Past, present and future of AI in marketing and knowledge management

Reza Marvi, Pantea Foroudi and Maria Teresa Cuomo

Abstract

Purpose – *This paper aims to explore the intersection of artificial intelligence (AI) and marketing within the context of knowledge management (KM). It investigates how AI technologies facilitate data-driven decision-making, enhance business communication, improve customer personalization, optimize marketing campaigns and boost overall marketing effectiveness.*

Design/methodology/approach – *This study uses a quantitative and systematic approach, integrating citation analysis, text mining and co-citation analysis to examine foundational research areas and the evolution of AI in marketing. This comprehensive analysis addresses the current gap in empirical investigations of AI's influence on marketing and its future developments.*

Findings – *This study identifies three main perspectives that have shaped the foundation of AI in marketing: proxy, tool and ensemble views. It develops a managerially relevant conceptual framework that outlines future research directions and expands the boundaries of AI and marketing literature within the KM landscape.*

Originality/value – *This research proposes a conceptual model that integrates AI and marketing within the KM context, offering new research trajectories. This study provides a holistic view of how AI can enhance knowledge sharing, strategic planning and decision-making in marketing.*

Keywords *Artificial intelligence, Knowledge management, KM, Co-citation, Text mining, Leximancer*

Paper type *Research paper*

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Introduction

An important area in the marketing and business domain is artificial intelligence (AI), which has recently gained significant attention. While Alan Turing initially initiated the field in 1950 by posing the question, "Can machine think?", the domain received minimal scholarly consideration until very recently. The past few years have witnessed the emergence of various stream of AI-related articles, each with its own conceptual foundation, unique agenda and disciplinary orientation, but rarely placed in context of knowledge management (KM) (Del Giudice *et al.*, 2023; Jarrahi *et al.*, 2023).

Collectively, studies related to AI have portrayed a diverse and complex picture of AI within the rapidly changing marketing landscape (Huang and Rust, 2018, 2021a, 2021b; Verma *et al.*, 2021). However, these studies appear to have been developed independently, with limited convergence and interaction. For instance, marketing scholars (Gill, 2020; Granulo *et al.*, 2021; Longoni *et al.*, 2019; Verma *et al.*, 2021) seldom consider the socioeconomic impact of AI, while management researchers seem unfamiliar with comprehensive models of technology adoption. Although diverse foci and theoretical orientations are common in most developing research domains, they can also impede the progress of a developing domain. Therefore, the purpose of this article is to provide an integrative and comprehensive review of these diverse AI-related studies to develop a relevant conceptual map for the domain within the context of KM (Dwivedi *et al.*, 2011; Paschen *et al.*, 2019).

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The growth of this fruitful domain has sparked an increasing number of meta-analyses (Blut *et al.*, 2021) and literature review articles (Akter *et al.*, 2023; Di Vaio *et al.*, 2020; Mustak *et al.*, 2021). Such meta-analyses have worked to summarize the empirical findings and include conflicting results in the literature, whereas literature reviews benefit from the identifying general themes in the research domain by reporting findings. Despite portraying a diverse and complex picture of AI in marketing streams, both types of studies have important limitations. First, they tend to focus on a specific subset of the AI domain and use qualitative methods for finding a limited number of research articles. For example, Di Vaio *et al.*'s (2020) review offers an indication of the articles published in management journals in which sustainable business models were regarded as outcomes, which could contradict to a broader body of research on AI beyond a purely management scope. Similarly, Blut *et al.* (2021) acknowledged that their approach to understand anthropomorphism is based primarily on examining "the relationship between anthropomorphism of service robots." Second, both meta-analyses and literature reviews (e.g. Kopalle *et al.*, 2021) overlook the influence of individual scholarly contributions to the field, thus not offering comprehensive insight into a domain's knowledge nodes and intellectual structures that are vital for conducting a conceptual, more meaningful future study. In particular, the integration of AI in marketing can significatively impact how organizations handle, analyze and use knowledge (Dwivedi *et al.*, 2011) related to marketing strategies, customer insights and marketing trends (Del Giudice *et al.*, 2023; Anayat and Rasool, 2024).

Using citations, co-citations and text mining, our goals herein are to provide a detailed and comprehensive picture of the AI literature and propose a conceptual model for future research. By combining these techniques, we can synthesize previous studies and elucidate different perspectives that have shaped the intellectual foundation of the AI literature domain. Given the importance of AI for marketing and KM studies, a better understanding of AI literature is crucial in terms of the diverse views that have shaped its foundation. Thus, by exploring the intersection of AI and marketing within the context of KM, we can delve into how AI technologies facilitate data-driven decision-making (Campbell *et al.*, 2020) and business communication (Iaia *et al.*, 2023), enhance customer personalization, optimize marketing campaigns and improve overall marketing effectiveness (De Bruyn *et al.*, 2020; Akter *et al.*, 2023).

Importantly, gaining a comprehensive understanding of AI literature in the marketing and business domain can help develop a literature-based and objective framework that highlights unexplored research areas requiring scholarly attention such as creativity, innovation, marketing and strategy (Del Giudice *et al.*, 2023). To the best of our knowledge, no studies have used text mining or the configuration of AI nodes to propose future pathways. Therefore, our aim is to review the history of the AI together with marketing domain, integrate the current literature and delineate the different perspectives that have shaped AI and marketing as a basis for proposing our conceptual model within the KM landscape. This proposed model can then be used to identify research opportunities within the AI domain using an organized and detailed approach.

In conjunction with these goals, our study aims to address three interconnected questions: (RQ1) Which specific body of knowledge has exerted the most influential in the different periods? (RQ2) What is the spatial configuration of the different research areas that support AI literature on marketing within KM context? (RQ3) How can a conceptual framework based on AI literature capture emerging topics for advancing the AI and marketing domains within the context of KM?

In the following sections, we will delve into these questions after providing an explanation for our methodology.

Artificial intelligence in marketing

Researchers define AI as encompassing programs, algorithms, systems and machines that display intelligence, shown by machines that emulate aspects of human cognition

(Huang and Rust, 2018) and entail machines replicating intelligent human behavior (Syam and Sharma, 2018). AI relies on several core technologies, including machine learning, natural language processing, rule-based expert systems, neural networks, deep learning, physical robots and robotic process automation (Davenport and Ronanki, 2018). Using these tools allows AI to accurately interpret external data, learn from it and adapt flexibly (Kaplan and Haenlein, 2019). Another perspective on AI focuses on its marketing and business applications rather than its technological foundations, such as automating business processes, deriving insights from data or interacting with customers and employees (Davenport and Ronanki, 2018).

Previous studies in marketing categorized AI in three categorize including mechanical, thinking and feeling AI. Mechanical AI aims to automate tasks that are repetitive and routine (Huang and Rust, 2021a, 2021b). It is created to enhance efficiency and reduce variability, making it perfect for standardizing services (Huang and Rust, 2017, 2018). Services that resemble goods more closely are better suited for automation to achieve scale and efficiency. This approach aligns with the McService strategy proposed by Huang and Rust (2017); when customers have similar service demands and low potential lifetime value, mechanical AI should be used to boost efficiency.

Thinking AI is intended for analyzing data to generate new conclusions or decisions, often working with unstructured data (Huang and Rust, 2021a, 2021b). It excels at identifying patterns and regularities in data, such as through text mining, speech recognition and facial recognition (Koponen *et al.*, 2023). Current methods for processing data in thinking AI include machine learning, neural networks and deep learning (which involves neural networks with additional layers) (Akter *et al.*, 2023). The more sophisticated intuitive AI aims to maximize decision-making accuracy, such as solving problems and improving the precision of answers in data science. Therefore, thinking AI is perfect for personalizing services to achieve optimal productivity (Rust and Huang, 2012). Examples of thinking AI include in-car smart systems gather driving data and offer analytics to enhance car technicians' ability to diagnose vehicle issues and to support safer driving for human drivers (Huang and Rust, 2022a, 2022b).

Feeling AI is intended for interactive engagements with humans and for interpreting human emotions and sentiments (Huang and Rust, 2022a, 2022b). Feeling AI has two distinct applications. At the lower end, it is used in virtual agents and chatbots to provide customer service similar to mechanical AI. This approach aligns with the relational service strategy described by Huang and Rust (2017), where customer demand is uniform and the potential lifetime value of the customer is high. At the high end, feeling AI is capable of delivering customer care that necessitates empathy and understanding, beyond merely acting as a customer contact interface (Schepers *et al.*, 2022). Automatic speech emotion recognition is anticipated to be the next major advancement in AI (i.e. next-gen AI), with broad applications in health, information retrieval, robotics and security (Mende *et al.*, 2024). This type of AI must genuinely interpret human emotions and respond similarly to a human conversational partner (Schuller, 2018). In the next section, we will discuss in more detail how AI literature and various types have evolved and shaped the current landscape of AI in marketing.

Method

This study used co-citation and text-mining approaches to conduct an assessment of the knowledge domain and illuminate the cognitive epistemological structure to understand how the concept of AI and marketing are intellectually organized. In addition, using two methods helps lessen researchers' biases (Podsakoff *et al.*, 2005; Wilden *et al.*, 2017). We first used co-citation analysis, which is grounded in the use of citations to measure the influence and interaction of entire academic disciplines and subject areas. By means of co-citations, we explored the historical development and foundations of the AI domain and assessed how other studies have incorporated the concept intellectually. Then, we used text mining via Leximancer to discover the themes and main concepts in the AI domain.

