.8
	RM 6000 and above	7	1.8
Occupation	Employed work (Contractual)	42	10.6
	Self-Employed (Business)	85	21.4
	Retired	269	32
Education	Bachelor (Degree)	174	43.9
	Master (Degree)	203	51.3
	PhD	19	4.8
AI Customer Service Interaction in the last 6 months (Phone/Web service)	1 to 3 times	83	20.9
	4–5 times	298	75.3
	More than 5 times	15	3.8

interaction will have a similar cognitive and affective influence. Recent studies on insurance-based chatbot interaction have used similar methods to standardize interactions across different organizations' chatbot services to establish the anthropomorphic characteristic (Patil et al., 2024). A total of 396 respondents completed the questionnaire. Also, as the retirement age in Malaysia is 60, most respondents were retired, while the others were either self-employed (business) or engaged in contractual work. The demographic profile of the sample respondents included in this study and the frequency of chatbot/AI-based service interaction and is shown in Table 1.

4.2. Survey instrument and measurement scale

All items used in the study were drawn directly from previous research that employed validated measurement scales, which is considered an essential requirement for effective measurement. Although some items on the scales were slightly adjusted to fit the study domain, no significant changes were made, which is considered acceptable when using pre-validated items (Roth-Cohen et al., 2025). All the chosen studies utilized the 7-point Likert scale which allowed standardization in terms of measurement and analysis. In total, 27 items were utilized to assess seven constructs, each measured on a 5-point Likert scale. Specifically, subjective norms (SN) and chatbot characteristics (CC) comprised 4 and 5 items, respectively, sourced from Choi and Chung (2013) and Nordheim et al. (2019). Three items were used for FC, PT, and PC, taken from Terblanche and Kidd (2022), Yen and Chiang (2021), and Adapa et al. (2020). PTA was measured using four items from Li et al. (2021), while BI comprised five items adapted from Kasilingam (2020). Table 2 below indicates the measurement of the items and constructs described in this section.

Table 2. Estimation of the assessment items and constructs.

Constructs	Item description	LF	AVE	CR	α
SN	**Subjective Norm**		**0.720**	**0.877**	**0.870**
SN1	Other people think that using of insurance chatbots is important to me.	0.811			
SN2	Many of the people that I know expect me to continuously use insurance chatbots	0.871			
SN3	Others would probably make me feel guilty if I quit using insurance chatbots.	0.845			
SN4	Many of the people that I know would be surprised if I just did not use insurance chatbots	0.866			
CC	**Chatbot Characteristics**		**0.679**	**0.884**	**0.884**
CC1	The content of the insurance chatbot reflects expertise	0.801			
CC2	I feel very confident about the chatbot's competence in managing my inquiry	0.810			
CC3	The insurance chatbot is well equipped for the task it is expected to do	0.842			
CC4	The insurance chatbot appears knowledgeable about the different service inquiries	0.841			
CC5	I have experienced to get my question answered by the insurance chatbot	0.838			
FC	**Facilitating Condition**		**0.673**	**0.757**	**0.756**
FC1	I have the resources necessary to use the insurance chatbots	0.774			
FC2	I have the knowledge necessary to use the insurance chatbots	0.843			
FC3	I think that using the chatbot for insurance purpose fits well with the way I like to develop myself.	0.841			
PT	**Perceived Trust**		**0.747**	**0.832**	**0.831**
PT1	This chatbot as a conversational agent is trustworthy	0.856			
PT2	I trust the ability of this chatbot as a conversational agent	0.863			
PT3	This chatbot as a conversational agent is adequate for my need	0.875			
PTA	**Perceived Technology Anxiety**		**0.731**	**0.900**	**0.875**
PTA1	I have avoided insurance chatbot services because they are unfamiliar to me.	0.877			
PTA2	I hesitate to use insurance chatbot services for fear of making mistakes I cannot correct	0.918			
PTA3	I have difficulty understanding most technological matters relating to insurance chatbot services.	0.901			
PTA4	I am not able to keep up with important technological advances, such as the development of chatbot services	0.708			
PC	**Perceived Complexity**		**0.814**	**0.888**	**0.886**
PC1	Insurance chatbots are complex in nature	0.894			
PC2	Understanding the use of chatbot takes a lot of effort	0.918			
PC3	Communicating with chatbots is confusing	0.894			
BI	**Behavioural Intention**		**0.708**	**0.898**	**0.897**
BI1	Now I intend to use insurance chatbots to solve my insurance related inquiries	0.839			
BI2	Assuming that I have access to insurance chatbots, I intend to use it.	0.846			
BI3	During the next 6 months, I intend to use chatbots for shopping.	0.852			
BI4	I intend to use insurance chatbots for the next 5 years	0.820			
BI5	Using insurance chatbots is pleasant for me	0.851			

5. Data analysis and results

5.1. Measurement model assessment

This study employed SPSS version 26.0 for descriptive statistical analyses and to assess common method bias, while SmartPLS 4 was used for structural equation modelling and hypothesis testing. The Partial Least Squares Structural Equation Modelling (PLS-SEM) was chosen over covariance-based SEM (CB-SEM) based on the study's analytical aims and data properties, which align with the circumstances in which the methodological literature recommends PLS-SEM (Chatterjee et al., 2025). In particular, the study emphasizes prediction and the estimation of a comparatively complex structural model, requiring a multi-attribute modeling approach (Chatterjee et al., 2025; Hameed et al., 2024). In addition, the model specification includes formative measurement constructs and necessitates the computation of latent variable scores for subsequent analyses (Hair et al., 2019). The distributional properties of several observed indicators deviate from multivariate normality, further limiting the suitability of CB-SEM. Finally, given the modest sample size relative to the number of model parameters, PLS-SEM offers more robust parameter estimation and statistical power. Contemporary advances, such as consistent PLS algorithms, additionally allow results to be interpreted within a common-factor framework when appropriate, thereby mitigating one of the traditional limitations of variance-based SEM approaches (Hair et al., 2021). Table 2 shows the estimates of Cronbach's alpha values (0.750 to 0.897), which are well above the required threshold value of 0.70 (Black et al., 2010). Next, the composite reliability estimates range from 0.757 to 0.900, and the average variance extracted (AVE) ranges from 0.673 to 0.814, thereby fulfilling the threshold values for strong convergent validity (Hair et al., 2019). (Table 2).

