






Engaging consumers through artificially intelligent technologies: Systematic review, conceptual model, and further research

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Abstract

While consumer engagement (CE) in the context of artificially intelligent (AI-based) technologies (e.g., chatbots, smart products, voice assistants, or autonomous cars) is gaining traction, the themes characterizing this emerging, interdisciplinary corpus of work remain indeterminate, exposing an important literature-based gap. Addressing this gap, we conduct a systematic review of 89 studies using the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) approach to synthesize the AI-based CE literature. Our review yields three major themes of AI-based CE, including (i) *Increasingly accurate service provision through AI-based CE*; (ii) *Capacity of AI-based CE to (co)create consumer-perceived value*, and (iii) *AI-based CE's reduced consumer effort in their task execution*. We also develop a conceptual model that proposes the AI-based CE antecedents of personal, technological, interactional, social, and situational factors, and the AI-based CE consequences of consumer-based, firm-based, and human-AI collaboration outcomes. We conclude by offering pertinent implications for theory development (e.g., by offering future research questions derived from the proposed themes of AI-based CE) and practice (e.g., by reducing consumer-perceived costs of their brand/firm interactions).

KEYWORDS

artificial intelligence, consumer engagement, PRISMA, systematic review

1 | INTRODUCTION

Consumer engagement (CE), a consumer's resource investment in their interactions with an object (e.g., a brand; Kumar et al., 2019), has been heralded as a key business performance indicator in recent years (Kumar & Pansari, 2016). Engaged consumers have been shown to exhibit elevated psychological and behavioral outcomes (e.g.,

enhanced loyalty or recommendation behavior; Brodie et al., 2011), lifting firm-based competitive advantage. While the literature has, traditionally, centered on consumers' engagement with brands, growing attention is being afforded to their engagement with specific technologies and its effect on their brand engagement, which has been designated *technology-facilitated brand engagement* (Hollebeek & Belk, 2021).

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Prior research has examined consumers' technology-facilitated brand engagement in the context of technologies, including social media, virtual-, augmented-, or mixed reality applications, and automated or artificially intelligent technologies, among others (e.g., Puntoni et al., 2021), which have been demonstrated to boost corporate performance (Huang & Rust, 2021). Here, consumers' engagement with artificially intelligent technologies—in particular, those able to perform tasks without human intervention (e.g., generative or predictive artificial intelligence [AI]; Dwivedi et al., 2023)—is receiving widespread attention in the consumer psychology and marketing literatures (Sampson, 2021; Wu & Monfort, 2023). Among these, the AI subclasses of machine learning (i.e., an AI subset, which uses algorithms that flexibly adapt to data constellations to improve task performance) and deep learning (i.e., a machine learning subset that involves computing multilayer neural networks) technologies are able to offer improved decisions or predictions over time based on the deployed (e.g., big) data (Hollebeek et al., 2021; Pradeep et al., 2019), thus offering consumers increasingly accurate (e.g., product) solutions (Leung et al., 2018), provided high-quality training data and state-of-the-art algorithms are used. For example, while Google's machine learning-based predictive text (predictive AI) improves (*learns*) over time, Amazon's Echo or Apple's Siri likewise, provide increasingly customized solutions to their users (Pitardi et al., 2023).

However, despite the importance of fostering consumers' engagement with or through AI-based technologies, authors have adopted myriad theoretical perspectives and methods to investigate this multidisciplinary topic, yielding theoretical inconsistencies and fragmentation. That is, the adoption of different theoretical lenses and approaches to explore AI-based CE has yielded potentially incompatible findings, generating an important literature-based tension. For example, some authors suggest that AI technology (e.g., chatbot)-based *social presence*, “the extent to which [an AI technology] make[s] consumers feel ...they are in the company of another social entity” (Van Doorn et al., 2017, p. 44), acts as key driver of users' engagement (e.g., McLean et al., 2021; Schuetzler et al., 2020). However, other researchers, like Tsai et al. (2021), identify opposing effects in that a chatbot's high (vs. low) social presence-based communication was not found to significantly affect user engagement.

To clarify these conflicting literature-based findings, we systematically review the AI-based CE literature. By elucidating the key themes characterizing this multidisciplinary literature stream, we uncover AI-based CE's hallmarks and dynamics. Following prior systematic reviews (e.g., Ameen et al., 2022), we also develop a conceptual model of AI-based CE and its nomological network (i.e., key antecedents and consequences; MacInnis, 2011). The development of new insight in this rapidly growing area is important, given the myriad applications of AI-based CE that are forecast to continue redefining consumer behavior and marketing alike (McKinsey, 2023), thus serving as a springboard for further AI-based CE research. We view AI as “a system's ability to interpret external data..., to learn from such data, and to use those learnings to achieve specific goals

and tasks through flexible adaptation” (Haenlein & Kaplan, 2019, p. 5), and *engagement* as a consumer's resource investment in their brand-related (e.g., AI) interactions (e.g., Hollebeek et al., 2019; Kumar et al., 2019). Overall, by collating and assessing the corpus of AI-based CE research, our analyses pave the way for this cross-disciplinary area's further development (Page et al., 2021; Pollock & Berge, 2018).

This review paper makes the following contributions to the CE, AI, and the broader consumer psychology/behavior- and marketing literatures. First, adopting the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) approach (e.g., Page et al., 2021; Shobhit et al., 2023), we obtain a sample of 89 AI-based CE studies that are analyzed to deduce their theoretical hallmarks (e.g., deployed theories or methods; Rehman et al., 2020) and to uncover their main themes (Creswell & Creswell, 2018). We also develop a model of AI-based CE, reflecting MacInnis' (2011) notion of *relating* and, thus, unlocking acumen of the concept's position vis-à-vis its antecedents and consequences, a widely-adopted approach in prior PRISMA-based studies (e.g., Ameen et al., 2022; Rehman et al., 2020). These analyses matter, given AI's unique capabilities that have shaped, and which are expected to continue shaping, CE in important ways (Hollebeek et al., 2021). Moreover, though the scope of AI-based CE has already expanded in recent years (e.g., through the launch of ever-evolving new technologies, like generative AI/ChatGPT), it is also forecast to continue growing in the years to come (McKinsey, 2023), warranting its strategic importance.

Second, following prior authors (e.g., Page et al., 2021; Verma et al., 2021), we derive an agenda for further AI-based CE research from our findings. This is also important, given the continued growth of, and the predicted ongoing (e.g., innovative) developments in, AI-based CE, providing rich opportunities for further exploration. Specifically, given AI's relative newness in marketing, coupled with its potentially unique and evolving effects on CE, we expect our findings to hold value for researchers (e.g., by serving as a foundation for further exploration), warranting AI-based CE's importance in the coming years.

We next review AI-based CE literature (Section 2), followed by an outline of the deployed methodology (Section 3). We, then, present our main findings (Section 4), followed by an overview of key implications that emerge from our work (Section 5).