The data

To identify the most suitable keywords, we initially contacted researchers who are expert in the AI in the business and management domain. The outcome of this stage along with extensive review of recent articles on AI (e.g. Davenport *et al.*, 2020; Huang and Rust, 2021a, 2021b). Following these two stages resulted in finding the most suitable keywords in the literature including "AI" OR "Artificial Intelligence" OR "intelligence automation" OR "anthropomorphism" OR "robotic" OR "robots" OR "service robot" OR "social robot" OR "feeling robot" OR "mechanical AI" OR "thinking AI" OR "feeling AI." All the chosen keywords were searched in the keywords, title, keywords, title, article-specific identifiers articles in WOS between 1970 and 2021. As noted, 1950 is often considered the formal starting point of AI research (Turing, 1950). However, the Web of Science (WOS) does not list articles before 1970, and therefore we had to choose 1970 as our starting point.

Furthermore, WOS is considered one of the most comprehensive and leading sources for conducting bibliometric studies (Chabowski *et al.*, 2023; Zha *et al.*, 2024). This platform serves as a multidisciplinary research database, allowing simultaneous searches across citation databases and indices covering diverse academic fields. Previous studies (e.g. Balstad and Berg, 2020; Foroudi *et al.*, 2021) suggest that WOS provides more comprehensive and comparable data in management and business domains compared to Scopus and Google Scholar. In addition, unlike these databases, WOS results are not limited by institutional subscriptions (Antons and Breidbach, 2018; Mahavarpour *et al.*, 2023).

We initially restricted our search to the business and management domain to focus solely on articles relevant to this field. We ensured that articles in our database:

- were complete articles and not call for papers or proceedings;
- included at least one keyword in the abstract, title and keywords section;
- were available in either online archives or databases; and
- were published in English.

This yielded 1,129 publications. Subsequently, all editorial notes, book chapters and less relevant texts that had not undergone peer review were excluded ($N = 141$). We then scrutinized the remaining articles to confirm that they predominantly discussed AI. Notably, articles where AI was mentioned solely as a methodology or where the topic was unrelated to AI were excluded. This process resulted in identifying 502 articles forming the basis of our analysis. We ran our co-citation analyses (both historical development and cluster analysis) on cited publications by the focal articles.

Analysis: citation and co-citation assessment

Common practice dictates that co-citation analysis is performed not on the focal articles themselves (i.e. 502 articles found in Web of Science) but on the articles cited by them (Foroudi *et al.*, 2021; Zupic and Čater, 2015). The underlying idea of citation analysis is that citations show a relationship between citing and cited articles (Donthu *et al.*, 2021), offering a paper trail of links among authors, scientific communities and ideas that can help visualize a research field (Di Stefano *et al.*, 2010). Co-citations occur when two references are cited by a third document, with the frequency of co-citations indicating the most influential articles in a research domain.

As our sample comprises 502 articles with more than 30,000 cited references, it would be impossible for us to include all the references in our analysis. Therefore, following previous research (Samiee and Chabowski, 2021; Wilden *et al.*, 2017), we set a threshold on the number of citations for visualization. No specific threshold level exists in previous studies, so to guide our analysis, we derived different threshold (both low and high values). We then used these levels as a starting point for running our analysis. In line with Zupic and Čater (2015), our objective was to exclude all the articles that were not central to our visualization but could still provide a meaningful representation of the research domain. After testing various thresholds, we included all the articles with at least four citations for our historical analysis ($n = 35$). The threshold for our second analysis was higher, as our sample has more cited articles with overall higher citations ($n = 66$).

For our second analysis, we used the Louvain modularity method to identify the clusters of closely linked articles. According to Lambiotte *et al.* (2008), a resolution coefficient can help researchers adjust the sensitivity of an algorithm. A smaller resolution coefficient value will result in smaller (in terms of number of articles) and more clusters, whereas a larger value will result in fewer and larger clusters. To find the appropriate number of clusters, we tested different resolution coefficients, starting from the default value of 1.0. We assessed the quality of results by the modularity parameter and judged only the clustering with modularity higher than 0.4 as satisfactory.

Analysis: text mining

Next, we used the Bayesian learning algorithm implemented in Leximancer for the text-mining assessment (Wilden *et al.*, 2017) to understand the relational (semantic) and conceptual (thematic) analysis of the concepts to provide a conceptual map and overview and to represent the concepts and how they are interconnected (Rooney, 2005). Leximancer uses a clustering algorithm to determine the contextual associations of textual and nontextual data via "term-occurrence" (e.g. co-occurrence), as well as the frequencies and positions of verbs and nouns to examine concepts (common text elements) and themes (groupings of revealed concepts).

This approach is suitable for the purpose of our review. Leximancer makes clustering and concept identification highly reliable, which can help reduce the bias and risks often associated with a manually coded texting process (Wilden *et al.*, 2019). Use of this approach can also lead to correlational validity. To avoid any biases, we cleaned each article by excluding any postscripts and prefaces. Furthermore, we opted to merge the word variations (e.g. technology and technological). As a result, the algorithm generates concept seeds that automatically use a ranking algorithm for finding seed words that reflect the themes present in the data. This algorithm looks for words near the "centre of local maxima in the lexical co-occurrence network" (Wilden *et al.*, 2019, p. 1574).

Findings

The study conducted a co-citation analysis to understand the historical evolution of research streams in AI and used textual examination to map the central themes and concepts. The findings provide a comprehensive understanding of the AI domain and support the first two research questions: RQ1 and RQ2. The discussion section will address the third research question: RQ3.

Once upon a time: brief historical development of artificial intelligence

The AI studies in the marketing and business domain, influenced by technology literature, focus on consumer evaluations of services/products impacted by new technology. Scholars such as Parasuraman (2000) and Venkatesh *et al.* (2012) have explored different aspects of adoption, including technology acceptance and readiness, to determine the market success of emerging technologies. Consumer evaluation remains a key element in the development of AI literature in this field. Building upon the framework proposed by Orlikowski and Iacono (2001) for conceptualizing technology, we propose a framework for categorizing the historical development of AI. Our analysis proposes a conceptual model that identifies AI as a proxy, tool and ensemble within the context of knowledge management (KM). Each role represents a distinct perspective on how AI can be integrated into marketing practices. In the subsequent paragraphs, we provide a comprehensive overview of the historical development of AI within each of these categories.

First period – The initial phase of AI's historical development, referred to as the "proxy" view (1950–2012), focused on measuring new technology adoption and the role of users. Scholars viewed technology as a stable entity and examined users' efficacy in resisting or accepting technological innovations. Studies during this period explored the impact of technology on customers' behavioral and cognitive responses, often using variables such as technology readiness. The proxy view also investigated acceptance and rejection motivational drivers, drawing on the Technology Acceptance Model (TAM) and perceived value. AI as a proxy refers to the use of AI to replicate or substitute human decision-making and actions in marketing processes. This perspective views AI as an intermediary that performs tasks traditionally carried out by humans, thereby enhancing efficiency and scalability in marketing operations. The concept is grounded in the TAM and theories of automation and substitution, which explain user acceptance of technology and highlight factors influencing the adoption of AI systems as proxies for human tasks. AI as a proxy is used in areas such as customer service (e.g. chatbots), automated content creation and personalized recommendations. These applications demonstrate AI's ability to mimic human behavior and decision-making (Garousi Mokhtarzadeh *et al.*, 2021), enhancing productivity and customer interactions in marketing and business. Notable studies have used the proxy view to understand why certain customers are more or less interested in adopting AI-based technologies (Parasuraman, 2000; Venkatesh and Davis, 2000; Mori, 1970; Venkatesh *et al.*, 2003; Rust and Huang, 2012).

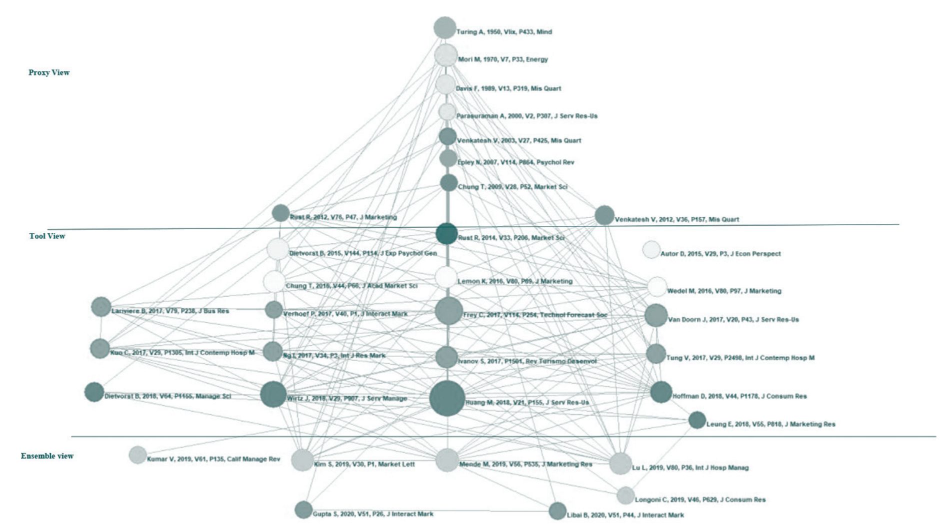
Second period – In the "tool" view (2012–2018), research on AI initially progressed slowly with a limited number of publications. However, after 2016, there was a notable increase in AI-related studies from various perspectives, contexts and implications. During this period, three distinct research streams emerged. The first stream focused on AI as a tool for labor substitution, exploring how service automation could replace or substitute human labor, with authors like Autor *et al.* (2015) and Frey and Osborne (2017) examining the impact of automation on the labor market. The second stream viewed AI as a productivity tool that extended and improved performance in social and individual institutions, suggesting it could handle time-consuming tasks. Huang and Rust (2018) investigated four types of intelligence required for service tasks and developed a theory of job replacement. The third stream regarded AI as a relationship tool, emphasizing its potential to enhance customer-firm interactions through personalization. Research highlighted AI as an optimal tool for improving customer–firm relationships. AI as a tool focuses on augmenting human capabilities and performance rather than replacing humans.