Subsequently, Table 3 shows the factorial loadings of all measurement items that are above the required benchmark value of 0.60. The average variance extracted (AVE) scores ranged from 0.673 to 0.814, which is well above the threshold value requirement of 0.5 (Fornell & Larcker, 1981). It is also observed that the AVE square root of each construct was greater than its correlation with any other construct (Table 3). Additionally, in reference to the HTMT criterion, all the construct values fall below the threshold of 0.9 (Sarstedt et al., 2021). Thus, the measurement model shows good fit indices, including reliability and convergent and discriminant validity. 5.2 Structural model and hypothesis testing

5.1.1. Direct effect

Figure 2 presents the structural model assessment. The hypothesis testing was conducted utilizing Smart PLS4, which involved 5,000 resamples with specified multiple iterations (Hair et al., 2019), and the results are presented in Table 4. The direct effect hypothesis, which included hypotheses H1, H2, H3, and H4, respectively, was supported (p 0.05). However, the direct effects of FC and PTA, pertaining to hypotheses H5a and H5b, respectively, are not supported ($p > .05$).

Table 3. Test for discriminant validity.

Constructs	BI	CC	FC	PC	PT	PTA	SN	PC x PT	AVE
BI									0.708
CC	0.793								0.683
FC	0.885	0.806							0.673
PC	0.530	0.447	0.550						0.814
PT	0.890	0.819	0.889	0.486					0.748
PTA	0.564	0.461	0.527	0.572	0.468				0.731
SN	0.763	0.793	0.858	0.425	0.826	0.428			0.720
PC x PT	0.849	0.763	0.797	0.360	0.794	0.458	0.706		
PTA x PT	0.865	0.760	0.802	0.451	0.835	0.427	0.713	0.876	

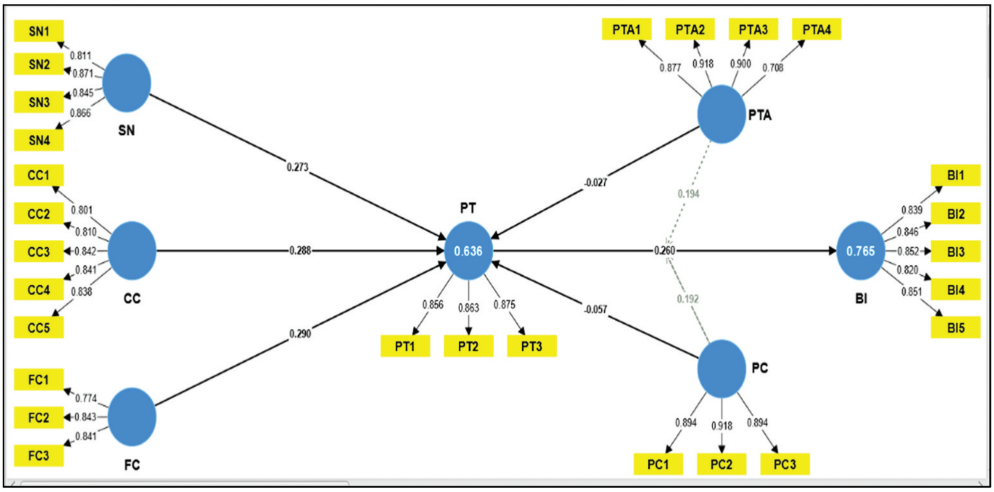


Figure 2. Structural model.

Table 4. Hypothesis testing.

Linkages	Hypotheses	Path coefficients (β values)	p-values	t-statistics
SN→PT	H1	0.273	.000	3.502
CC→PT	H2	0.288	.001	3.299
FC→PT	H3	0.290	.000	4.017
PT→BI	H4	0.260	.000	6.024
PTA→PT*	H5a	−0.027	.487	0.695
PC→PT*	H5b	−0.057	.078	1.766
(PT→BI) × PTA	H6a	0.194	.014	2.465
(PT→BI) × PC	H6b	0.192	.019	2.342
SN→PT→BI	H7a	0.071	.001	3.211
CC→PT→BI	H7b	0.075	.006	2.762
FC→PT→BI	H7c	0.076	.001	3.338

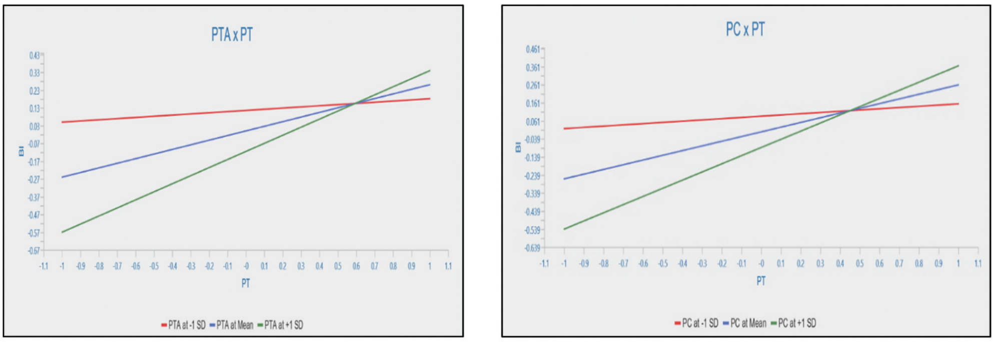
*Not supported.

5.1.2. Mediation effect

The hypotheses H7a ($\beta = 0.071$, $t = 3.211$, $p < 0.05$), H7b ($\beta = 0.075$, $t = 2.762$, $p < 0.05$) and H7c ($\beta = 0.076$, $t = 3.338$, $p < 0.05$) proposed the mediating impact of perceived trust (PT) on subjective norms (SN), chatbot characteristics (CC), and facilitating conditions (FC). They are all observed to be significant and accepted. Table 4 shows the hypothesis testing.

5.1.3. Moderation effect

Hypotheses H6a and H6b were taken to investigate the moderation effect of PTA and PC on individuals' behavioral intention (BI) towards insurance chatbots. They are observed to be significant based on the path coefficient values of H6a ($\beta = 0.194$; $p < 0.05$) and H6b ($\beta = 0.192$; $p < 0.05$). Additionally, the effects of PTA and PC on PT are further illustrated through the graphical interpretation of their relative intersection points. As depicted in Figures 3(a,b), respectively, both PTA and PC had a conditional, indirect effect that was significant at low (-1SD) and high (+1SD) with respect to the impact of PT on BI. Therefore,



(a) (b)

Figure 3. (a) PTA and PT (Slope). 3(b) PC and PT (Slope).

the moderation effect is further established through this representation. Figures 3(a,b) show the moderation effects.

6. Discussion

This study examined cognitive and affective determinants of AI-powered chatbot adoption among older insurance customers. Anchored in the stimulus – organism – response (SOR) model and the social interaction dimension of electronic relational theory (ERT), the research tested how cognitive factors – subjective norms, chatbot characteristics, and facilitating conditions – influence perceived trust. It further assessed the role of trust in shaping behavioral intention (BI) toward chatbot use, as well as the direct and moderating effects of perceived technological anxiety (PTA) and perceived complexity (PC) on trust.