2 | THEORETICAL BACKGROUND

2.1 | Consumer engagement

Given its demonstrated effect on firm performance (Beckers et al., 2018), CE is heralded as a key consumer psychology/behavior, and marketing, metric (Kumar & Pansari, 2016; Lim et al., 2022). However, CE's definition is contested. For example, though Brodie et al. (2011, p. 260) define CE as “a motivational state that occurs by virtue of interactive co-creative, [consumer] experiences with a focal

agent/object,” Hollebeek et al. (2019, p. 166) conceptualize it as a consumer’s “investment of ...operant resources [e.g., cognitive/behavioral knowledge/skills], and operand resources [e.g., equipment] in [their] brand interactions.” Notwithstanding these differences, we distill the following generic CE traits.

First, CE is an *interactive* concept that centers on the consumer’s interactions with a brand or (a) specific brand-related object(s) (e.g., brand-related AI technologies; Hollebeek et al., 2023; Perez-Vega et al., 2021). Here, *interaction* reflects “mutual or reciprocal action or influence” (Vargo & Lusch, 2016, p. 9) between the engagement *subject* (e.g., consumer) and the engagement *object* (e.g., an AI technology; Hoffman & Novak, 2018; Hollebeek, 2011; Sung et al., 2021). When consumers interact with AI technologies, they may be aware, or unaware, of their interaction with a machine, as gauged by the *Turing Test*.

Second, CE is, typically, modeled as a multidimensional construct comprising cognitive, emotional, and behavioral dimensions (Hollebeek et al., 2023; Vivek et al., 2014). While *cognitive engagement* reflects the consumer’s cognitive resource investment in their brand interactions (Schaarschmidt & Dose, 2023), *emotional engagement* denotes a consumer’s emotion (e.g., passion) invested in their brand interactions (Herrando et al., 2017). *Behavioral engagement*, then, reflects consumers’ investment of time, energy, and effort in their brand interactions (Hollebeek et al., 2014).

Third, scholars have adopted manifold theories to explore CE, including S-D logic (Brodie et al., 2011), relationship marketing (Vivek et al., 2014), and congruity theory (Islam et al., 2018), among others, revealing the concept’s theoretical versatility (Hollebeek et al., 2023). CE has also been explored in online (digital), offline, and hybrid (phygital) contexts (Mele & Russo-Spena, 2022). For example, while offline CE has been explored in sectors, including hospitality/tourism (e.g., So et al., 2014), coffee shops (e.g., Ornelas Sánchez & Vera Martínez, 2021), or gyms (e.g., Menidjel et al., 2023), digital engagement has been studied in settings, including online communities (Ozuem et al., 2021), social media (Hollebeek et al., 2014), augmented, virtual, and mixed reality (Rather et al., 2023), AI technologies (Moriuchi, 2021), among others. Digital engagement researchers have adopted perspectives, including the Technology Acceptance Model (e.g., Moriuchi, 2019), diffusion of innovations, and technology readiness (e.g., Yin et al., 2023), to name a few. We next review marketing-based AI literature.

2.2 | Artificial intelligence

AI, “a system’s ability to interpret external data..., to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation” (Haenlein & Kaplan, 2019, p. 5), has, likewise gained momentum in consumer psychology/behavior, and marketing, research (Mehta et al., 2022). For example, while Apple’s Siri allows consumers to seamlessly execute tasks through voice commands, Google Home permits users to remotely perform tasks at home (e.g., monitoring the alarm; Xiao & Kumar, 2021). Through their

ability to perform specific tasks increasingly accurately over time, AI applications that incorporate machine- or deep learning, or generative AI, technology may help consumers complete their tasks more efficiently or effectively (Huang & Rust, 2021; Xie et al., 2022). For example, chatbots tend to offer consumers more accurate, comprehensive, or personalized product recommendations or solutions over time (Dwivedi et al., 2023).

Scholars classify AI in different ways. For example, Huang and Rust (2018) propose a tri-partite typology comprising *mechanical AI* (i.e., able to perform repetitive or routine tasks), *thinking AI* (i.e., able to learn from data to make decisions), and *feeling AI* (i.e., able to display empathy; Hollebeek et al., 2021). Another pertinent AI classification is (a) *generative AI*, which is used to create novel, original, or creative (e.g., textual/image-based) content (e.g., ChatGPT/Copy.ai; Dwivedi et al., 2023), and (b) *predictive AI*, which uncovers patterns in historical data to predict or forecast specific future outcomes, behaviors, or events (e.g., predictive SMS; Hollebeek et al., 2021). By helping consumers execute specific tasks more efficiently or effectively (e.g., through predictive text), AI technologies can boost their engagement, whether with the technology or with the brand/firm (Hyun et al., 2022; Kull et al., 2021). For example, personalized AI-generated solutions can help raise consumers’ (e.g., monetary/referral-based) resource investments in their brand interactions (Barnes & de Ruyter, 2022), boosting their engagement (Bertrandias et al., 2021). AI adoption can, thus, help foster value-laden customer relationships (Singh et al., 2021), demonstrating AI-based CE’s strategic value.

3 | METHODOLOGY

To synthesize the corpus of AI-based CE literature, we conducted a systematic review to identify and assess published work in this multidisciplinary area (Petticrew & Roberts, 2006; Siddaway et al., 2019). To perform the review, we followed a three-step search process that comprised initial and secondary searches, followed by a snowball search, to ensure all relevant studies were identified and included in our article sample (see Figure 1; Giang Barrera & Shah, 2023; Swaminathan & Venkitasubramony, 2024). In our initial search, we focused on articles published in Marketing and Business journals, which we later broadened to include relevant articles published in non-Marketing and non-Business journals (e.g., Arts/Humanities, Psychology, and Decision Sciences) in our secondary search. In the snowball search, we further scanned the literature, including the reference lists of the studied articles, to ensure no relevant studies were missed.

We, then, developed a protocol specifying the inclusion criteria for our articles (Hollebeek et al., 2023). Specifically, relevant articles addressing AI-based CE that were published in English, peer-reviewed Scopus-indexed journals with an impact factor of ≥ 3 were considered eligible for inclusion in our review (Giang Barrera & Shah, 2023; Rehman et al., 2020). We did not restrict our search to any particular start date, and instead considered any eligible articles published up until October 8, 2023 (Le et al., 2022).