This perspective is informed by the resource-based view (RBV) and Dynamic Capabilities Theory. RBV posits that unique resources and capabilities, such as AI, can provide a competitive advantage, whereas Dynamic Capabilities Theory explains how organizations can adapt, integrate and reconfigure competencies to address rapidly changing environments. AI tools are applied in areas such as data analytics, market research and campaign optimization. For instance, AI-driven analytics platforms help marketers derive insights from vast data sets, improving decision-making (Garousi Mokhtarzadeh *et al.*, 2021) and strategic planning. Overall, the "tool" view of AI equates it with a set of techniques and tools designed to benefit customers and firms. During this period, the functionality, features and expected outcomes of different AI technologies were well-defined and categorized. While there was limited theoretical or conceptual development, notable articles categorized various types of AI (Huang and Rust, 2018) and examined its macrolevel impact (Autor *et al.*, 2015; Frey and Osborne, 2017).

Third period – The "ensemble" view (2019–today) considers AI as part of an integrated system that combines various AI technologies to achieve synergistic effects. Researchers in this view focus on additional capabilities and resources, such as training, skilled staff and policies, that are necessary for the successful implementation of AI technologies. This perspective highlights the importance of the social context in which AI operates, emphasizing the interactions between AI, institutional frameworks and technology actors. Unlike the proxy and tool views, the ensemble view sees AI as an evolving technology, with a primary focus on its design, development and implementation within organizations. This concept draws on Systems Theory and Sociotechnical Systems Theory. Systems Theory underscores the interdependence of various components within an organization, whereas Sociotechnical Systems Theory highlights the interaction between people and technology in the workplace. Examples of AI ensembles include comprehensive customer relationship management (CRM) systems, integrated marketing platforms and omnichannel strategies. These systems leverage multiple AI functionalities, such as predictive analytics, natural language processing and machine learning, to deliver coordinated and seamless marketing efforts.

Figure 1 categorizes the historical development of AI in marketing into three distinct periods. The proxy view (1950–2012) primarily focused on measuring user interactions and technology adoption. The tool view (2012–2018) saw AI as a means to improve productivity, with significant research on labor substitution and enhanced performance. The ensemble view (2019–present) emphasizes the interaction of AI with social and institutional contexts, acknowledging AI as a dynamic and evolving technology.

Figure 1 AI historical development



Source: Authors' elaboration

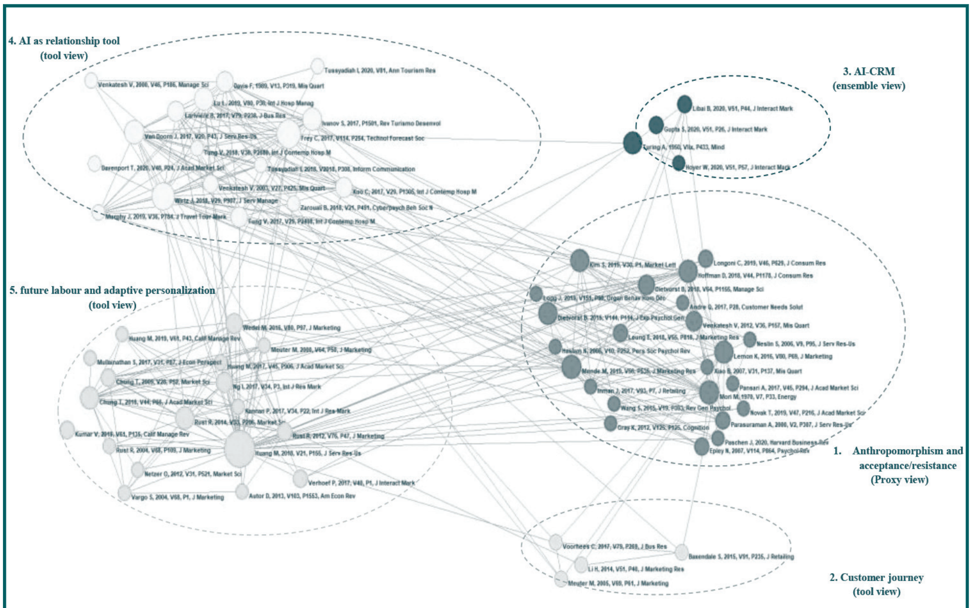
The root: knowledge foundation in artificial intelligence

Collectively, evolving trends can offer evidence of the significant breadth of scholarly writings in a research domain (e.g. AI), along with the widespread works that have influenced it. Furthermore, we find indicators of other sophisticated AI-related studies that have borrowed and extended relevant theories and leveraged established scales. Given such theoretical diversity in recent years related to the development of AI, investigating how AI research has been diffused is vital to gain a better understanding of the extended impact of the AI field in the marketing domain within KM context. As such, we examined other research areas that have been cited alongside AI research. We carried out a co-citation analysis on all references of the articles that cited our focal articles. Figure 2 maps the network of references of the citing articles, which resulted in five clusters of related articles featuring a distinct research area and reflecting an AI connection with a specific research stream. In Figure 2, the nodes represent individual articles, and the connection between each individual article shows the relationship strength based on the number of co-citations. The size of each node in the clusters is based on the number of citations by the sample articles. The network algorithm shows the position of the articles based on their connection strength and thus the proximity of each cluster indicates the relatedness of different research streams. Accordingly, we provide a broad outline of proposed directions and domains for future scholars highlighting the specific body of knowledge for each period (i.e. RQ1).

Cluster 1 (anthropomorphism and acceptance/resistance). Cluster 1 group studies that focused on AI acceptance/resistance drivers (i.e. proxy view). As other comprehensive reviews of most of these constructs appear in other scholarly works (Blut and Wang, 2020; Blut *et al.*, 2021; Xiao and Kumar, 2021), we provide a broad outline of these studies and accordingly propose some potential directions for further studies.

In consumer research, *anthropomorphism* refers to the consumer tendency to ascribe human characteristics to nonhuman objectives. Anthropomorphism goes beyond the attribution of just physical features to the attribution of capabilities that are also unique to

Figure 2 Dispersion of AI in marketing literature



Note: Modularity = 0.45
Source: Authors' elaboration

humans. By giving human characteristics to nonhuman entities, anthropomorphism facilitates consumer–AI interactions by satisfying consumers' basics needs for social connection and control (Epley *et al.*, 2007). Although anthropomorphism in AI can help marketers create an effective consumer interface, such humanlike features can also lead to undesirable, negative outcomes. Some notable examples are uncanny theory (Mori, 1970) and algorithm aversions (Dietvorst *et al.*, 2015), which focus on feelings of creepiness and unease and negative responses to algorithm outcomes, respectively.

Our review of the cluster suggests two promising directions. First, consumer researchers focusing on consumer–AI interactions can further investigate the features of AI that are likely to evoke *human likeness*. That is, they can further specify what combinations of features can evoke human likeliness in different consumption contexts. Accordingly, studies on how individual anthroponomic AI differences (e.g. different accent/language) can influence consumption experiences are limited. An important research question is whether consumers will be more biased toward certain anthropomorphic AI with different skin color. In other words, will consumers' racist or sexist tendencies arise when interacting with an anthropomorphistic AI that exhibits a different cultural background from them? Second, research dealing with aesthetic design in the AI domain has focused mainly on the most served customer groups. This includes all the articles in the cluster along with the focal articles dealing with how consumers respond to anthropomorphism. Despite previous calls for more research to examine consumer differences, all the studies that have investigated anthropomorphism relate to the most served communities (Americans). Therefore, future research might benefit from investigating how consumers' individual characteristics affect their anthropomorphism preferences. Accordingly, we advise consumer researchers to assess the extent to which technophobia may play a role in consumer behavior in reaction to AI technologies.

Early studies on AI provided a comprehensive view of consumer *acceptance* of and *resistance* to the use of AI technologies, such as unsupervised technologies (e.g. automated teller machines). As there are extensive literature reviews on acceptance/resistance drivers (Blut and Wang, 2020; Blut *et al.*, 2021), we provide an overview of possible fruitful paths for researchers.

First, tasks perceived as involving more risks reduce customer adoption intentions (Longoni *et al.*, 2019). Thus, when outcomes of tasks are consequential, consumers are less likely to adopt the new technologies. Second, previous studies also suggest that customers are not likely to use AI if the task is vital to consumer identity (Castelo, 2019). To overcome this, we suggest future research to investigate how personalization can curb consumer resistance to AI adoption in consequential tasks (e.g. health care). A broader research question is whether reliance on AI will lead to diminished consumer capacity to think critically or to perform the tasks. That is, will losing the ability to perform tasks result in consumption experience dissatisfaction?