The findings reveal that all cognitive stimulus components – subjective norm (SN), chatbot characteristics (CC), and facilitating conditions (FC) – exert a statistically significant, direct influence on perceived trust (PT) in chatbot use. These results are broadly consistent with prior empirical evidence, albeit derived from divergent contextual and demographic settings. First, the cognitive salience of SN and CC as antecedents of technology-related behavioural responses has been documented across various digital service domains, including hotel booking applications, where social influence and system-related attributes jointly shape user perceptions and behavioural intentions (Islam et al., 2024). In the context of ageing consumers, this suggests that communal endorsement, peer alignment, and shared experiential narratives function as critical social referents that legitimize the adoption of emergent service technologies.

Second, the instrumental significance of facilitating conditions (FC) has been similarly corroborated in AI-enabled healthcare applications, such as informational systems designed for pregnant women in hospital settings (Liew et al., 2023), indicating that infrastructural support, accessibility of resources, and guidance mechanisms collectively enhance trust formation in technologically mediated interactions. Extending this logic, the present study demonstrates that, in complex, technology-intensive service encounters, the availability of enabling support structures serves as a foundational mechanism for trust building. Notably, within phygital service environments – characterized by limited physical service options and increased reliance on reciprocal human – technology interaction – the theoretical and empirical substantiation of FC remains underdeveloped. The current findings, therefore, contribute to the literature by empirically validating the direct effect of facilitating conditions on perceived trust, thereby expanding the nomological network of cognitive antecedents relevant to chatbot interactivity in settings where traditional face-to-face service access is limited.

Moreover, these results underscore the strategic challenge faced by organizations operating in phygital ecosystems, in which the effectiveness of chatbot deployment depends not only on technological sophistication but also on enhancing socially interactive capabilities and providing tailored educational resources for ageing users. In this regard, the phygital consumer experience necessitates organizational competencies that integrate adaptive interface design, user-centric guidance, and continuous support mechanisms to mitigate technological uncertainty and foster trust-based engagement among elderly consumers during the adoption process.

The central organism or emotional construct, PT, directly affected the aging consumer's intention to use chatbots. The role of PT in chatbot interaction has been observed previously. However, in a consumer-based setting, the focus has been either on chatbot usage as an antecedent (Mostafa & Kasamani, 2022) or on a comparative analysis of human versus AI-based trust levels (Seitz et al., 2022). The current study augmented the implied trust that acts as a bridging factor between understanding a chatbot and using it in everyday life. However, PTA and PC had no direct impact on trust. This outcome both supports and contradicts previous results, though in a limited manner. The perceived level of AI anxiety during technology adoption was found to play both a direct and a moderating role in perceived trust. The current study builds upon prior work on the role of anthropomorphism in facilitating chatbot engagement (Nyagadza et al., 2022). It asserts the cognitive importance of proper guidance and social support in creating a phygital insurance chatbot experience.

The current study also found a strong mediating effect of PT on the relationship between cognitive factors and BI. The mediating role of perceived trust in a phygital context underscores the relative importance of organism-level (affective) mechanisms in shaping user responses. This finding is particularly novel considering aging consumers' interactions with technology in hybrid service environments. Nevertheless, comparable evidence has been reported in prior studies, where trust was found to significantly mediate the relationship between antecedents and performance expectancy in the context of student engagement with ChatGPT (Amin et al., 2025).

7. Implications of the study

7.1. Theoretical implications

First, the current study is a pioneering effort to examine the BI of aging consumers in relation to AI-powered insurance chatbots in a physical context. Earlier studies observing phygital consumers have focused on the cognitive affective dichotomy, but not on the complex trichotomic intervention involving affective factors that includes the perceived level of anxiety. Applying the SOR model, the current study extends the work by augmenting AI-oriented phygital consumer engagement and by further exploring the knowledge-emotive complexity of human-computer interactions in insurance service design. Furthermore, this finding relates to the strategic aspects of customer lifetime value (CLV) from a triadic impact perspective. As it is envisaged that, from a strategic standpoint, effective service engagement augments the propensity to derive a higher CLV from each customer segment (Kmet & Copulsky, 2024), the current outcome aligns with this premise; however, from a phygital service orientation perspective. This is considered a novel implication, as the tri-component-based affective dimension is a new extension of the organism component of the SOR model.

Secondly, the impact of perceived trust on the use of new technology (e.g. insurance chatbots) among older consumers remains underexplored. Earlier studies have observed trust as a mediator of perceived usefulness and perceived ease of use for intended use technologies such as 5 G mobile wallets and mobile payments (Chawla & Joshi, 2023). and navigation systems. From a marketing strategy perspective, this outcome underscores the role of affective trust in developing a competitive advantage in the service domain. This also substantiates the strength of trust interactivity and its ability to influence other affective components in a service domain (Ng & Zhang, 2025) and provides a new perspective on an augmented technology-based marketing strategy.

Thirdly, the moderating effects of PTA and PC on trust in the BI route have not been examined in prior studies. The moderating effect of PTA on the relationship between service failure severity and blame attribution has been observed in the context of negative attribution in mobile services. The current study reiterates the earlier finding that PTA and PC are components of direct or mediating effects. However, it extends the co-existential aspect of technology and anxiety towards PT as an affective influence. This is a novel implication, as the PC of chatbot-based interactive applications is considered an extraneous or conditional impact or as a cognitive antecedent to the human-computer exchanges that even impacts intra-human behavior (Xia et al., 2025). The trichotomous affective relationship in chatbot interactions among older adults has not been examined through a theoretical lens prior to this study.

7.2. Practical implications

The study provides several practical implications for insurance and other service organizations planning to employ chatbot-based consumer services. Firstly, the cognitive-affective dichotomy and its associated components provide a novel pathway towards interpreting the physical and emotional input required by aging consumers. A few recent studies have documented this for hotel- and hospital-based (Islam et al., 2024) AI applications, where superior cognitive input has helped to reduce the perceived complexities of interaction. However, the emotional triadic impact indicates that, even when chatbot physical features and service facilitation conditions are well endowed, strategic input through effective marketing communication is necessary to address organism-based components such as trust, anxiety, and complexity. It asserts a reassessment of the service design strategy for chatbot-based encounters and proposes a segmented approach to this group of consumers, allowing differential service treatment.

Secondly, the direct and mediating effects of affective trust indicate that such an effort can improve consumers' belief in the system and influence their behavior toward the chatbot, rather than focusing solely on improving cognitive or information-based trust. This emphasizes the strategic marketing communication that should resonate with the chatbot's trust from a socially accepted viewpoint. It extends the earlier implications, pinpointing the realignment of chatbot promotional efforts (Majid et al., 2024) by incorporating ERT-based sensory input into communication to strengthen awareness of the phygital experience, which can be delivered through a chatbot interaction.