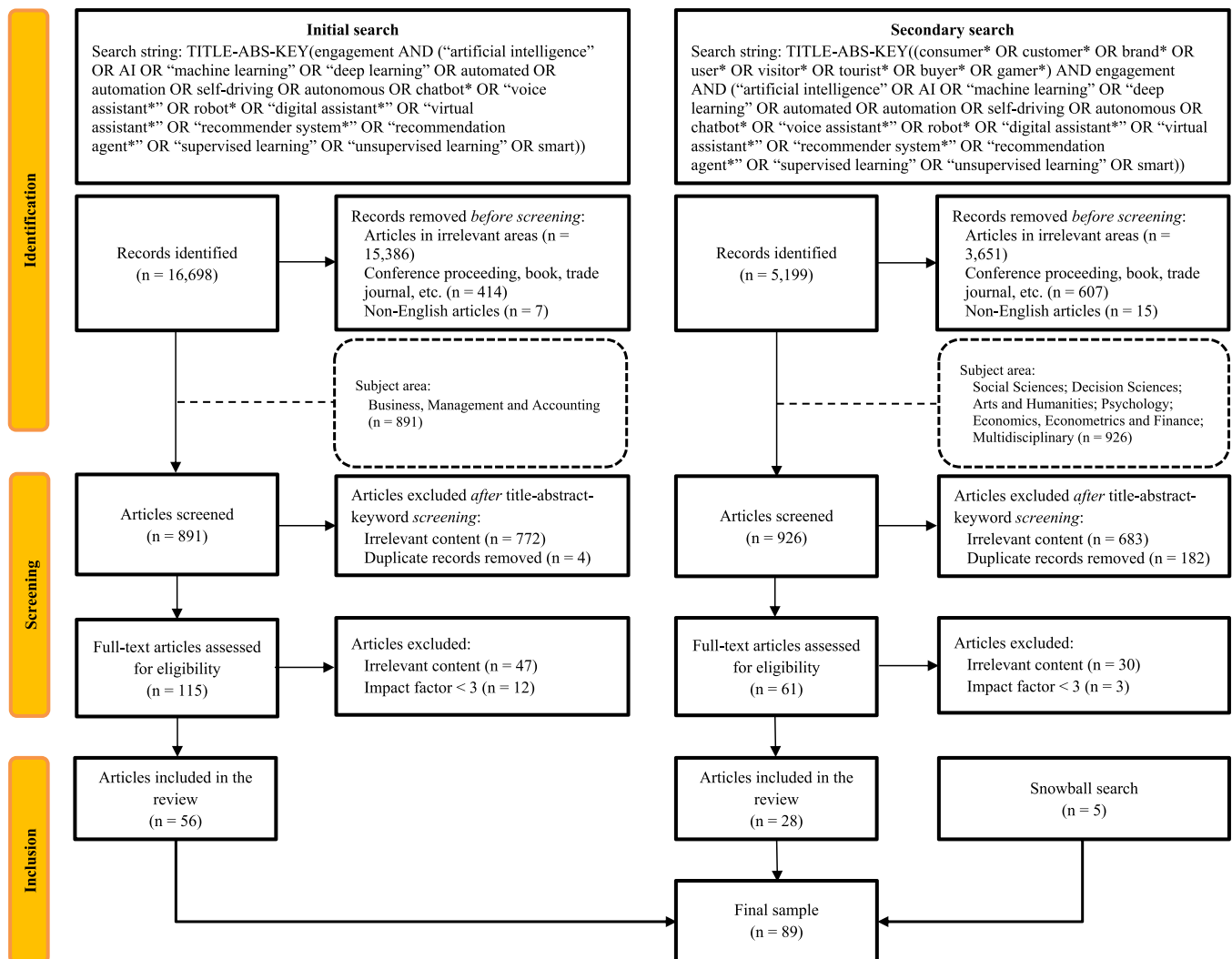


FIGURE 1 PRISMA-based model of the article selection process. PRISMA, Preferred Reporting Items for Systematic reviews and Meta-Analyses.

To guide our analysis, we adopted the widely-used PRISMA protocol (e.g., Hollebeek et al., 2023; Moher, 2009), which comprises three main phases, including Identification, Screening, and Inclusion (Page et al., 2021). First, in the Identification phase, we searched the titles, abstracts, and keywords of eligible Scopus-indexed journals for the following keywords (Shobhit et al., 2023): (engagement AND (“artificial intelligence” OR AI OR “machine learning” OR “deep learning” OR automated OR automation OR self-driving OR autonomous OR chatbot* OR “voice assistant*” OR robot* OR “digital assistant*” OR “virtual assistant*” OR “recommender system*” OR “recommendation agent*” OR “supervised learning” OR “unsupervised learning” OR smart)). We focused on original research, thus excluding prior (e.g., systematic or bibliometric) reviews (e.g., Lim et al., 2022; Mehta et al., 2022) from our article sample (Clarke, 2011).

The search conducted on October 8, 2023, which covered all eligible articles published up until this date, yielded a total of 16,698 records. However, of these, we only considered those published in

English-language, Scopus-indexed Marketing and Business journals (Hollebeek et al., 2023). Therefore, studies published in other disciplines (e.g., Neuroscience/Microbiology, $n = 15,386$), in other languages ($n = 7$), or those in other outlets (e.g., conference proceedings, books/trade journals; $n = 414$), were excluded (Zorzela et al., 2016), yielding a sample of 891 publications eligible for further assessment.

In the Screening phase, we undertook title-abstract-keyword screening of the 891 articles (Page et al., 2021; Rehman et al., 2020), limiting our analysis to those articles exploring the interface of specific AI technologies and CE. For example, we excluded Acar and Toker (2019), who address sharing economy-based AI adoption vis-à-vis consumers' personality traits (vs. AI-based CE). This part of the Screening phase yielded a total of 115 articles eligible for full-text review (Moriuchi, 2019; Perez-Vega et al., 2021). From these, we removed another 59 articles, either given their lack of relevance to our objective, or because the relevant journal's impact factor was < 3. For example, we removed Jain and Gandhi's (2021) work that is

focused on AI and impulse buying behavior (vs. AI-based CE). Therefore, in the Inclusion phase, we retained a total of 56 articles from our initial literature search (see Figure 1).

We, then, conducted a secondary search to ensure that all eligible articles were, indeed, included in our sample (Page et al., 2021; see Figure 1). Given AI-based CE's multidisciplinary nature (Sung et al., 2021), we broadened the search to articles published in Social Sciences, Arts/Humanities, Psychology, Decision Sciences, and Multidisciplinary journals. Using the same keyword combination: ((consumer* OR customer* OR brand* OR user* OR visitor* OR tourist* OR buyer* OR gamer*) AND engagement AND ("artificial intelligence" OR AI OR "machine learning" OR "deep learning" OR automated OR automation OR self-driving OR autonomous OR chatbot* OR "voice assistant*" OR robot* OR "digital assistant*" OR "virtual assistant*" OR "recommender system*" OR "recommendation agent*" OR "supervised learning" OR "unsupervised learning" OR smart)), we identified a total of 5,199 records (see Figure 1).