Cluster 2 (customer journey). Cluster 2 comprises articles that deal with the impact of AI on the customer journey. The research in this cluster focuses on how AI can enhance customer journey quality and, consequently, increase firm performance in terms of innovation capability (Taghizadeh *et al.*, 2018; Sukumar *et al.*, 2020). Customer experience is shaped by customers' interactions in various service encounters during their journey. Service encounters include process-related, interactional and outcome-related aspects. Therefore, future research should try to shed light on what consumers expect from AI-infused encounters and how their expectations play a role in their overall satisfaction, impacting on data-driven decision process and KM initiatives.

Our review of this cluster suggests important future theoretical development directions. The integration of AI in different stages of the service encounter seems a promising future research avenue. First, linking Cluster 1 to this one, future research could investigate how use of anthroponomic AI can influence each stage of the customer journey (i.e.

prepurchase, purchase and postpurchase). Does using anthroponomic AI in postcore service encounters, especially during service recovery efforts, increase customer dissatisfaction? Choi *et al.* (2020) showed that humanlike AI can recover a service failure by restoring the perception of warmth. Building on this, we also advise to investigate how to manage service failure in consequential tasks (e.g. medical context). How effective are other types of service recovery methods in service failure incidents (Foroudi *et al.*, 2024)? Second, AI and humans increasingly work side by side to deliver services, and this can raise questions of what performance looks like in such mixed service environments. Furthermore, we recommend that researchers emphasize work settings in which frontline employees play an important role in shaping service experiences, particularly when self-uniqueness is central to service delivery (e.g. health care, human resource management). Third, future research could investigate how combinations of human and AI employees can be used to shape functional and emotional consumption cues. Functional cues refer to utilitarian aspects of consumption, whereas emotional cues refer to humanistic aspects of consumption (Bolton *et al.*, 2021; Gelbrich *et al.*, 2021). Having this in mind, future research could investigate how AI can help promote functional cues and human employees the humanistic aspects of consumption.

Cluster 3 (artificial intelligence customer relationship management). In many recently published works, Cluster 3 articulates the capabilities required for AI CRM development through customer identification, customer attraction, customer retention and customer development. In addition, researchers (Tong *et al.*, 2020) have focused on how AI techniques can be useful in creating a*n ultra*-personalized shopping journey for customers. As such, Cluster 3 shows important research opportunities that scholars can exploit in the context of KM.

First, there is pressing need for understanding how offering personalized consumer journeys affects customer decisions and behavior. Future research needs to understand how consumers' privacy concerns will influence their satisfaction (Kannan, 2017). Accordingly, researchers should investigate the contexts in which consumers are less concerned about their privacy and do not mind receiving personalized offers. Second, additional research is necessary on AI–CRM capabilities. AI–CRM capabilities at the firm level are firm abilities in generation and integration and include responses to information gleaned from customer interactions facilitated by AI-related technologies. Thus, it is vital for marketers to know – within the landscape of KM – how firms should combine CRM with AI systems to enhance the customer journey. Third, future research should explore how AI–CRM capabilities can affect new product development and innovation (Sukumar *et al.*, 2020). Fourth, a review of the clusters and literature suggests that, methodologically, studies do not offer much empirical support for their fundamental propositions that AI-related capabilities can improve firm performance. Such methodological limitations affect the generalizability of the studies, which inevitably leads to biased conclusions. In turn, managers are left with high uncertainty about which AI capabilities are essential for competitive advantage. Thus, the lack of AI–CRM capabilities constitutes a research gap in terms of developing AI capabilities and tying them to firm performance.

We also contend that the risks associated with AI consumption equally need further attention and priority from firms. AI can generate social risks that need attention. For example, Amazon.com had to scrap an AI–human resource management system with gender bias, and X (formerly Twitter) had to shut down Tay (an AI chatbot) because of its offensive tweets. Such issues are not small risks for companies; thus, further investigations are greatly needed. Questions that need further attention include the following: How should managers respond in such times? What are the risks associated with integrating AI in the whole consumer journey? How should firms minimize such risks?

Cluster 4 (artificial intelligence as a relationship tool). Cluster 4 comprises articles that focus on service robots. From a broad perspective, these articles provide information on the socioeconomic impact of AI on the market (mainly tourism). In addition, studies have examined the influence of the development of AI on labor and focused on the robotic aspect of the AI domain (Murphy *et al.*, 2019; Tung and Law, 2017). In more detail, articles in this cluster highlight the advent of service robots, an automated computer program that can comprehend, act and respond to certain situations. Articles in this cluster show that following the emergent of AI technologies, firm hierarchies, social interaction roles and business processes might change. Articles in this group also investigate the shift in communication patterns and social networks associated with the introduction of AI technology. In particular, research has explored the introduction of service robots in terms of customer perceptions and beliefs related to service robot acceptance and robot-delivered interactions. Taken together, these views reflect AI as a relationship tool (i.e. the tool view).

Articles in cluster 4 show prior scholarly attempts to operationalize anthropomorphism (Lu *et al.*, 2019). However, the review of this cluster shows that current literature does not agree on the measurements of AI–customer interactions (e.g. anthropomorphism). Confusion prevails, as in some studies, anthropomorphism overlaps with other outcome variables such as willingness to use, whereas in other studies, it is an independent variable related to intention to use. Furthermore, some studies view anthropomorphism as a characteristic of AI rather than as a consumer response (Choi *et al.*, 2020), which deeply conflicts with the established tradition that anthropomorphism is a consumer subjective deduction. Such confusion warns of a fragile theoretical underpinning of service robotic research. We strongly urge future research to distinguish anthropomorphism from service robot characteristics (Kim *et al.*, 2019; Sheehan *et al.*, 2020; Xiao and Kumar, 2021). This means operationalizing anthropomorphism not on characteristic scales (e.g. warmth) but on customer responses. Current consumption literature offers some sound measures as a starting point (Puzakova *et al.*, 2013), whereas a integrative viewpoint should recommend building measures on the basis of the most common customer responses used in the literature (i.e. cognitive, emotional and social).

Cluster 5 (future labor and adaptive personalization). Cluster 5 clearly specifies the influence of types of AI on marketing decisions. In this regard, research mostly emphasizes mechanical and thinking AI for use in data collection and marketing analysis, respectively. Mechanical AI can help automate the data collection process, such as the Internet of things (IoT) (Ng and Wakenshaw, 2017; Wedel and Kannan, 2016), whereas thinking AI in market analysis can help derive a product's competitive advantage. Grounded in different types of AI in the literature, Huang and Rust (2018) proposed replacement theory, which describes how AI can first replace some service tasks and then take over the entirety of job tasks. In addition, this cluster comprises research related to machine learning with a great focus on adaptive personalization.

Considering the research streams in this cluster, we recommend to complement with further work that links the studies in this cluster with those in cluster 3. Owing to machine learning and the increasing types of social media, machine-learning algorithms can offer personalized offers to customers and improve a knowledge-based approach. As such, firms' direct contact opportunities, on which communication, sales tactics, CRM and other relationship marketing activities have been traditionally grounded, will be diminished. Accordingly, some research questions worthy of further attention are as follows: Which firms do consumers trust and thus build relationships with? To what extent do they trust AI personalization applications (e.g. Amazon Alexa)? If these applications fail, what happens to customer loyalty? Will consumers show no loyalty to brands because of the wide range of personalized offers?

Moreover, an emerging trend involves designing inclusive customer journeys. As such, future research also should examine how personalization will affect the design of an inclusive consumption experience for the individual consumer. We also encourage researchers to investigate whether designing a more inclusive customer journey for diverse customer base through personalization can help create value cocreation opportunities in the consumption experience (Vargo and Lusch, 2004). Another worthwhile consideration for future research is to explore consumer emotional responses (e.g. awe vs happiness) to personalization techniques and how such emotions shape the consumption experience.

Overall, our co-citation analysis reveals the influence of varied theoretical frameworks in the AI research stream, illustrating how AI bridges diverse research streams (proxy, tool, ensemble views). Furthermore, our results show that AI is applied in multiple contexts; however, the loose connection with other respective research streams or disciplines indicates significant potential for further development, as described in the first research question (RQ1).

As white as snow, as black as coal: text-mining results

To gain additional insights into the broader context of AI in the marketing and business domain, we applied a text-mining approach using Leximancer software. The analysis portrays the strength of the relationship between AI and other keywords in the literature and allows the discovery of unstructured conceptual insights and ontology (Biesenthal and Wilden, 2014). We then analyzed each concept for the inherent relationship that provided the basis for grouping them into themes, shown by colored circles (red and green), where more important colors are shown in brighter and larger circles and cooler colors (e.g. blue) represent less investigated and important topics in the research domain. The overlap of different circles shows the degree to which different topics have been investigated together (Kumar *et al.*, 2019) to identify the spatial configuration of the different research areas that support AI and marketing domains within the Km context (named RQ2).