Finally, the moderating impact of affective factors, namely perceived technology anxiety and perceived trust, leads the path to a stronger persuasive intent that should be delivered to cater to the emotions of the elderly user group. In managerial terms, this finding paves the way for a novel chatbot implementation framework that should primarily focus on strategizing the affective influence factors and the perceived trust associated with them, before delving into a conducive environment. This will ensure a smoother transition and acceptance by concurrently increasing trust in the organism and reducing the technology-anxiety component among the elderly group.

8. Limitations, conclusion, and future research scope

This study has several limitations that are inherent to its scope. Elaborating on the scope, the study applies only to insurance-based chatbot inquiries. Though it can be hypothesized that a similar behavioral impact will be reflected in customer query-based chatbot interactions across the financial industry, the generalizability of the findings requires further corroboration. In the context of model development, the combined SOR model and the ERT framework were utilized to investigate the triadic impact of the affective domain variables on the aging population. Hence, the outcomes are valid only for older consumer groups, as the cognitive-affective congruence across age varies significantly. Secondly, from a data perspective, utilizing purposive sampling and restricting the sample to English-speaking populations also limits the study's generalizability. However, as a pioneer attempt to gauge chatbot interactivity among insurance service users, the purposive sampling with restrictive language barriers was deemed suitable. The cross-sectional design, however, facilitated capturing the essence of interactivity concurrently across demographics, but it does limit the interpretation of causality to a certain extent. Additionally, the current study does not account for associated demographic factors, such as the respondents' location and ethnicity, which may influence the behavioral outcome, as these factors in a phygital setting are considered uncontrollable (Jacob et al., 2023).

Future research may focus on extending the findings of this study by applying them to various service settings and incorporating longitudinal research to test the replicability of the results. Studies can be undertaken to gain a deeper understanding of the psychosocial determinants of attitudes and causal influences on the aging cohort's perceptions of chatbot-based service design, particularly in the context of human-chatbot interaction. Given the comprehensive scope of the ERT framework, it is also advisable that future research further explore the dimensional construct that reflects the socialization aspect of phygital interactions in service-based AI and chatbot applications.

Disclosure statement

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ORCID

Sheshadri Chatterjee http://orcid.org/0000-0003-1075-5549
Demetris Vrontis http://orcid.org/0000-0001-7570-6241

References

Adapa, S., Fazal-E-Hasan, S. M., Makam, S. B., Azeem, M. M., & Mortimer, G. (2020). Examining the antecedents and consequences of perceived shopping value through smart retail technology. *Journal of Retailing & Consumer Services*, *52*, 101901. https://doi.org/10.1016/j.jretconser.2019.101901

Alexander, B., & Varley, R. (2025). Retail futures: Customer experience, phygital retailing, and the experiential retail territories perspective. *Journal of Retailing & Consumer Services*, *82*, 104108. https://doi.org/10.1016/j.jretconser.2024.104108

Al Shamsi, J. H., Al-Emran, M., & Shaalan, K. (2022). Understanding key drivers affecting students' use of artificial intelligence-based voice assistants. *Education and Information Technologies*, *27*(6), 8071–8091. https://doi.org/10.1007/s10639-022-10947-3

Amin, M. A., Kim, Y. S., & Noh, M. (2025). Unveiling the drivers of ChatGPT utilization in higher education sectors: The direct role of perceived knowledge and the mediating role of trust in ChatGPT. *Education and Information Technologies*, *30*(6), 7265–7291. https://doi.org/10.1007/s10639-024-13095-y

Ayanwale, M. A., Sanusi, I. T., Adelana, O. P., Aruleba, K. D., & Oyelere, S. S. (2022). Teachers' readiness and intention to teach artificial intelligence in schools. *Computers and Education: Artificial Intelligence*, *3*, 100099. https://doi.org/10.1016/j.caeai.2022.100099

Bagozzi, R. P., & Yi, Y. (1988). On the evaluation of structural equation models. *Journal of the Academy of Marketing Science*, *16*(1), 74–94. https://doi.org/10.1007/BF02723327

Batat, W. (2022). *Strategies for the digital customer experience: Connecting customers with brands in the phygital age*. Edward Elgar Publishing.

Batat, W. (2023). Experiential research as a methodological framework for studying consumer behaviors in phygital settings. *Qualitative Market Research: An International Journal*, *26*(3), 269–277. https://doi.org/10.1108/QMR-12-2022-0178

Batat, W. (2024a). Guest editorial: The phygital research paradigm: Philosophical foundations for examining consumer experiences and behaviors in hybrid physical-digital realms. *Qualitative Market Research: An International Journal*, *27*(3), 357–365. https://doi.org/10.1108/QMR-06-2024-202

Batat, W. (2024b). Phygital customer experience in the metaverse: A study of consumer sensory perception of sight, touch, sound, scent, and taste. *Journal of Retailing & Consumer Services*, *78*, 103786. https://doi.org/10.1016/j.jretconser.2024.103786

Batat, W. (2024c). What does phygital really mean? A conceptual introduction to the phygital customer experience (PH-CX) framework. *Journal of Strategic Marketing*, *32*(8), 1220–1243. https://doi.org/10.1080/0965254X.2022.2059775

Batat, W., & Hammedi, W. (2023). The extended reality technology (ERT) framework for designing customer and service experiences in phygital settings: A service research agenda. *Journal of Service Management*, *34*(1), 10–33. https://doi.org/10.1108/JOSM-08-2022-0289

Bialkova, S. (2024). Core theories applied in chatbot context. In *The rise of AI user applications: Chatbots integration foundations and trends* (pp. 41–59). Springer Nature Switzerland.

Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate data analysis: A global perspective*. Pearson.

Brachten, F., Kissmer, T., & Stieglitz, S. (2021). The acceptance of chatbots in an enterprise context-a survey study. *International Journal of Information Management*, *60*, 102375. https://doi.org/10.1016/j.ijinfomgt.2021.102375

Chatterjee, R. S., Hameed, I., Chaudhuri, R., Vrontis, D., Chaudhuri, S., & Chatterjee, S. (2025). Do food planner apps enhance responsible food consumption? The impact of perceptual antecedents and moderating effects on usage intention. *British Food Journal*, *127*(8), 2929–2951. https://doi.org/10.1108/BFJ-11-2024-1161

Chatterjee, R. S., Kliestik, T., Singh, D. K., Sivarajah, U., & Chatterjee, S. (2025). Ethical and structural determinants of generative AI-driven healthcare data sharing for financial analysis. *Information Systems Frontiers*. https://doi.org/10.1007/s10796-025-10663-6

Chatterjee, S., Chaudhuri, R., & Vrontis, D. (2023). Masstige marketing: An empirical study of consumer perception and product attributes with moderating role of status, emotion, and pride. *Journal of Business Research*, *155*, 113401. https://doi.org/10.1016/j.jbusres.2022.113401

Chatterjee, S., Kar, A. K., & Gupta, M. P. (2017). Critical success factors to establish 5G network in smart cities: Inputs for security and privacy. *Journal of Global Information Management*, *25*(2), 15–37. https://doi.org/10.4018/JGIM.2017040102

Chatterjee, S., & Mariani, M. (2022). Exploring the influence of exploitative and explorative digital transformation on organization flexibility and competitiveness. *IEEE Transactions on Engineering Management*, *71*, 13616–13626. https://doi.org/10.1109/TEM.2022.3220946

Chaudhuri, R., Chatterjee, S., Vrontis, D., & Chaudhuri, S. (2022). Innovation in SMEs, AI dynamism, and sustainability: The current situation and way forward. *Sustainability*, *14*(19), 12760. https://doi.org/10.3390/su141912760

Chaudhuri, R., Kumar, A., Wang, C. L., & Gupta, S. (2023). Impacts of consumer cognitive process to ascertain online fake review: A cognitive dissonance theory approach. *Journal of Business Research*, *154*, 113370.