We, again, excluded articles featuring limited relevance, including those in Physics/Astronomy ($n = 3,651$), those published in non-peer-reviewed journals ($n = 607$), and those in non-English outlets ($n = 15$), leading us to retain 926 articles for inclusion in title-abstract-keyword screening. Of these, a further 683 were removed due to lacking relevance, and another 182 owing to duplication, yielding a total of 61 articles for full-text review. For example, we removed Chen et al. (2019), given its focus on the interface of consumer-perceived value, past experience, and behavioral intention (vs. AI-based CE). Of the 61 remaining articles, a further 30 were removed (e.g., Lee et al., 2019), as they, upon closer inspection, did not address AI-based CE or were published in journals with an impact factor of <3 , yielding 28 additional articles for further analysis (e.g., Jiang et al., 2022; Wen et al., 2022). Finally, on October 11, 2023, we further verified that all eligible articles were included in our review by scanning the reference lists of the articles in our initial ($n = 56$) and secondary ($n = 28$) searches, uncovering five additional studies (e.g., Kumar et al., 2021). Overall, our sample contains 89 articles addressing AI-based CE (see Table 1 and Supporting Information: Appendix 1).

4 | FINDINGS

4.1 | Descriptive analysis

Analyzing the 89 articles, we observed that most were published in the period from 2020 until October 2023 (93.26%), with the others (6.74%) appearing from 2015 to 2019 (e.g., Bretan et al., 2015; Moriuchi, 2019). This observation makes sense, given marketing scholars' rising interest in AI in recent years (Lin & Wu, 2023; Rahman et al., 2023) and, thus, in AI-based CE. For example, in late 2018, Hollebeek, Sprott, and Brady launched a *Journal of Service Research* special issue call titled "Customer Engagement in Automated Service Interactions" (Hollebeek et al., 2021).

The most-cited AI-based CE articles (as of October 11, 2023) were Huang and Rust (2021; i.e., 275), followed by Moriuchi (2019)

(i.e., 141) in *Psychology & Marketing*, and Xiao and Kumar (2021) (i.e., 113). Our article sample was sourced from 54 journals, including the *Journal of Business Research* (5 articles), *Journal of Service Research* (4), *Computers in Human Behavior* (4), *International Journal of Human-Computer Interaction* (4), *Journal of Research in Interactive Marketing* (4), *Journal of Retailing & Consumer Services* (4), and *Frontiers in Psychology* (3). Average citations for each of our studied articles are also included in Supporting Information: Appendix 2.

The sample reveals different AI subareas, including conversational AI (32.58%), robotics (17.98%), smart technology (8.99%), machine learning (3.37%), recommender systems (2.25%), and automation (1.12%), among others. The articles address several AI-based CE contexts, including tourism and hospitality (Wei & Prentice, 2022), branding (Rahman et al., 2023), healthcare (Kumar et al., 2021), and social media (Ghouri et al., 2022), among others. Moreover, while 28.09% of the articles did not explicitly use a guiding theory, the remaining 71.91% did. The most common theories include stimulus-organism-response theory (14 articles; e.g., Asante et al., 2023; Gao et al., 2022), the Technology Acceptance Model (6 articles; e.g., Moriuchi, 2019; Xiao & Kumar, 2021), and social presence theory (3 articles; e.g., McLean et al., 2021; Yu et al., 2022). Overall, our review uncovered AI-based CE authors' adoption of 56 different theories. Furthermore, 92.13% of the articles are empirical (7.87% conceptual). Relatedly, 62 of the empirical studies deployed quantitative methods (e.g., Asante et al., 2023; Moriuchi, 2021), 7 employed qualitative approaches (e.g., Ghouri et al., 2022; Singh et al., 2021), and 13 used mixed-methods (e.g., Chandra et al., 2022; Kumar et al., 2021).

4.2 | AI-based CE themes

We next content-analyzed the articles to uncover the main themes of AI-based CE, including: (i) *Increasingly accurate service provision through AI-based CE*; (ii) *Capacity of AI-based CE to (co)create consumer-perceived value*, and (iii) *AI-based CE's reduced consumer effort in their task execution*, as detailed below.

4.2.1 | Increasingly accurate service provision through AI-based CE

AI technologies are heralded to provide more accurate service or (service) outcomes compared to traditional human-to-human interactions (Huang & Rust, 2021). Based on our analysis, this elevated accuracy is due to two main factors. First, the ability of thinking/feeling, machine/deep learning, or generative/predictive AI technologies to gradually improve their performance is central to increasingly accurate service provision (Hollebeek et al., 2021; Huang & Rust, 2018). For example, since its Q4, 2022 launch, generative AI ChatGPT's capabilities have already considerably improved (e.g., through people's data sharing with it, enabling it to learn; Dwivedi et al., 2023). Moreover, by logging and monitoring users' clickstream

TABLE 1 AI-based CE's nomological network.

Author(s)	Antecedents	Consequences
Bretan et al. (2015)	Robot's ability to express emotion	-
Rodriguez-Lizundia et al. (2015)	Embodiment, robot's greeting, and active-looking robot	-
Aluri et al. (2019)	-	Value co-creation
Molinillo et al. (2019)	-	-
Moriuchi (2019)	Subjective norms and perceived usefulness	Customer loyalty
Mulcahy et al. (2019)	Technology readiness (optimism, innovativeness, discomfort, and insecurity), perceived risk, and trust	Intention to adopt
Bindewald et al. (2020)	Automation	-
Cheng and Jiang (2020)	Active communicative action	-
Fan et al. (2020)	Customer smart experience quality (human–interaction, smart system quality, self-service quality, and product content quality)	Purchase loyalty and positive word-of-mouth
Prentice and Nguyen (2020)	Service experience with employees and service experience with AI	Customer loyalty
Prentice et al. (2020)	Customer satisfaction with AI	-
Schuetzler et al. (2020)	Chatbot conversational skill and social presence	-
Baabdullah et al. (2021)	Acceptance of AI practices	-
Bertrandias et al. (2021)	-	Perceived benefits (freeing time, overcoming human weaknesses, and outperforming human capacities) and perceived risks (risk of loss of competencies, performance risk, and security and privacy risk)
Çakar and Aykol (2021)	-	-
Cheung et al. (2021)	Value cocreation	Perceived brand value
Grimes et al. (2021)	Conversational AI capability	-
Henkens et al. (2021)	Perceived personalization and perceived intrusiveness	Customer well-being (self-efficacy and technology anxiety)
Hollebeek et al. (2021)	-	-
Huang and Rust (2021)	-	-
Kull et al. (2021)	Warm (vs. competent) chatbot message and brand-self distance	-
Kumar et al. (2021)	Responsible AI	Perceived value (instrumental value and terminal value)
McLean et al. (2021)	AI attributes (social presence, perceived intelligence, and social attraction), technology attributes (perceived usefulness and ease of use), and situation attributes (utilitarian benefits, hedonic benefits, and distrust)	Brand usage intention and purchase intention
Moriuchi (2021)	Anthropomorphism	Intention to re-use
Nasir et al. (2021)	-	-
Oh and Kang (2021)	-	-
Perez-Vega et al. (2021)	-	-
Riva and Mauri (2021)	-	-
Shumanov and Johnson (2021)	Congruent consumer-chatbot personality	-
Singh et al. (2021)	-	-

(Continues)

TABLE 1 (Continued)