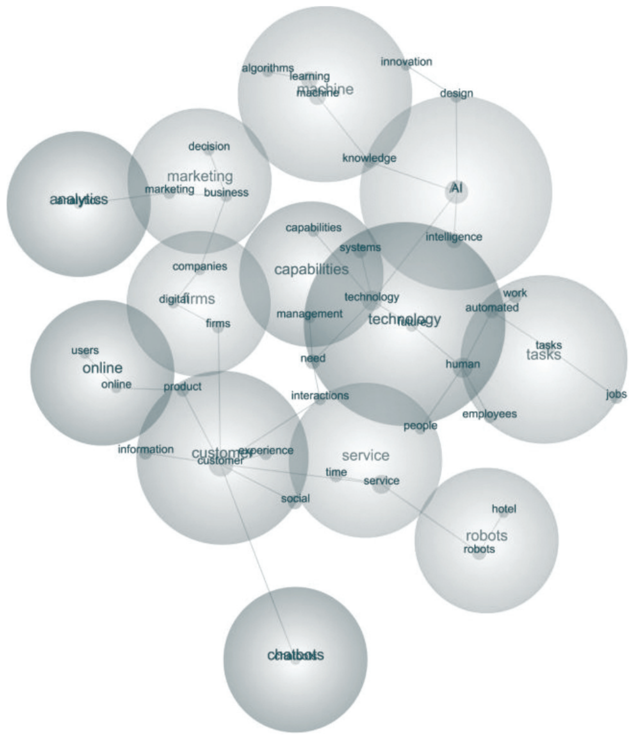
Figure 3 depicts the results of text mining for the focal articles. In the remainder of this part, words in italics indicate identified themes and words with quotation marks show concepts. As we show in Figure 3, AI literature is deeply rooted in technology literature; *technology* (bright red) and the *customer* (red-brown) both show the central themes in AI literature. The *technology* theme possesses the concepts “needs” and “people,” and it shares the concepts “management,” “technology” and “system” with the *capabilities* theme. Such interaction suggests that the creation of a supportive ecosystem for radical innovations (here AI) is one of the most crucial factors for success or failure. Tracking the overlap between technology and capability suggests that, like in previous technological innovations, to realize the full potential of AI technology, firms need a specific set of AI-specific capabilities (e.g. machine learning) for application and impact. Thus, we recommend that future research investigates what these capabilities are in terms of security, technological and strategic capabilities.

Technology also overlaps with the *task* theme by sharing “automated” and “human” concepts. This interaction clearly shows the impact of AI on three levels (i.e. ‘tasks,” “jobs” or “work,” and “employee”). Despite its importance, of the studies that focused on how automation affects task replacement, none addressed consumer adoption issues. Thus, we also advise researchers to assess how resisting or disliking automation in specific segments will affect task automation.

Notably, AI service encounters have received scholarly attention in the AI domain (*technology* shares the “people” and “interaction” concepts with *service*). Highlighted in the *service* theme are technology-based services that can help firms reduce costs and time (“time” concept), develop interactions with frontline employees (“interaction” and “people” concept) and overall improve the customer experience (“experience” concept in the *customer* theme). Taken together, we call for further work on the sweepingly changing role of human employees in increasingly automated contexts, in which automation is becoming the norm for improving consumer and service interactions.

The *customer* theme, which is the second most important theme in the text mining, comprises “product,” “information,” “experience” and “social.” A review of this theme shows

Figure 3 Dispersion of AI ideas with all focal articles



Source: Authors' elaboration

the impact of personalization (i.e. "product" and "information" concept) and the customer journey (i.e. "experience"). Linking these two topics together, we call for further investigation into how personalization can influence decision-making during the customer journey. Furthermore, using consumer culture theory, research could explore how personalization can optimize the customer journey in various cultural contexts (Hollebeek and Belk, 2021). For example, customers in high-uncertainty-avoidance countries are more likely to rely on peers' information than a recommendation algorithm (Nam and Kannan, 2020). As such, future research could investigate the following question: Do chatbots boost the social influence of peers more in individualism or collectivism cultures?

The *machine*, which is also worthy of attention, comprises "algorithm," "innovation," "learning" and "knowledge." This theme highlights the impact of machine learning on service innovation through topic algorithms that can automatically describe, identify and quantify the topic from a data set. This represents a promising pathway for stimulating and accumulating new knowledge in the service innovation and service design literature.

However, although this theme stresses the importance of machine learning in service innovation and design, it has not been linked to important customer perspective indicators, such as loyalty, or the creation of new markets. Finally, the overlap among "marketing," "firms" and "analytics" reflects the AI impact on the business process and decision-making in various firms.

Discussion

Our study builds on and extends the existing knowledge of AI in marketing by integrating bibliometric analysis and text mining techniques. While previous studies, such as those by

Huang and Rust (2018), focused on AI's role in enhancing customer service and personalization, our findings reveal additional dimensions, particularly the significant impact of AI on KM practices and the broader organizational environment (Jafari-Sadeghi *et al.*, 2022). For instance, Blut *et al.* (2021) highlighted the importance of anthropomorphism in AI interactions. Our study expands on this by identifying specific themes related to anthropomorphic AI in various contexts, including its role in customer journey stages and service recovery efforts. This provides a deeper understanding of how AI's human-like features can be effectively used in different marketing scenarios. Marketing academics have extensively explored the relationship between AI and marketing within the KM context. They have observed technological advancements, conducted diverse research and provided valuable insights. These efforts have significantly advanced the understanding of AI. However, as AI technology rapidly evolves, new pathways will emerge. It is essential for marketers to investigate the connection between AI and marketing within the KM framework to understand how AI technologies can facilitate data-driven decision-making, enhance customer personalization, optimize marketing campaigns, reinforce business communication and improve overall marketing effectiveness.

In this section, we detail the basis for proposing an integrative future research agenda for AI based on the conceptual model able to capture emerging topics on AI and marketing domains in the context of KM (RQ3). We evaluate the articles reflected in our results along with our focal articles to establish a general fundamental premise for proposing possible future AI research in the marketing and business domain. The starting point is investigating our three analyses and synthesizing the underlying theoretical lenses. Then, by integrating different views (proxy, tool and ensemble), we propose and explain our conceptual model. Before discussing the theoretical underpinnings, however, we need to explain what we mean by AI.

Definition of artificial intelligence in consumption literature

As noted, the idea of an intelligent machine is not new, with many scholars regarding the subject of AI as beginning with Turing's (1950) discussion of how a machine can be programmed to play chess. Since then, although articles on AI have become popular in recent years (see as Figure 1), an agreed-on definition of AI is missing, warning of a fragmented future. Just like in the Indian parable of the blind men and the elephant (there is more than one man touching the animal) in which the elephant is described in various ways depending on where the blind men touch it, the same is true for AI depending on how researchers define it. For example, Huang and Rust's (2021a, 2021b) working definition does not clearly show the difference between smart products and AI and importantly neglects the role of intelligence in AI devices. Accordingly, the connectivity characteristic of their definition seems to be related more to smart products than to an AI device. To resolve such inconsistencies in the literature, we first stress the need to clearly define AI and distinguish it from similar concepts.

First, studies focused on the impact of AI on society have widely misused AI as a term for automation (Huang *et al.*, 2019). We observe this in our text-mining result in which the *technology* and *tasks* themes overlap and are linked with "work" and "human" concepts. Thus, AI research needs to clearly distinguish between AI and automation. In marketing literature, automation refers to the process whereby technology takes over active service inputs that customers and employees used to perform. The most common factor that results in automation is when tasks are repetitive, are routine and can be codified (Sampson, 2021). With this in mind automation does not necessarily reflect the importance of intelligence and needs to be clearly distinguished from AI.

Second, we need to distinguish AI from machine-learning algorithms. We observe such confusion in our text-mining results in which the *machine* theme overlaps with the *AI* theme, thus sharing the "knowledge" concept. Machine learning reflects a sophisticated, evidence-based formula for analytical pattern recognition (Rai, 2020). Similarly, Davenport *et al.* (2020) defined machine learning as programs that can provide meaning from external data. These programs' ability to extract meaningful insights render them suitable for innovation ("innovation" concept in the *machine* theme) and marketing decisions (*decision* theme in marketing). Although machine-learning algorithms can provide meaningful insights, they are still not AI because they cannot exhibit intuition and subjective awareness.

Third, despite being widely studied in marketing literature, service robots should be distinguished from AI as well. Service robots are a broad concept in marketing and service literature that refer to any mechanical machine that is used to perform rule-based work, and they are configured with basic features such as logins, authentication and security (Xiao and Kumar, 2021) without direct help and support from people (Huang and Rust, 2017).

As outlined, AI is conceptually distinct from other similar concepts; moreover, given this fast-growing domain, having a clear definition of AI seems more important than ever before. We recognize a need to revise the AI definition to reflect the inconsistencies and reflect on future opportunities. Consequently, to facilitate consistent progressive knowledge building on the topic, we define AI as a configuration of systems that are capable of learning, envisaging and acting independently. AI is fully equipped with hardware stacks required for automation and also features machine-learning algorithms. These algorithms enable AI to react to any environmental changes, connect with a larger network and to reason (i.e. show intelligence). Therefore, AI is not only algorithm based (similar to machine-learning algorithms) but also automatically active in providing appropriate responses. In our definition, the ability to reason and make independent decisions is at the core of our conceptualization. Decision-making and reasoning are interrelated with AI's *self-management*, *autonomy* and *autonomous* actions, which means that AI does not require any human intervention and can perform on its own. Technically, machine-learning algorithm, along with neural networks, can enable AI to learn, reason and act on any environmental changes (Novak and Hoffman, 2019). A basic example of AI is driverless cars. In a similar vein, AI can engage i*n proactive*, predictive behaviors. For example, driverless cars can spot potential risks even before their appearance and take necessary countermeasures.