Chaves, A. P., & Gerosa, M. A. (2020). How should my chatbot interact? A survey on social characteristics in human-chatbot interaction design. *International Journal of Human-Computer Interaction*, *37*(8), 729–758.

Chawla, D., & Joshi, H. (2023). Role of mediator in examining the influence of antecedents of mobile wallet adoption on attitude and intention. *Global Business Review*, *24*(4), 609–625. https://doi.org/10.1177/0972150920924506

Chen, M.-J. (2023). Antecedents and outcomes of virtual presence in online shopping: A perspective of SOR (stimulus-organism-response) paradigm. *Electronic Markets*, *33*(1), 58. https://doi.org/10.1007/s12525-023-00674-z

Choi, G., & Chung, H. (2013). Applying the technology acceptance model to social networking sites (SNS): Impact of subjective norm and social capital on the acceptance of SNS. *International Journal of Human-Computer Interaction*, *29*(10), 619–628. https://doi.org/10.1080/10447318.2012.756333

Choung, H., David, P., & Ross, A. (2023). Trust in AI and its role in the acceptance of AI technologies. *International Journal of Human-Computer Interaction*, *39*(9), 1727–1739. https://doi.org/10.1080/10447318.2022.2050543

Cicek, M., Gursoy, D., & Lu, L. (2025). Adverse impacts of revealing the presence of "artificial intelligence (AI)" technology in product and service descriptions on purchase intentions: The mediating role of emotional trust and the moderating role of perceived risk. *Journal of Hospitality Marketing & Management*, *34*(1), 1–23. https://doi.org/10.1080/19368623.2024.2368040

Dassouli, S., Satt, H., & Senhaji, N. (2025). Attitude and behavior towards chatbots: Case of the beauty care industry. *International Journal of Pharmaceutical and Healthcare Marketing*, *19*(1), 51–74. https://doi.org/10.1108/IJPHM-09-2023-0086

De Kimpe, L., Walrave, M., Verdegem, P., & Ponnet, K. (2022). What we think we know about cybersecurity: An investigation of the relationship between perceived knowledge, internet trust, and protection motivation in a cybercrime context. *Behaviour & Information Technology*, *41*(8), 1796–1808. https://doi.org/10.1080/0144929X.2021.1905066

Dutta, S., & Dixit, S. (2025). Examining the impact of media type and perceived interactivity on virtual tour intentions: Empirical evidence using SOR framework. *Asia Pacific Journal of Tourism Research*, *30*(9), 1–20. https://doi.org/10.1080/10941665.2025.2486025

Elayat, A. M. A., & Elalfy, R. M. (2025). Using SOR theory to examine the impact of AI chatbot quality on Gen Z's satisfaction and advocacy within the fast-food sector. *Young Consumers*, *26*(2), 352–383. https://doi.org/10.1108/YC-08-2024-2199

Featherman, M., Jia, S. J., Califf, C. B., & Hajli, N. (2021). The impact of new technologies on consumers beliefs: Reducing the perceived risks of electric vehicle adoption. *Technological Forecasting and Social Change*, *169*, 120847. https://doi.org/10.1016/j.techfore.2021.120847

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50. https://doi.org/10.1177/002224378101800104

Gao, L., & Waechter, K. A. (2017). Examining the role of initial trust in user adoption of mobile payment services: An empirical investigation. *Information Systems Frontiers*, *19*(3), 525–548. https://doi.org/10.1007/s10796-015-9611-0

Grover, P., Kar, A. K., & Dwivedi, Y. K. (2022). Understanding artificial intelligence adoption in operations management: Insights from the review of academic literature and social media discussions. *Annals of Operations Research*, *308*(1–2), 177–213. https://doi.org/10.1007/s10479-020-03683-9

Gustafsson, A., Öberg, C., & Shams, P. (2025). Enhancing the phygital customer experience in the digital world. In *Service innovation and management: Digitalization, service infusion and customer experience* (pp. 113–126). Springer Nature Switzerland.

Hair, J. F., Jr., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial least squares structural equation modeling (PLS-SEM) using R: A workbook*. Springer Nature.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Hameed, I., Chatterjee, R. S., Khan, Y., Zainab, B., & Khan, K. (2025). Willing to drive green? Exploring behavioral and policy influences on electric vehicle ownership. *International Journal of Energy Sector Management*, 1–20. https://doi.org/10.1108/IJESM-05-2025-0046

Hameed, I., Chatterjee, R. S., Zainab, B., Tzhe, A. X., Yee, L. S., & Khan, K. (2024). Navigating loyalty and trust in the skies: The mediating role of customer satisfaction and image for sustainable airlines. *Sustainable Futures*, *8*, 100299. https://doi.org/10.1016/j.sftr.2024.100299

Huang, D., Markovitch, D. G., & Stough, R. A. (2024). Can chatbot customer service match human service agents on customer satisfaction? An investigation in the role of trust. *Journal of Retailing & Consumer Services*, *76*, 103600. https://doi.org/10.1016/j.jretconser.2023.103600

Huang, M., & Ki, E. J. (2024). Examining the effect of anthropomorphic design cues on healthcare chatbots acceptance and organization-public relationships: Trust in a warm human vs. a competent machine. *International Journal of Human-Computer Interaction*, *40*(24), 8781–8793. https://doi.org/10.1080/10447318.2023.2290378

Huang, R. T. (2024). Reducing the perceived complexity of mobile learning in organizations: A moderated mediation model. *International Journal of Human-Computer Interaction*, *40*(23), 7854–7863. https://doi.org/10.1080/10447318.2023.2276523

Huang, R.-T., Jabor, M. K., Tang, T.-W., & Chang, S.-C. (2022). Examine the moderating role of mobile technology anxiety in mobile learning: A modified model of goal-directed behavior. *Asia Pacific Education Review*, *23*(1), 101–113. https://doi.org/10.1007/s12564-021-09703-y