Author(s)	Antecedents	Consequences
Tsai et al. (2021)	Chatbots' social presence communication, parasocial interaction, and perceived dialogue	-
Vernuccio et al. (2021)	Brand experience-based in-car name-brand voice assistants	-
Xiao and Kumar (2021)	Customer satisfaction and -emotions	-
Blasi et al. (2022)	-	-
Chandra et al. (2022)	Human-like AI competencies (AI cognitive-, AI relational-, and AI emotional competency) and user trust in AI	-
Chen, Keng, et al. (2022)	Trust in the platform and trust in the host	Customer loyalty
Chen, Prentice, et al. (2022)	Interaction experience	-
Fang et al. (2022)	Need satisfaction, tourist emotion, and social bond with robots	-
Fuentes-Moraleda et al. (2022)	-	Acceptance of social robots
Gao et al. (2022)	Perceived interactivity and -personalization	Value co-creation
Ghouri et al. (2022)	-	-
Hari et al. (2022)	Time convenience, interactivity, compatibility, complexity, observability, and trialability	Satisfaction and brand usage intent
Hernández-Ortega et al. (2022)	Relational cohesion	-
Hlee et al. (2022)	Attitude toward using service robots	-
Hollebeek, Menidjel, et al. (2022)	Perceived behavioral control	Purchase intent
Hyun et al. (2022)	Socio-functional elements (perceived hospitability, -coolness, -robot safety, and robot performance competence)	Viability of human-robot team service and intention to use service robots
Jiang et al. (2022)	Customers' satisfaction with chatbot services	Purchase intention and price premium
Kang and Lou (2022)	Human-AI collaboration (agency negotiation and agency synergy)	-
Li et al. (2022)	Robots' proactive behavior and trust in service robots	-
Lim and Zhang (2022)	Perceived contingency and attitude toward AI-powered news	Adoption of AI-powered news
Loureiro et al. (2022)	Lifestyle congruency and chatbot identification	Chatbot advocacy
Maslowska et al. (2022)	Consumers' recommender system use and perceptions ('visits, page views,' relevance, discovery/curation, surprise, 'privacy, security,' and 'trust, agency')	Brand's long-term outcomes (lifetime value, (e)word-of-mouth, brand equity, and provider retention)
Mele and Russo-Spena (2022)	-	-
Mele et al. (2022)	Integration of high-tech and high-touch	Well-being
Mostafa and Kasamani (2022)	Chatbot initial trust	-
Wei and Prentice (2022)	AI service quality	Customer loyalty
Wen et al. (2022)	Customers' perception of AI (perceived personalization and -autonomy), subject factor (trust in AI and self-efficacy), and environment factor (community identification)	Value co-creation behaviors
Yang and Lin (2022)	-	-
Yu et al. (2022)	Social presence	Intention to purchase

TABLE 1 (Continued)

Author(s)	Antecedents	Consequences
Zhu et al. (2022)	Flow experiences	-
Acikgoz et al. (2023)	Attitudes towards using voice assistants and willingness to provide privacy information	-
Akdim and Casaló (2023)	Perceived value	-
Asante et al. (2023)	AI elements (chatbot efficiency, image search functionality, recommendation system efficiency, and automated after-sales service)	-
Aslam (2023)	-	-
Chang et al. (2023)	Perceived smart travel technologies experience	Behavioral intentions
Dong et al. (2023)	Source credibility and content control	Perceived ad intrusiveness
Gauer et al. (2023)	-	-
Guo and Jiang (2023)	AI-generated personalized advertising copy	-
Hobert et al. (2023)	ICAP modes (i.e., passive, active, constructive, and interactive)	-
Kumar, Sharma, et al. (2023)	-	-
Kumar, Vrontis, et al. (2023)	-	Customer benefit
Li et al. (2023)	Perceived competence, -warmth, and -usefulness	-
Lin and Wu (2023)	Consumer gratifications (information seeking-, social interaction-, and entertainment gratification)	Brand intimacy, affective commitment, chatbot-related behavioral intention, and purchase intention
Nazir et al. (2023)	AI technology	Satisfying consumer experience
Nguyen et al. (2023)	Anthropomorphic language and perceived authenticity	-
Paul et al. (2023)	-	-
Prentice et al. (2023)	Autonomy, competence, and relatedness	Consumer well-being and attachment
Rahman et al. (2023)	AI-powered digital assistance	Customer's luxury brand shopping experience
Sattarapu et al. (2023)	-	-
Shah et al. (2023)	Robot service quality	Customer acceptance
Sharma et al. (2023)	Share	-
Swan et al. (2023)	Digital self-efficacy and relational service quality	Anticipatory AI value cocreation and intention to adopt AI
Upadhyay and Kamble (2023)	Anthropomorphism and smart experience	Brand love
Xie et al. (2023)	Loneliness, trust, and chatbot personification	Relationship development
Xie-Carson et al. (2023)	Entertainment value, emotional connection, and educational content	-
Xiong et al. (2023)	Smart tourism technologies	Memorable tourism experiences
Xue et al. (2023)	Voice assistant interactions, competence perception, and warmth perception	-
Yin et al. (2023)	Conspicuous AI environment, ideal self-congruity, and trust	-
Yu et al. (2024)	Emotional displays (happiness, sadness, disgust, and surprise)	-

Abbreviations: AI, artificial intelligence; CE, consumer engagement.

behavior, online recommender systems are able to provide increasingly personalized solutions to their users (Maslowska et al., 2022).

AI's capacity to learn will help boost consumers' *in-* and/or *extra-* role performance (e.g., by enhancing the efficiency or effectiveness of the customer journey; Heller et al., 2021; Hollebeek et al., 2023). For example, while voice assistants (e.g., Amazon's Echo) allow their users to multitask, AI-based Google Ads' capacity to provide multiple offerings in a matter of seconds can facilitate or accelerate their purchase decision-making (Kumar et al., 2016). Overall, AI's ability to learn, whether through thinking/feeling, machine/deep learning, or generative/predictive AI, permits firms to progressively pinpoint, estimate, or pre-empt those offerings that consumers are interested in, the communications they are likely to respond to, their responses to specific promotions, and so on (Lin et al., 2021), thus influencing CE. However, to leverage AI's capacity to learn, high-quality training data is pivotal (Pradeep et al., 2019), as poor data will suboptimize its learning, yielding low-quality (e.g., incorrect) solutions (i.e., *garbage-in, garbage-out*; Hair & Sarstedt, 2021).