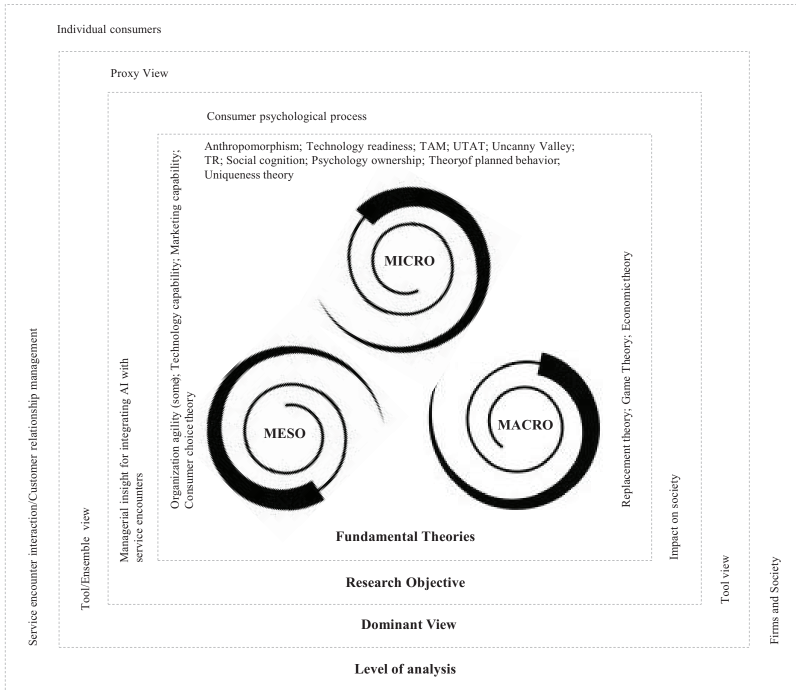
Artificial intelligence theoretical development

An overarching goal in the development of each field is to extend its boundaries beyond the fundamental theory (see Figure 4). Each field tends to be specialized, and thus all three theoretical lenses (micro, meso and macro) would gain from integrating one another's theoretical perspective to achieve a holistic view for theoretical development.

Theoretical lenses in the artificial intelligence domain. Based on Cluster 1 and the text-mining findings (*customer* theme), the first theoretical underpinning shows that AI scholars have applied a *micro* lens by investigating consumers' psychological and individual reactions to AI. The main unit of analysis in this theoretical underpinning is the consumer/individual level. Researchers in this area tend to use theories that capture consumers' internal processes. Applying a proxy view, researchers have heavily relied on social psychology in general and customer adoption in particular. During the years, this level has moved from acceptance theories to social psychology theories such as social cognition theories. Our results show that our largest cluster (also see our text-mining results) relies on some of these interpersonal relationship theories.

Aligning with Clusters 2 and 3, firms' capabilities and marketing themes, the next theoretical underpinning pertains to the investigation into how AI can be integrated with service encounters. This level of analysis has mainly applied the *meso* lens. Therefore, a typical unit of analysis for these studies is customers' interactions with AI-integrated services and, to a lesser extent, their interactions with frontline employee in such situations. The ultimate

Figure 4 Theoretical underpinnings in AI



Source: Authors' elaboration

objective of research in this area has been to provide managerial insights into improving AI and service encounter integration. Accordingly, many researchers have used representative theories such as marketing or technology capabilities.

Consistent with our co-citation analysis (Clusters 4 and 5) and text-mining results (*task* theme), the last theoretical underpinning features the macro lens by focusing on the impact of AI on society. For example, Huang and Rust (2018) largely examined how AI will replace tasks in the future. Similarly, Huang *et al.* (2019) introduced the concept of the feeling economy to the literature. More recent works on newer trends have shifted the focus and adopted a "meso-er" lens, which encompasses firm performance and behavior. The unit of analysis of this newer trend seems to be at the investor or firm levels, which are predominantly based on marketing-economic or game theories within the context of knowledge sharing (Al-Gharaibeh and Ali, 2022; Olan *et al.*, 2022; Rezaei *et al.*, 2023).

Future theoretical underpinnings development. A key takeaway derived from our findings and theoretical synthesis is that all three theoretical underpinnings can benefit from a broadening of their boundaries and integration with other areas (i.e. within the context of KM). All the underpinnings need to develop their theoretical background to their fullest potential. To do so, first we recommend that individual (or micro-) level underpinning theories focus more on generating managerial insights to become "meso-er." We recommend that researchers integrate insights from relationship theories, which have often used managerially relevant relationship concepts (e.g. satisfaction, performance). Second, as a way forward, researchers with a meso focus should use a theoretical perspective that offers a "micro-er" view. The potential exists to go beyond adoption of a business-to-business capability lens to better integrate with more interpersonal relationship theories. Operationalizing service quality in AI-integrated encounters would be a good start for researchers. Studies with a meso theoretical lens would also benefit from adopting the marketing–finance interface to better investigate the impact of AI on firm performance. The last theoretical underpinning would benefit from reinvigorating interest in the micro–meso lens, to close the gap between these two rather disparate lenses.

In terms of implementation, moving from a micro to a meso theoretical lens can be challenging for researchers because of a need to find real AI service encounters. However, shifting from a micro or meso lens to a more macro lens can be quite straightforward for researchers because most studies in this area are experimental, so researchers can use the context of their choice.

An integrated view of artificial intelligence development

As noted, our review reveals three main views (proxy, tool and ensemble) that have shaped the foundation of AI in marketing. Given significant changes in AI technologies, however, marketing scholars will be investigating unknown research questions in the future, so understanding the findings of previous studies will help them predict possible future questions easier. This section is not intended to offer a comprehensive list of the research questions that future scholars will face; rather, its goal is to provide a systematic investigation of the relationship between different views in the AI domain in marketing and business within the KM studies (Del Giudice *et al.*, 2023).

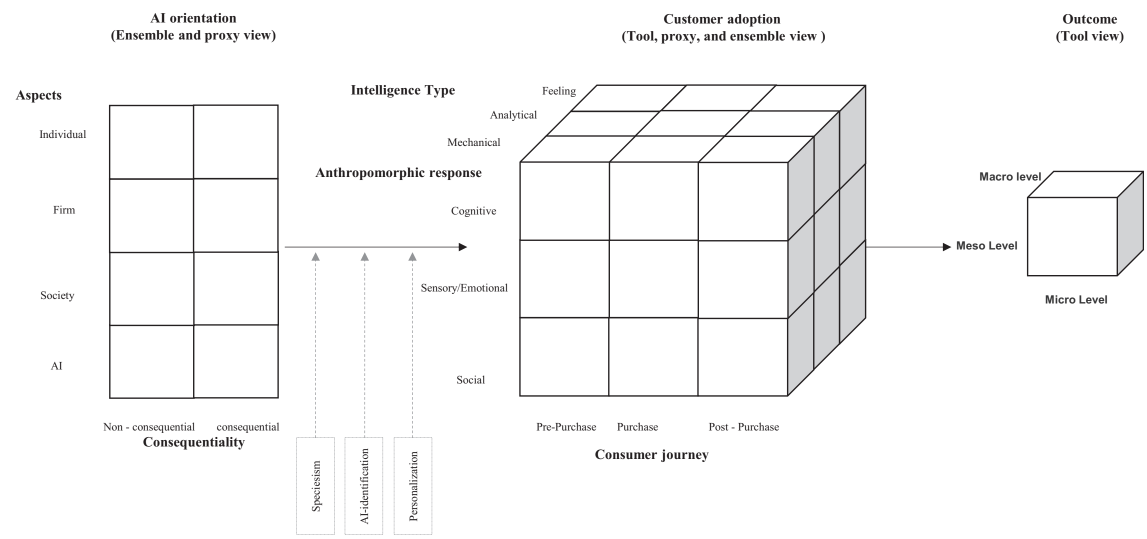
First, when examining the impact of AI on business as a technology that can replace job, researchers could adopt the perspective of AI as a tool and investigate how it can generate a competitive advantage by changing the workforce structure. They can the assess the implications for society. Research could also take a proxy view and investigate why some consumers feel more positively about AI technology than others. Alternatively, research could take the ensemble view to determine how AI technology affects different parts of the customer service journey, as well as the organizational environment and what capabilities are required to better integrate AI into the firm. We suggest that future research focuses on both the bright and dark sides of AI (De Bruyn *et al.*, 2020). In addition, they should not only examine customer adoption but also address, for example, the needs of frontline employees for AI integration and KM sharing.

Second, increasingly more firms are using AI as a productivity tool to process their data. Thus, research could investigate whether AI technology results in increasing profitability for a firm. We also encourage scholars to evaluate how AI will displace some of the decision-making tasks now undertaken by highly trained employees to improve knowledge. The proxy view can also be helpful for researchers considering the level of consequentiality when investigating AI technology effectiveness. Although customers might have more positive feelings about AI technologies that have less consequential outcomes (e.g. chatbots), they might not be willing to adopt AI technologies that are used for more consequential tasks (e.g. medicine AI, driverless cars). The ensemble view can be useful for investigating how meso and macro contextual features can enhance the effectiveness of AI decision-making and firm profitability.