Huang, S., Qu, H., & Wang, X. (2024). Impact of green marketing on peer-to-peer accommodation platform users' repurchase intention and positive word-of-mouth: Mediation of trust and consumer identification. *International Journal of Contemporary Hospitality Management*, *36*(3), 691–712. https://doi.org/10.1108/IJCHM-10-2022-1300

Irimia-Diéguez, A., Liébana-Cabanillas, F., Blanco-Oliver, A., & Lara-Rubio, J. (2023). What drives consumers to use P2P payment systems? An analytical approach based on the stimulus-organism-response (SOR) model. *European Journal of Management and Business Economics*. In press. https://doi.org/10.1108/EJMBE-12-2022-0374

Islam, M. S., Tan, C. C., Sinha, R., & Selem, K. M. (2024). Gaps between customer compatibility and usage intentions: The moderation function of subjective norms towards chatbot-powered hotel apps. *International Journal of Hospitality Management*, *123*, 103910. https://doi.org/10.1016/j.ijhm.2024.103910

Jacob, F., Pez, V., & Volle, P. (2023). Shifting to phygital experience management with design science: A six-step method to manage customer journeys. *Journal of Strategic Marketing*, *31*(5), 961–982. https://doi.org/10.1080/0965254X.2021.2016894

Jafar, S. H., Akhtar, S., & Johl, S. K. (2023). AI in insurance. In *Artificial intelligence for business* (1 ed. pp. 164–173). Productivity Press.

Jaspers, E. D., & Pearson, E. (2022). Consumers' acceptance of domestic internet-of-things: The role of trust and privacy concerns. *Journal of Business Research*, *142*, 255–265. https://doi.org/10.1016/j.jbusres.2021.12.043

Jeon, M. (2024). The effects of emotions on trust in human-computer interaction: A survey and prospect. *International Journal of Human-Computer Interaction*, *40*(22), 6864–6882. https://doi.org/10.1080/10447318.2023.2261727

Jermsittiparsert, K., Wongsuwan, N., & Akkaya, B. (2023). Subjective norms and behavioural intention of e-Banking adoption: Mediating role of perceived usefulness. In *Two faces of digital transformation: Technological opportunities versus social threats* (pp. 177–193). Emerald Publishing Limited.

Ju, J., Meng, Q., Sun, F., Liu, L., & Singh, S. (2023). Citizen preferences and government chatbot social characteristics: Evidence from a discrete choice experiment. *Government Information Quarterly*, *40*(3), 101785. https://doi.org/10.1016/j.giq.2022.101785

Kasilingam, D. L. (2020). Understanding the attitude and intention to use smartphone chatbots for shopping. *Technology in Society*, *62*, 101280. https://doi.org/10.1016/j.techsoc.2020.101280

Kim, J. J., Soh, J., Kadkol, S., Solomon, I., Yeh, H., Srivatsa, A. V., Nahass, G. R., Choi, J. Y., Lee, S., Nyugen, T., & Ajilore, O. (2025). AI anxiety: A comprehensive analysis of psychological factors and interventions. *AI and Ethics*, 1–17.

Kmet, C. T., & Copulsky, J. (2024). Augmenting customer lifetime value with omnichannel engagement. *Applied Marketing Analytics*, *10*(3), 205–215. https://doi.org/10.69554/WKCP1506

Koechling, A., Wehner, M. C., & Warkocz, J. (2023). Can I show my skills? Affective responses to artificial intelligence in the recruitment process. *Review of Managerial Science*, *17*(6), 2109–2138. https://doi.org/10.1007/s11846-021-00514-4

Kumar, A., Shankar, A., Behl, A., Chakraborty, D., & Gundala, R. R. (2025). Anthropomorphic generative AI chatbots for enhancing customer engagement, experience and recommendation. *Journal of Consumer Marketing*. In press. *42*(4), 472–483. https://doi.org/10.1108/JCM-06-2024-6922

Kumar, J., Rana, S., Rani, G., & Rani, V. (2024). How phygital customers' experience transforms the retail banking sector? Examining customer engagement and patronage intentions. *Competitiveness Review: An International Business Journal*, *34*(1), 92–106. https://doi.org/10.1108/CR-04-2023-0076

Küper, A., & Krämer, N. (2025). Psychological traits and appropriate reliance: Factors shaping trust in AI. *International Journal of Human-Computer Interaction*, *41*(7), 4115–4131.

Lee, J., Lee, D., & Lee, J. G. (2024). Influence of rapport and social presence with an AI psychotherapy chatbot on users' self-disclosure. *International Journal of Human-Computer Interaction*, *40*(7), 1620–1631. https://doi.org/10.1080/10447318.2022.2146227

Leite, H., Hodgkinson, I. R., Volochtchuk, A. V. L., & Nascimento, T. C. (2024). 'It's not the boogeyman': How voice assistant technology is bridging the digital divide for older people. *Technovation*, *136*, 103080. https://doi.org/10.1016/j.technovation.2024.103080

Li, L., Lee, K. Y., Emokpae, E., & Yang, S.-B. (2021). What makes you continuously use chatbot services? Evidence from Chinese online travel agencies. *Electronic Markets*, *31*(3), 1–25. https://doi.org/10.1007/s12525-020-00454-z

Li, Y., Song, Y., Sun, Y., & Zeng, M. (2024). When do employees learn from artificial intelligence? The moderating effects of perceived enjoyment and task-related complexity. *Technology in Society*, *77*, 102518. https://doi.org/10.1016/j.techsoc.2024.102518

Liew, T. W., Tan, S. M., Yoo, N. E., Gan, C. L., & Lee, Y. Y. (2023). Let's talk about sex!: AI and relational factors in the adoption of a chatbot conveying sexual and reproductive health information. *Computers in Human Behavior Reports*, *11*, 100323. https://doi.org/10.1016/j.chbr.2023.100323

Liu, M., Yang, Y., Ren, Y., Jia, Y., Ma, H., Luo, J., Fang, S., Qi, M, & Zhang, L. (2024). What influences consumer AI chatbot use intention? An application of the extended technology acceptance model. *Journal of Hospitality and Tourism Technology*, *15*(4), 667–689. https://doi.org/10.1108/JHTT-03-2023-0057

Liu, S. Q., Vakeel, K. A., Smith, N. A., Alavipour, R. S., Wei, C., & Wirtz, J. (2024). AI concierge in the customer journey: What is it and how can it add value to the customer? *Journal of Service Management*, *35*(6), 136–158. https://doi.org/10.1108/JOSM-12-2023-0523

Magni, D., Del Gaudio, G., Papa, A., & Della Corte, V. (2024). Digital humanism and artificial intelligence: The role of emotions beyond the human-machine interaction in society 5.0. *Journal of Management History*, *30*(2), 195–218. https://doi.org/10.1108/JMH-12-2022-0084

Mahmoud, A. B. (2024). Aging in the digital age: Public beliefs about the potential of virtual reality (VR) for the aging population. *Journal of Macromarketing*, 02761467241253286.