Second, AI technologies are, typically, heralded to provide more accurate service (e.g., given their capacity to reduce human error compared to human-to-human service delivery (Hollebeek et al., 2021). That is, if AI technologies are suitably trained with high-quality data, they are expected to complete tasks more efficiently, safely, and consistently than humans (Lin et al., 2021), thus lowering service variability and raising service quality (Bertrandias et al., 2021). For example, autonomous cars, reportedly, cause fewer accidents (Schneble & Shaw, 2021), potentially wiping out the car insurance sector (Mills, 2021). However, if poor-quality (e.g., biased) training data is used, which may also be subject to human error (e.g., in cases of supervised learning; Pradeep et al., 2019), AI technologies are likely to provide inaccurate suggestions or solutions. Relatedly, substantial human inputs are, still, needed to facilitate AI-based learning (e.g., by manually entering, sorting, or annotating the data that are used as the inputs for AI-based learning; Dzieza, 2023), which can, likewise, incur human error (e.g., inaccuracies/mistakes; Mehta et al., 2023).

4.2.2 | Capacity of AI-based CE to (co)create customer-perceived value

When consumers interact with AI technologies, they are likely to derive a particular perceived value level from these interactions (e.g., through the technology's perceived usefulness, convenience, or personalization; Huang & Rust, 2021). Here, *consumer-perceived value* denotes a consumer's "overall assessment of the utility of a product based on perceptions of what is received and what is given" (Zeithaml, 1988, p. 14). For example, AI technology may be applied to mow the lawn or clean the house (e.g., robotic vacuum cleaners/lawn mowers). In these processes, consumers may cocreate value with the technology (Gao et al., 2022; Wen et al., 2022), where *cocreation* refers to a consumer's "perceived value arising from joint, interactive, collaborative, or personalized

brand-related activities" (Hollebeek et al., 2019, p. 167). When consumers perceive their AI interactions to be of value, they will tend to derive positive perceived (cocreated) value from their interactions with these, and vice versa (Fang et al., 2022; Prentice et al., 2020), typically fueling their desire to continue engaging with these (Lalicic & Weismayer, 2021).

Customer-perceived AI value is likely to differ across AI subtypes and/or contexts. For example, while mechanical AI is able to automate routine tasks (e.g., a company's automated phone menu), it—unlike machine or deep learning, thinking or feeling, or generative or predictive AI technologies (e.g., conversational agents)—is not designed to learn or improve its performance over time (Hari et al., 2022). Likewise, while students may see more value in specific (e.g., essay) content being created for them through generative AI (e.g., ChatGPT/Google Bard), on holiday, they may wish to primarily interact with predictive AI (e.g., Google Ads to facilitate their purchase decision-making). Overall, our analyses suggest that as technologies increasingly mimic human thinking or feeling processes, their customer-perceived (cocreated) value is likely to rise (e.g., given their capacity to personalize service or to display empathy; Liu-Thompkins et al., 2022; Van Doorn et al., 2017). The consumer-perceived value of generative (vs. predictive) AI may also differ (e.g., based on users' unique needs).

While the literature highlights AI-based CE's *positive* effects, insight into AI's potentially negative impact on engagement is also emerging (Hepziba & John, 2020; Thaichon et al., 2023). For example, Saxena (2022), Xiao and Kumar (2021), and Grundner and Neuhofer (2021) suggest that AI may reduce, or (co)destroy, perceived value, including in cases of service failure or unmet expectations (e.g., when the algorithm is still learning). Likewise, while authors, including Hlee et al. (2022) and Hyun et al. (2022), show that elevated AI friendliness, coolness, or competence boost CE, at low levels, these may hamper the development of these variables.

4.2.3 | AI-based CE's reduced consumer effort in their task execution

To perform their *in-* role activities (e.g., by researching, evaluating, or purchasing goods; Piercy, 2006) and *extra-* role activities (e.g., by providing brand-related word-of-mouth; Karaosmanoglu et al., 2016), consumers are, traditionally, required to invest specific cognitive, emotional, and/or behavioral resources, reflecting their engagement (Hollebeek et al., 2019). Consumers may perceive their resource investments to vary in terms of their perceived difficulty, exposing differing levels of role-related effort (Sweeney et al., 2015). While AI technologies do not necessarily remove consumers' required resource investments in their *in-* or *extra-* role activities (or role-related effort) *altogether*, these technologies may, indeed, *reduce* their required resource investments or effort (e.g., by performing specific tasks *for them*; Sampson, 2021). For example, video-tag recommender systems suggest specific tags to be added to online videos (Yang & Lin, 2022), reducing the user's necessary (e.g., cognitive) resource

investment (e.g., in determining suitable tags) and boosting the technology's perceived *ease of use*, as proposed in the Technology Acceptance Model (Davis, 1989), while lowering their technological *effort expectancy*, as professed in the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003). Likewise, companies like Amazon or McDonald's are increasingly delivering their orders through land-based or airborne robots (e.g., drones), removing consumers' need to collect their order and enabling faster delivery. In turn, consumers' technology adoption and continued usage are expected to rise.

The AI-induced reduction in consumers' required resource investments, or effort, to execute their *in-* or *extra-*role activities exposes an interesting literature-based tension: While the CE literature, conventionally, suggests that raising or optimizing CE will boost firm performance (e.g., Brodie et al., 2011), AI's role in *lowering* users' required resource investments may engender a need to revise this original CE-based assertion in the AI context (i.e., as AI may *reduce* their required effort; Hollebeek et al., 2021). Relatedly, rather than reducing consumers' required resource investments per se, their AI interactions may also *shift* the nature or composition of their engagement. For example, the use of AI-generated (vs. human-generated) product recommendations may lower their cognitive resource investment or effort.

4.3 | Conceptual model

Following prior systematic reviews (e.g., Ameen et al., 2022; Rehman et al., 2020), we next develop a model that depicts AI-based CE vis-à-vis its key antecedents and consequences (Figure 2). By synthesizing AI-based CE's nomological network, the model serves as an important resource for further AI-based CE scholarship. For definitions of the model's constituent concepts, please refer to Supporting Information: Appendix 3.

4.3.1 | AI-based CE antecedents

Reviewing the corpus of AI-based CE research, we uncovered five categories of AI-based CE antecedents, including personal, technological, interactional, social, and situational factors, as detailed below.

Personal factors address the consumer's individual characteristics, perceptions, and expectations, which we further subdivide into *consumers' expected AI benefits* and *perceived AI congruency/identification*. First, *expected AI benefits* refer to consumers' anticipated benefit of (using) specific AI technologies (Bertrandias et al., 2021; Kumar et al., 2021). Key constructs examined in this area include