Accordingly, for each new AI technology, researchers can develop important research questions by combining the three views. Here, we map possible future AI paths by considering the multiple aspects of AI orientation (ensemble and proxy views) that influence customers' adoption of technology, which in turn improves firm productivity (tool view). Accordingly, drawing on these different views, we introduce the proposed framework for future research in Figure 5.

Artificial intelligence orientation. The first block is *AI orientation* which was quite prevalent in the studies focused on the effectiveness of multiple aspects of AI (ensemble view) and the level of consequentiality on customer adoption (proxy view). In terms of the ensemble view, we acknowledge that different AI contextual aspects (e.g. individual, firm, society) will affect

Figure 5 Proposed AI conceptual model



Source: Authors' elaboration

customer adoption; these consist of the intelligence type (feeling, analytical and mechanical), anthropomorphic response (cognitive, sensory/embodiment and social) and service experience (prepurchase, purchase or postpurchase) (Castelo, 2019; Fountaine *et al.*, 2019; Wamba *et al.*, 2017). While previous research has focused predominantly on the role of individual (employee or customers) aspects (e.g. consumer readiness) (Kumar *et al.*, 2019; Odekerken-Schröder *et al.*, 2020) and AI aspects (e.g., autonomy), it has largely neglected the firm- and society-related aspects.

Taking an ensemble view, a fruitful area for future research would be to pursue the effectiveness of firm- and society-related aspects in consumers' anthropomorphic responses. For example, do developed and developing country citizens have the same anthropomorphic response to AI? If not, what are the most important characteristics that lead to a positive anthropomorphic response, and how can societies empower their citizens? Considering dynamic capability theory, how can firms acquire the most desirable characteristics to achieve a positive anthropomorphic response? Previous research suggests that acquiring human capability (Xiao and Kumar, 2021) and firm agility (Kalaignanam *et al.*, 2021) can provide a head start toward realizing firm capabilities. Furthermore, future studies could investigate the influence of a society's characteristics on AI-related consumer behavior (Auer and Papies, 2020). Parasuraman and Colby (2015) called for further investigation into how the social context influences technology readiness. Similarly, Kumar *et al.* (2019) asserted that macrolevel characteristics influence the new TAM and thus need further attention. Therefore, future studies based on culture theory can investigate how the cultural characteristics of a society influence AI evaluation.

According to the proxy view, the level of consequentiality can affect customer adoption response. Consequential tasks are tasks that involve affect, intuition, subjectivity and empathy and are salient to consumer identity. For example, Dietvorst *et al.* (2015) suggested that consumers are more likely to trust human forecasting than algorithm forecasting, especially after encountering an algorithm error. Resistance to using AI in consequential tasks occurs in a variety of settings, ranging from employee performance prediction (Kuncel *et al.*, 2013) to medical settings (Longoni *et al.*, 2019). Thus, scholars can investigate the impact of task consequentiality on cognitive customer response. To do so, we encourage them to conceptualize consequential tasks as tasks that involve measurable, quantifiable outcomes. By contrast, nonconsequential tasks are tasks that are open to consumer opinion, interpretation and intuition. It is important to note that people differ in their decision-making (Garousi Mokhtarzadeh *et al.*, 2021) approaches, and future research should also consider these differences as well. Thus, it would be fruitful to investigate the potential relationship among task consequentiality, consumer anthropomorphic response and intelligence type.

Moderating role of speciesism, artificial intelligence-identification and personalization. We also advise researchers to investigate the roles of personalization, identification and speciesism in the relationship between AI orientation and customer adoption. As AI is becoming increasingly more humanized, future research could investigate how *speciesism* can influence customer interactions with AI. Caviola *et al.* (2019, p. 2) define speciesism as "different inherent moral status based solely on an individual's species membership." Consumer researchers could investigate whether speciesism, in addition to uncanny valley theory, plays as a role in anthropomorphic AI, which accordingly can result in disadvantages in service or retailing settings. This is a promising avenue for researchers investigating how AI can be integrated with frontline employees. One question is: Will groups of employees act against a firm's AI system?

Similarly, prior consumer research has failed to provide a complete picture of how consumers are likely to identify with AI. According to classic intergroup theories, cognitive similarities play a fundamental role in shaping social identification. Thus, viewing similarities between AI and humans is likely to play an important role in consumer identification with AI. Future experimental studies could systematically investigate the different dimensions of identification (e.g. cognitive similarity) with AI and test their respective casual relationships. We also advise researchers, to integrate a more traditional perspective, to identify the factors that promote consumer identification with AI to uncover people's attitudes and behavior toward AI. Linking studies with AI's different categories, consumer researchers could more directly focus on the processes and outcomes of identification with each AI types (e.g. mechanical AI, feeling AI). Accordingly, a diverse array of socially relevant and theoretically important questions associated with the antecedents and consequences of the AI–consumer identification relationship await further research investigation.

Finally, we urge researchers to investigate how personalization can moderate the AI–consumer identification relationship. Previous studies have investigated this relationship and found that personalization can influence customer adoption in the health-care context (Hoffman and Novak, 2018); however, an integrative understanding such as what we proposed in our model is widely missing in the literature. Future investigations could answer the question of how personalization can affect customer adoption across the consumer journey stages. Another question is whether personalization can moderate the relationship between consequentiality and customer adoption.

Customer adoption. Customer adoption is our next block, which comprises the intelligence type (tool view), the anthropomorphic response (proxy view) and the consumer journey (ensemble view). The studies focusing on AI as a substitutional tool investigated how consumers can adopt different AI types for various tasks (tool view). Another group of articles drawing on proxy view can focus on why some individual anthropomorphic responses are more favorable than others. Finally, grounded in the ensemble view, researchers can investigate how AI can be integrated in the different stages of the consumer journey.

As we identified in Cluster 5, different AI intelligence types play an important in the AI literature (Huang and Rust, 2021a, 2021b) and therefore can be determinants of customer adoption. To continue making advances in the AI field, future research should consider the different types of AI. In addition, the AI literature has widely investigated consumers' anthropomorphic responses to determine how different design features of AI influence their evaluations. As we discussed in Cluster 4, future research should not only focus on emotional (i.e. warmth) and cognitive (i.e. competence) aspects but also investigate other important consumer responses (e.g. sensory and social) to AI. Finally, we identified the customer journey as an emerging trend (Cluster 2). Thus, we call for more attention to the role of the customer journey and how AI affects the different stages of this journey.

Outcome. The last block of AI literature consists of articles that are focused on influence of AI on macro-, meso- and microlevel. By integrating different perspectives, we suggest that the joint impact of AI adoption should influence the outcome (tool view) at the macro-, meso-, or microlevels (Granulo *et al.*, 2021; Gurkaynak *et al.*, 2016; Huang *et al.*, 2019; Liu *et al.*, 2020; Makridakis, 2017; Sepehri *et al.*, 2021; Singh *et al.*, 2021; Sohrabpour *et al.*, 2021). Many studies have investigated the influence of anthropomorphism responses on outcomes. However, an integrative view of the impact of consumer adoption on outcomes has mostly been neglected in the literature. Therefore, to fill this gap, we suggest that research examines the micro-related metrics (e.g. satisfaction and loyalty) related to positive outcomes. For the meso outcome, firm performance can be evaluated using monetary-related measures (e.g. market share and profitability).

Given the development in terms of measuring AI performance (Samaha *et al.*, 2014), additional measures, such as relationship value, can add more insight into the mesolevel performance as well. Researchers have tended to focus on the micro- and mesolevel outcomes of AI while ignoring the impact of AI on macrosystem outcomes (Granulo *et al.*, 2021). In addition, the influence of consumer orientation on the macrolevel has been limited in economic scale, and other outcomes have been less investigated.

As such, we advise researchers to examine performance as an amalgamation of different outcome categories. To do so, they need to define their outcome construct explicitly and provide justification for their chosen construct. We also recommend that future research applies multiple outcome categories. Thus, operationalization should be based on outcome categories. For example, perceived quality should be measured as a separate rather than a meso-related outcome variable of profit.

Our review of the literature suggests that AI literature has not used different outcome categories. As the AI research field is still developing, many different outcome relationships (e.g. willingness to pay) have not yet been investigated and thus need further attention.

Table 1 lists some possible research questions related to the proposed conceptual model.

Researchers could begin by investigating how service robots in particular influence brand experience. Importantly, studies with a focus on micro-related outcomes should investigate not only the positive relationships but also the negative relationships.

Limitations

Our first limitation pertains to the articles we chose for inclusion in our data analysis. Although we used a well-established and trusted source of journal ranking for finding our articles (ABS list), our approach *inevitably* will be influenced by the subjectivity of the scholarly perception. That is, perceived differences can influence which articles should be included and which should be excluded. To resolve this issue, we tried to include all the articles that were ranked 4*, 4 or 3 stars in the ABS list. We chose this ranking because of its scope and with the intent of inclusion, while offering sufficient rigor for us to draw valid conclusions. Second, in contrast with meta-analyses, bibliometrics is a generalized method for analyzing a given literature domain. For example, investigating a research chain will result in only a broad understanding and identification of only the main themes of a research chain. However, following a rigorous examination of the cited and citing scholarly works, a more integrated and complete understanding of the domain can emerge. Moreover, the ability to identify relationships between different variables from various analyses is limited.