Majid, G. M., Tussyadiah, I., Kim, Y. R., & Chen, J. L. (2024). Promoting pro-environmental behaviour spillover through chatbots. *Journal of Sustainable Tourism*, 1–19. https://doi.org/10.1080/09669582.2024.2393256

Mehrabian, A., & Russell, J. A. (1974). The basic emotional impact of environments. *Perceptual and Motor Skills*, *38*(1), 283–301. https://doi.org/10.2466/pms.1974.38.1.283

Mele, C., & Russo-Spena, T. (2025). Agencement of onlife and phygital: Smart tech-enabled value co-creation practices. *Journal of Service Management*, *36*(2), 217–240. https://doi.org/10.1108/JOSM-03-2023-0113

Meng, F., Guo, X., Peng, Z., Ye, Q., & Lai, K.-H. (2022). Trust and elderly users' continuance intention regarding mobile health services: The contingent role of health and technology anxieties. *Information Technology and People*, *35*(1), 259–280. https://doi.org/10.1108/ITP-11-2019-0602

Mishra, S., Chaudhury, P., Tripathy, H. K., Sahoo, K. S., Jhanjhi, N. Z., Hassan Elnour, A. A., & Abdelmaboud, A. (2024). Enhancing health care through medical cognitive virtual agents. *Digital Health*, *10*, 20552076241256732. https://doi.org/10.1177/20552076241256732

Mladenović, D., Ismagilova, E., Filieri, R., & Dwivedi, Y. K. (2024). Metawom-toward a sensory word-of-mouth (WOM) in the metaverse. *International Journal of Contemporary Hospitality Management*, *36*(6), 2144–2163. https://doi.org/10.1108/IJCHM-04-2023-0474

Mostafa, R. B., & Kasamani, T. (2022). Antecedents and consequences of chatbot initial trust. *European Journal of Marketing*, *56*(6), 1748–1771. https://doi.org/10.1108/EJM-02-2020-0084

Mozafari, N., Weiger, W. H., & Hammerschmidt, M. (2022). Trust me, I'm a bot-repercussions of chatbot disclosure in different service frontline settings. *Journal of Service Management*, *33*(2), 221–245. https://doi.org/10.1108/JOSM-10-2020-0380

Ng, S. W. T., & Zhang, R. (2025). Trust in AI-driven chatbots: A systematic review. *Telematics and Informatics*, *102240*, 102240. https://doi.org/10.1016/j.tele.2025.102240

Nordheim, C. B., Følstad, A., & Bjørkli, C. A. (2019). An initial model of trust in chatbots for customer service-findings from a questionnaire study. *Interacting With Computers*, *31*(3), 317–335. https://doi.org/10.1093/iwc/iwz022

Nyagadza, B., Muposhi, A., Mazuruse, G., Makoni, T., Chuchu, T., Maziriri, E. T., & Chare, A. (2022). Prognosticating anthropomorphic chatbots' usage intention as an e-Banking customer service gateway: Cogitations from Zimbabwe. *PSU Research Review*. https://doi.org/10.1108/prr-10-2021-0057

Park, H. S. (2000). Relationships among attitudes and subjective norms: Testing the theory of reasoned action across cultures. *Communication Studies*, *51*(2), 162–175. https://doi.org/10.1080/10510970009388516

Patil, K. P., Kulkarni, M. S., & Hudnurkar, M. (2024a). Enhancing service quality in the insurance industry with AI-powered humanoid chatbots. *The TQM Journal*. In press. https://doi.org/10.1108/TQM-11-2023-0354

Patil, K. P., Kulkarni, M. S., & Hudnurkar, M. (2024b). Enhancing service quality in the insurance industry with AI-powered humanoid chatbots. *The TQM Journal*.

Pergantis, P., Bamicha, V., Skianis, C., & Drigas, A. (2025). AI chatbots and cognitive control: Enhancing executive functions through chatbot interactions: A systematic review. *Brain Sciences*, *15*(1), 47. https://doi.org/10.3390/brainsci15010047

Polisetty, A., Chakraborty, D., G, S., Kar, A. K., & Pahari, S. (2024). What determines AI adoption in companies? Mixed-method evidence. *Journal of Computer Information Systems*, *64*(3), 370–387. https://doi.org/10.1080/08874417.2023.2219668

Polyportis, A., & Pahos, N. (2025). Understanding students' adoption of the ChatGPT chatbot in higher education: The role of anthropomorphism, trust, design novelty and institutional policy. *Behaviour & Information Technology*, *44*(2), 315–336. https://doi.org/10.1080/0144929X.2024.2317364

Purwar, A., & Chawla, I. (2024). A systematic review on fall detection systems for elderly healthcare. *Multimedia Tools & Applications*, *83*(14), 43277–43302. https://doi.org/10.1007/s11042-023-17190-z

Raj, A., & Shetty, S. D. (2024). Smart parking systems technologies, tools, and challenges for implementing in a smart city environment: A survey based on IoT & ML perspective. *International Journal of Machine Learning and Cybernetics*, *15*(7), 2673–2694. https://doi.org/10.1007/s13042-023-02056-5

Ranjan, C., Mariani, M., & Wamba, S. F. (2023). The consequences of innovation failure: An innovation capabilities and dynamic capabilities perspective. *Technovation*, *128*, 102858.

Riley, B. K., & Dixon, A. (2024). Emotional and cognitive trust in artificial intelligence: A framework for identifying research opportunities. *Current Opinion in Psychology*, *58*, 101833. https://doi.org/10.1016/j.copsyc.2024.101833

Romero-Charneco, M., Casado-Molina, A. M., Alarcón-Urbistondo, P., & Cabrera Sánchez, J. P. (2025). Customer intentions toward the adoption of WhatsApp chatbots for restaurant recommendations. *Journal of Hospitality and Tourism Technology*. In press. *16*(4), 784–816. https://doi.org/10.1108/JHTT-01-2024-0024

Roth-Cohen, O., Segev, S., & Liu, Y. (2025). The effect of non-celebrity influencers' perceived authenticity on social media advertising outcomes. *International Journal of Advertising*, *44*(6), 1017–1039. https://doi.org/10.1080/02650487.2024.2440251

Saragih, H. S. (2025). Exploring the principle and competencies for phygital service inclusion. *The Journal of Services Marketing*, *39*(6), 673–694. https://doi.org/10.1108/JSM-04-2024-0159

Sarstedt, M., Ringle, C. M., & Hair, J. F. (2021). Partial least squares structural equation modeling. In *Handbook of market research* (pp. 587–632). Springer.

Satu, M. S., & Parvez, M. H. (2015). Review of integrated applications with AIML based chatbot. In *2015 International Conference on Computer and Information Engineering (ICCIE)*.