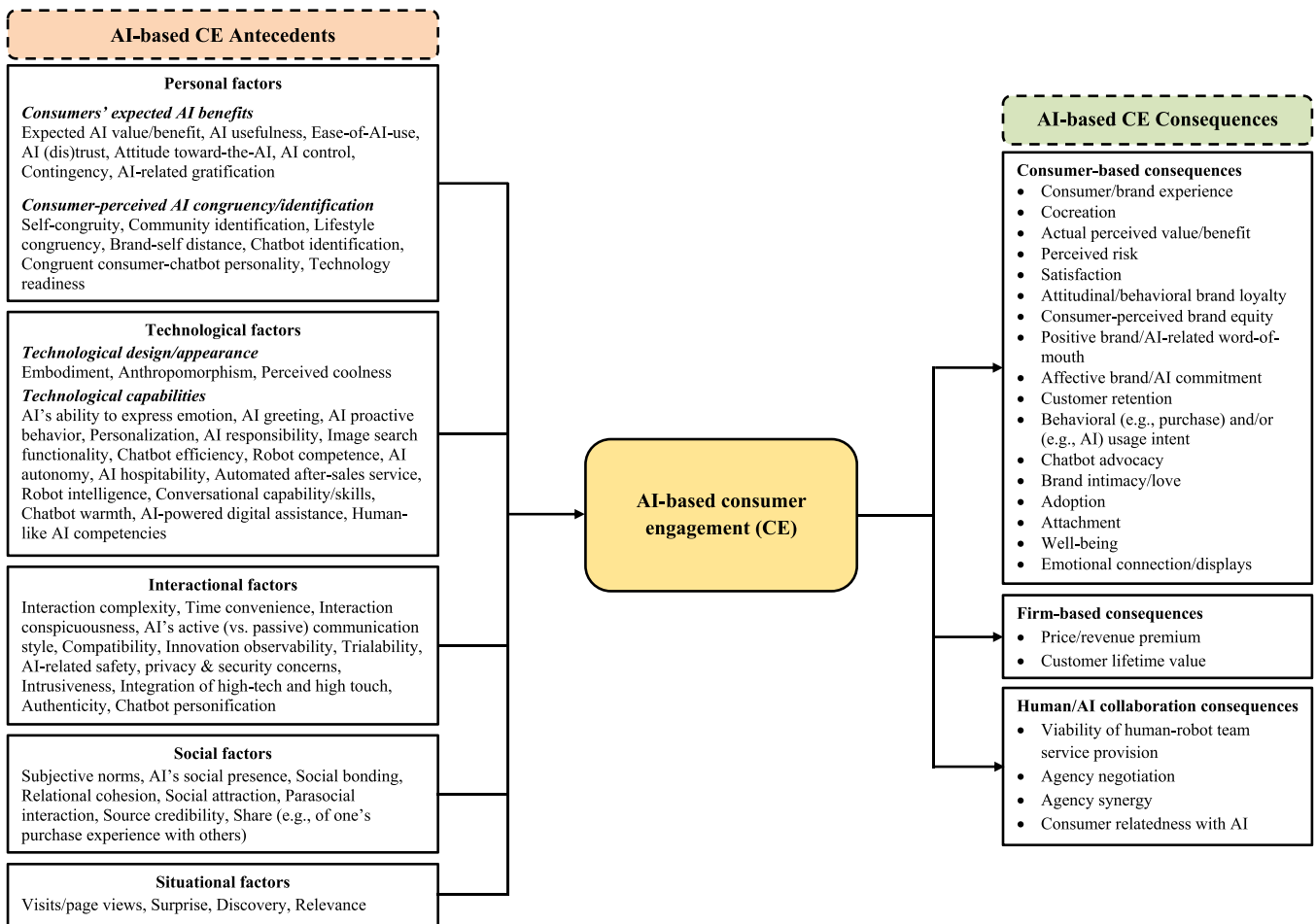


FIGURE 2 Model of AI-based CE. AI, artificial intelligence; CE, consumer engagement.

perceived usefulness (Moriuchi, 2019), perceived ease-of-use, expected value (McLean et al., 2021), trust (Mostafa & Kasamani, 2022), distrust (McLean et al., 2021), attitude toward the AI (Hlee et al., 2022), anticipated AI gratifications (Lin & Wu, 2023), and perceived behavioral control (Hollebeek, Menidjel, et al., 2022), among others. Consumers, thus, tend to assess upfront what they expect to get (vs. give) in their AI interactions (Zeithaml, 1988).

Second, *consumer-perceived AI congruency/identification* denotes the extent to which consumers perceive an AI technology to be congruent with (i.e., fit or match) their actual or desired self, and the degree to which they identify with it (Loureiro et al., 2022; Yin et al., 2023). These include brand-self distance (Kull et al., 2021), self-congruity (Yin et al., 2023), community identification (Wen et al., 2022), lifestyle congruency (Loureiro et al., 2022), and chatbot identification (Loureiro et al., 2022; Figure 2), among others. For example, Shumanov and Johnson (2021) identify the role of congruent consumer-chatbot personality as a key driver of AI-based CE. Overall, personal factors comprise consumers' functional or instrumental motives for engaging with AI technologies, alongside their more emotively driven (e.g., actual or ideal self-based) motives (Loureiro et al., 2022; Yin et al., 2023). The greater consumers' anticipated functional and emotive AI benefits, the greater the predicted initiation (e.g., uptake) and continuation (e.g., repeated use) of their AI engagement.

Technological factors refer to the characteristics of specific AI technologies, which are likely to differ across (e.g., mechanical, thinking, or feeling, or generative/predictive) AI (e.g., Huang & Rust, 2021). Based on our review, we further subdivide this category into *technological design/appearance* and *technological capabilities*. First, *technological design/appearance* captures the AI's embodiment and presentation (e.g., its anthropomorphic shape or perceived coolness; Ashfaq et al., 2021; Wirtz et al., 2018). Here, the *uncanny valley* suggests that an AI's more anthropomorphic (human-like) traits tend to yield users' more favorable evaluations, and engagement, up to a point, which, however, decrease *post*-this optimum (e.g., as users start to perceive *highly* human-like robots as creepy; Belanche et al., 2021).

Second, *technological capabilities* denote AI competencies (Rana et al., 2021), including its ability to learn (e.g., for machine/deep learning technologies), to greet its users, to express emotion, empathy, and warmth towards its users, to act responsibly, and to develop (e.g., personalized) solutions for its users (Kull et al., 2021; Li et al., 2022), reflecting AI's potential mimicking of human cognitive and emotive capabilities (Bretan et al., 2015; Chandra et al., 2022). In this regard, AI efficiency, capabilities, human-like competencies, hospitality, and autonomy emerged as key CE drivers (Asante et al., 2023; Grimes et al., 2021).

Interactional factors reflect the dynamics characterizing consumers' interactions with specific AI technologies (Fang et al., 2022), exposing AI-based CE's bilateral nature that may be instigated or maintained by the consumer or the AI (Hollebeek et al., 2021). Interactional factors may either facilitate or impede AI-based CE (e.g., high interaction compatibility vs. high interaction complexity). Prior

authors have identified the following main interactional factors that shape AI-based CE: Interaction conspicuousness, innovation (e.g., chatbot) observability, communication style, compatibility/triability, interaction complexity, and privacy, security, and safety concerns (e.g., Gao et al., 2022; Maslowska et al., 2022; Yin et al., 2023).