Table 1 Sample questions for future conceptual research on AI

Relationship	*Research question*	Example articles
AI orientation → customer adoption	■ Which characteristics' configuration leads to an (un)favorable anthropomorphic response? ■ Which characteristics relate to adoption of/resistance to AI? ■ How can the characteristics be changed and improved by firms and society? Which characteristic is the most influential? ■ Which level of consequentiality leads to an (un)favorable anthropomorphic response? Do different characteristics influence this relationship? ■ Do consumers perceive a consequential task more favorably when it is done by mechanical AI or feeling AI? ■ How does consequentiality differ between different types of intelligence? ■ How does consequentiality differ between customer journeys, so that it leads to a more (un)favorable anthropomorphic response? ■ Are there situations when consequential/nonconsequential tasks interrelate with the consumer journey, so it leads to a more (un)favorable anthropomorphic response? ■ Should researchers compare AI intelligence with human intelligence? If not, unlike humankind, can AI intelligence be improved? ■ How does consequentiality differ across customer journeys? ■ Is there a best configuration between intelligence type and the consumer journey? Should mechanical AI be used mainly in the prepurchase customer journey? Should feeling AI be mainly used in the postpurchase stage? ■ What is the role of different types of intelligence in a service ecosystem (e.g. meeting customer needs, engaging customers in their purchase journey)?	Ameen *et al.* (2021); Bag *et al.* (2021); Kietzmann *et al.* (2018); Longoni *et al.* (2019); Luo *et al.* (2019); Pantano and Pizzi (2020); Perez-Vega *et al.* (2021)
Customer orientation → outcome	■ How will consumers respond to different types of feeling AI? ■ How will the nature of the service ecosystem change with the implications of AI in the consumer journey? ■ What are the dark sides of AI for consumer well-being? Is this related more to feeling AI? ■ Does using mechanical AI instead of human workers result in customer anger? ■ Will customers be more satisfied when they interact with a feeling AI in their post-purchase journey? ■ Will different types of intelligence increase human agent skills? Is this true just for feeling AI, or is it also related to mechanical AI? ■ What jobs will emerge as a result of different types of intelligence? What skills are needed for those jobs? ■ Are there any ethical issues related to AI? Are they mainly related to feeling and analytical AI? If so, how can firms reduce such environmental threats? ■ How does AI interact with and influence the different levels of a company's marketing program? ■ What are the disadvantages of AI for a firm/society? ■ How long does it take for a firm to implement AI in its customer journey? ■ Will AI result in increasing inequity among developed, developing, and underdeveloped countries? If so, how can this inequality be tackled?	Daugherty *et al.* (2019); Huang *et al.* (2019); Koo *et al.* (2020); Rampersad (2020); Wilson *et al.* (2017); Zhu *et al.* (2019)

Source: Authors' elaboration

Results usually provide some key examples of possibilities, but ample opportunities also exist for scholars to choose their research direction. As such, a generalized pattern of identifying the fundamental premises of a large body of work is idiosyncratic to every bibliometric analysis. This pattern can be considered a limitation of the bibliometric method itself.

Implications

Theoretical implications

AI and marketing domains have the potential to revolutionize various aspects of business operations, including customer service, product development, marketing, supply chain management. Theoretical implications are evident in the previous sections whereas the citation analysis and text-mining offer a fresh perspective on the impact of AI and marketing domains in the context of KM studies (Verma *et al.*, 2021). Particularly, the investigation proposed by Brynjolfsson and McAfee (2014) argues that businesses that effectively integrate AI into their operations can achieve higher productivity, cost savings and innovation compared to their competitors (Del Giudice *et al.*, 2023). AI and marketing domains enable businesses to automate routine tasks, freeing up human resources to focus on higher-value activities such as strategic decision-making and creativity. This can lead to increased efficiency, reduced errors and improved overall performance.

Furthermore, AI technology can enhance decision-making processes by providing real-time insights and predictive analytics. By analyzing vast amounts of data, AI algorithms can identify patterns and make data-driven recommendations, enabling businesses to make more informed and accurate decisions. This can give businesses a competitive advantage by enabling them to respond quickly to market changes and capitalize on emerging opportunities. Davenport and Ronanki (2018) found that organizations that effectively use AI technologies have the potential to outperform their competitors in terms of revenue growth, profitability and market capitalization. By harnessing the power of AI, businesses can gain valuable insights, enhance operational efficiency and deliver personalized experiences to their customers. In conclusion, understanding the competitive advantage of AI in changing the workforce structure is crucial for businesses to thrive in today's rapidly evolving market. Researchers can contribute to the theoretical understanding of how businesses can leverage AI technology by investigating its potential benefits, challenges and best practices. By effectively integrating AI into their operations, businesses can achieve higher productivity, cost savings, innovation and improved decision-making, giving them a strategic edge over their competitors. In addition, our study proposes a new conceptual framework that categorizes the historical development of AI into proxy, tool and ensemble views. This framework not only maps the evolution of AI in marketing but also suggests future research trajectories, which is a novel contribution to the literature.

Practical implications

First, understanding the impact of AI on workforce structure and profitability is crucial for businesses to make informed decisions about AI adoption and integration. This insight can guide strategic planning and resource allocation to maximize benefits and mitigate potential risks. Additionally, employee training and support are essential for integrating AI and facilitating (Olan *et al.*, 2022; Rezaei *et al.*, 2023). Providing training programs, creating support systems and fostering a culture that embraces AI within the KM context can ensure a smooth transition to AI-based systems. A unique contribution of our study is the comprehensive integration of AI within the KM framework. Previous research often treated AI and KM as separate domains, but by combining these, our study provides a holistic view of how AI can enhance (Olan *et al.*, 2022; Rezaei *et al.*, 2023), decision-making and strategic planning in marketing.

Thirdly, customer adoption and satisfaction can investigate the factors that affect customer acceptance of AI technologies can help businesses design and implement AI and marketing domains that are more user-friendly and meet customer expectations. This can enhance customer adoption rates and satisfaction levels.

Societal implications

Examining the potential job displacement generated by AI technology can help policymakers and stakeholders anticipate and manage the social and economic consequences. This can inform discussions on workforce reskilling, job creation and income redistribution to ensure a smooth transition in the labor market. Researching both the positive and negative implications of AI technology can contribute to the development of ethical guidelines and regulations. This can help mitigate potential risks such as privacy breaches, algorithmic bias and the misuse of AI for harmful purposes. Thus, understanding consumer perceptions and concerns about AI and marketing domains can help ensure that AI technologies are developed to care societal needs and values. This can promote equitable access to AI and marketing benefits and reduce the potential for exacerbating existing social inequalities.

Overall, research on the theoretical, practical and societal implications of AI can provide valuable insights for businesses, policymakers and society at large in navigating the opportunities and challenges of AI and marketing domains within KM landscapes.

Future research advancements and conclusions

Present and past studies shape future scholarly works (Kuhn, 1996). Our study is the first to advance a theory-driven framework based on different prevalent views of AI, highlighting integrated potential future research directions. The novelty of this study lies in integrating the diverse topics studied in AI literature to date, providing a foundation for future investigations. This research explains that AI orientation drives evaluation and outcomes, demonstrating that an integrative view should be prominent in future scholarly works. Therefore, topics related to technology acceptance, technology readiness and the capability of the proposed components of the conceptual model provide a basis for future research, enhancing KM studies. Future research should delve deeper into specific areas where AI can further enhance marketing and KM practices. One key area is AI-driven customer personalization. Studies could investigate how AI can bolster customer loyalty across different market segments and assess the long-term effects on consumer behavior and brand perception. Longitudinal studies and experimental designs could measure the effectiveness of AI personalization techniques.

Another vital area is the integration of AI in KM to streamline decision-making processes and enhance (Olan *et al.*, 2022; Rezaei *et al.*, 2023) within organizations. This could be explored through case studies of successful AI integration and surveys with KM professionals to identify challenges and best practices. Ethical implications of AI in marketing, such as data privacy and algorithmic bias, also require detailed exploration. Research could focus on consumer perceptions of these ethical issues and develop frameworks to ensure responsible AI practices. This could be achieved through qualitative methods like focus groups and in-depth interviews, alongside the development and testing of ethical frameworks using action research methodologies. Investigating AI's impact on workforce dynamics is another promising avenue. Research should explore the new skill sets required for employees working alongside AI and how AI adoption influences job satisfaction and performance. Mixed-method studies combining quantitative surveys and qualitative interviews, as well as longitudinal research, could provide comprehensive insights into these dynamics.

In addition, examining AI's role in optimizing different stages of the customer journey, such as enhancing prepurchase interactions and improving service recovery efforts, could yield valuable findings. Field experiments and analysis of customer feedback and behavioral data would be suitable methodologies for these studies. Finally, the cross-cultural applications of AI in marketing strategies present a rich area for future research. Studies should investigate how cultural differences impact the acceptance and effectiveness of AI in marketing and identify best practices for implementing AI-driven strategies in diverse cultural contexts. Comparative studies across different cultural settings and ethnographic research could provide deep insights into these variations. By addressing these specific areas with detailed research questions and appropriate methodologies, future research can significantly advance the understanding and application of AI in marketing and KM.

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