Seitz, L., Bekmeier-Feuerhahn, S., & Gohil, K. (2022). Can we trust a chatbot like a physician? A qualitative study on understanding the emergence of trust toward diagnostic chatbots. *International Journal of Human-Computer Studies*, *165*, 102848. https://doi.org/10.1016/j.ijhcs.2022.102848

Sestino, A., Rizzo, C., Irgang, L., & Stehlíková, B. (2025). Redesigning healthcare service delivery processes through medical chatbot integrations: Balancing chatbot features and patients' individual differences. *Business Process Management Journal*, *31*(5), 1736–1762. https://doi.org/10.1108/BPMJ-07-2024-0655

Shabankareh, M., Khamoushi Sahne, S. S., Nazarian, A., & Foroudi, P. (2025). The impact of AI perceived transparency on trust in AI recommendations in healthcare applications. *Asia-Pacific Journal of Business Administration*. https://doi.org/10.1108/APJBA-12-2024-0690

Shahzad, M. F., Xu, S., An, X., & Javed, I. (2024). Assessing the impact of AI-chatbot service quality on user e-brand loyalty through chatbot user trust, experience and electronic word of mouth. *Journal of Retailing & Consumer Services*, *79*, 103867. https://doi.org/10.1016/j.jretconser.2024.103867

Shaikh, A. A., Kumar, A., Mishra, A., & Elahi, Y. A. (2024). A study of customer satisfaction in using banking services through artificial intelligence (AI) in India. *Public Administration and Policy*, *27*(2), 167–181. https://doi.org/10.1108/PAP-05-2023-0060

Shams, R., Chatterjee, S., & Chaudhuri, R. (2024). Developing brand identity and sales strategy in the digital era: Moderating role of consumer belief in brand. *Journal of Business Research*, *179*, 114689. https://doi.org/10.1016/j.jbusres.2024.114689

Sheshadri, C. (2015). Security and privacy issues in e-Commerce: A proposed guidelines to mitigate the risk. In *IEEE International Advance Computing Conference (IACC)* (Vol. 1, pp. 393–396).

Sheshadri, C. (2020). Factors impacting behavioral intention of users to adopt IoT in India: From security and privacy perspective. *International Journal of Information Security and Privacy*, *14*(4), 92–112.

Sixsmith, A., & Cosco, T. D. (Eds.). (2024). Technology, aging, and mental health: opportunities and challenges. Aging & Mental Health, 28(4), i-iii.

Song, S. W., & Shin, M. (2024). Uncanny valley effects on chatbot trust, purchase intention, and adoption intention in the context of e-Commerce: The moderating role of avatar familiarity. *International Journal of Human-Computer Interaction*, *40*(2), 441–456. https://doi.org/10.1080/10447318.2022.2121038

Strzelecki, A., & ElArabawy, S. (2024). Investigation of the moderation effect of gender and study level on the acceptance and use of generative AI by higher education students: Comparative evidence from Poland and Egypt. *British Journal of Educational Technology*, *55*(3), 1209–1230. https://doi.org/10.1111/bjet.13425

Subhra Chatterjee, R., Hameed, I., Chatterjee, S., Chaudhuri, R., Vrontis, D., & Foroudi, P. (2025). Aging consumer engagement with the mobile food planner apps in Malaysia: Investigating gender differences. *Journal of Macromarketing*, *45*(4), 02761467251325070. https://doi.org/10.1177/02761467251325070

Sun, E., & Ye, X. (2024). Older and fearing new technologies? The relationship between older adults' technophobia and subjective age. *Aging & Mental Health*, *28*(4), 569–576. https://doi.org/10.1080/13607863.2023.2241017

Teo, T., Lee, C. B., & Chai, C. S. (2008). Understanding pre-service teachers' computer attitudes: Applying and extending the technology acceptance model. *Journal of Computer Assisted Learning*, *24*(2), 128–143. https://doi.org/10.1111/j.1365-2729.2007.00247.x

Terblanche, N., & Kidd, M. (2022). Adoption factors and moderating effects of age and gender that influence the intention to use a non-directive reflective coaching chatbot. *SAGE Open*, *12*(2), 21582440221096136. https://doi.org/10.1177/21582440221096136

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425–478. https://doi.org/10.2307/30036540

Vrontis, D., Siachou, E., Sakka, G., Ghosh, R., Chaudhuri, A., & Ghosh, A. (2022). Societal effects of social media in organizations: Reflective points deriving from a systematic literature review and a bibliometric meta-analysis. *European Management Journal*, *40*(2), 151–162. https://doi.org/10.1016/j.emj.2022.01.007

Wang, W.-T., & Lu, C.-C. (2014). Determinants of success for online insurance web sites: The contributions from system characteristics, product complexity, and trust. *Journal of Organizational Computing and Electronic Commerce*, *24*(1), 1–35. https://doi.org/10.1080/10919392.2014.866501

Wang, X., & Qiu, X. (2024). Robotic moment: The influence mechanism of frequency of socializing on willingness to interact with AI robots. *International Journal of Human-Computer Interaction*, *40*(17), 4565–4575. https://doi.org/10.1080/10447318.2023.2212863

Wang, Y., Zhang, W., & Chu, J. (2023). What drives citizen's participate intention in smart city? An empirical study based on stimulus-organism-response (SOR) theory. *Journal of the Knowledge Economy*, *15*(3), 10088–10110. https://doi.org/10.1007/s13132-023-01472-w

Wu, J., & Song, S. (2021). Older adults' online shopping continuance intentions: Applying the technology acceptance model and the theory of planned behavior. *International Journal of Human-Computer Interaction*, *37*(10), 938–948. https://doi.org/10.1080/10447318.2020.1861419

Xia, H., Chen, J., Qiu, Y., Liu, P., & Liu, Z. (2025). The impact of human-chatbot interaction on human-human interaction: A substitution or complementary effect. *International Journal of Human-Computer Interaction*, *41*(2), 848–860.

Xiao, R., Yazan, M., & Situmeang, F. B. I. (2025). Rethinking conversation styles of chatbots from the customer perspective: Relationships between conversation styles of chatbots, chatbot acceptance, and perceived tie strength and perceived risk. *International Journal of Human-Computer Interaction*, *41*(2), 1343–1363. https://doi.org/10.1080/10447318.2024.2314348

Yen, C., & Chiang, M.-C. (2021). Trust me, if you can: A study on the factors that influence consumers' purchase intention triggered by chatbots based on brain image evidence and self-reported assessments. *Behaviour & Information Technology*, *40*(11), 1177–1194. https://doi.org/10.1080/0144929X.2020.1743362

Zhang, Q., Wong, A. K. C., & Bayuo, J. (2024). Chatbots in elderly health care: A scoping review. *Journal of the American Medical Directors Association*, *25*(9), 105108. https://doi.org/10.1016/j.jamda.2024.105108