Social factors refer to forces in the social environment or an AI's social characteristics that may impact AI-based CE. Key literature-based social drivers of AI-based CE include subjective norms (Moriuchi, 2019), AI-perceived social presence (Tsai et al., 2021), social bonding (Fang et al., 2022), relational cohesion (Hernandez-Ortega et al., 2022), and parasocial interaction (Tsai et al., 2021). While some social factors may enable or accelerate AI-based CE (e.g., the ability of friendship AI, like Replika, to foster social bonding; Marriott & Pitardi, 2023), others might reduce it (e.g., AI-hesitant social norms or values).

Situational factors are transient contextual (e.g., time/location-specific) variables that may impact AI-based CE (Hand et al., 2009). Our analysis reveals the particular role of situational variables in driving consumers' AI-based page visits or views, and that of discovery, surprise, and perceived relevance in shaping AI-based CE (Wen et al., 2022; Xiao & Kumar, 2021). For example, Maslowska et al. (2022) identify the effect of consumers' webpage visits on their engagement with AI-based recommendation agents. Given their ephemeral nature, situational factors are difficult to control or predict. We, however, expect more adaptable (e.g., thinking/feeling) AI to, generally, be better equipped to handle changing situational characteristics (Huang & Rust, 2021), thus exerting a more positive effect on AI-based CE.

4.3.2 | Consequences of AI-based CE

We next identify key AI-based CE consequences that emerged from our review, which we classify as *consumer*-, *firm*-, and *human/AI collaboration*-based consequences. First, *consumer-based consequences* comprise user-perceived outcomes of AI-based CE, including the technology's perceived contribution to their brand experience, *actual* (vs. expected) perceived value, satisfaction, attitudinal and behavioral brand loyalty, brand equity, positive brand or AI-related word-of-mouth, affective brand or AI commitment, behavioral (e.g., purchase) and/or (e.g., AI) usage intent, and customer retention (e.g., Aluri et al., 2019; Lin & Wu, 2023; Moriuchi, 2019; Rahman et al., 2023). While AI may be used to boost consumers' perceived brand-related outcomes (e.g., recommendations or advocacy), individuals may, likewise, recommend specific AI technologies in their own right (e.g., Loureiro et al.'s (2022) *chatbot advocacy*).

Second, *firm-based consequences* are the effects of AI adoption for the firm (Mishra et al., 2022), including the ability to command a price or revenue premium (Jiang et al., 2022) and to exploit customers' lifetime value (Maslowska et al., 2022), among others. Given the, typically, more challenging task of obtaining (e.g., commercially sensitive) firm data, studies in this subcategory, however, remain limited (vs. those addressing consumer-perceived consequences of AI-based CE).

Third, *human/AI collaboration consequences* are the outcomes that arise from AI-based CE for users or consumers, specific AI technology, and/or other stakeholders (Chen, Gong, et al., 2022; Hyun et al., 2022). Despite its importance, this subcategory of AI-based CE consequences, likewise, remains modest in size to-date. Thinking and feeling, or generative and predictive, AI technologies, in particular, are able to improve their performance over time (Dwivedi et al., 2023), yielding pertinent implications for human/AI collaboration. For example, while Hyun et al. (2022) propose that AI-based CE impacts the viability of service that is jointly provided by employees and service robots, AI-related learning also transpires by virtue of the technology's collaboration with other human or nonhuman agents (Pradeep et al., 2019). Overall, despite growing interest in the human/AI collaboration consequences of AI-based CE (Peng et al., 2022), our review reveals a relative paucity of studies—and, thus, a need for further exploration—in this area.

5 | IMPLICATIONS, LIMITATIONS, AND FURTHER RESEARCH

5.1 | Theoretical implications

In recent years, AI-based CE research has started to proliferate (Lin & Wu, 2023; Rahman et al., 2023). However, despite existing advances, this emerging research stream is becoming fragmented, with authors reporting different, potentially incompatible AI-based CE perspectives, methods, and findings. Addressing this literature-based tension, we systematically assessed this multidisciplinary research domain to

consolidate prior insight, yielding the following theoretical implications.

First, prior authors have conducted systematic reviews (e.g., Bilro & Loureiro, 2020), bibliometric analyses (e.g., Hollebeek, Sharma, et al., 2022; Lim et al., 2022), or meta-analyses of CE (e.g., De Oliveira Santini et al., 2020). Moreover, others have undertaken (e.g., systematic) reviews of marketing-based AI (e.g., Ameen et al., 2022; Mehta et al., 2022; Verma et al., 2021). However, despite budding insight into these areas *individually*, understanding of the AI-based CE *interface* remains scant to-date, as, therefore, assessed in this article. Correspondingly, we conducted a systematic review of AI-based CE research, thus consolidating scattered insight in this growing area. Our review identified three main themes of AI-based CE, including (i) *Increasingly accurate service provision through AI-based CE*; (ii) *Capacity of AI-based CE to (co)create consumer-perceived value*, and (iii) *AI-based CE's reduced consumer effort in their task execution*. These observations raise pertinent research questions, as organized by the identified themes in Table 2.

Second, following prior systematic reviews (e.g., Ameen et al., 2022; Rehman et al., 2020), we synthesized AI-based CE within its nomological network (Figure 2). Thus, while the identified AI-based CE themes pinpoint the concept's characteristics, the model highlights its core theoretical associations (MacInnis, 2011), collectively affording comprehensive insight into AI-based CE. We uncovered five AI-based CE antecedents (i.e., personal, technological, interactional, social, and situational factors/drivers), and three AI-based CE consequences (i.e., consumer-, firm-, and human/AI collaboration-based outcomes). By advancing and refining scholarly understanding of AI-based CE's theoretical associations, the model

TABLE 2 Sample theoretical implications.

AI-based CE theme	Sample research questions
<i>Increasingly accurate service provision through AI-based CE</i>	<ul style="list-style-type: none"> ○ How does the capacity of AI-based applications to learn impact consumers' (e.g., purchase) engagement? ○ To what extent do AI-based mistakes influence consumers' brand engagement? ○ How do AI-powered tools, such as chatbots or voice assistants, help consumers reduce the time/effort required for complete their tasks and how does this impact their brand engagement? ○ How does human/AI collaboration enhance the accuracy of AI-base predictions/recommendations and how does this impact consumers' brand engagement?
<i>Capacity of AI-based CE to (co)create consumer-perceived value</i>	<ul style="list-style-type: none"> ○ What contextual, and/or individual, factors may affect consumers' AI, or brand, engagement, and cocreation? ○ What are the key drivers of consumer-perceived AI privacy and security, and how does this impact their AI, or brand, engagement, and cocreated value? ○ How does consumer-perceived AI transparency affect consumers' AI, or brand, engagement, and cocreation? ○ What mediating, or moderating, factors may influence the association of AI-based CE and cocreation (codestruction)?
<i>AI-based CE's reduced consumer effort in their task execution</i>	<ul style="list-style-type: none"> ○ To what extent do specific AI applications reduce consumers' required effort in performing their specific role-related tasks? ○ Which (if any) automation level exerts the greatest impact on consumer-perceived effort reduction and/or convenience? ○ What factors motivate consumers to engage with AI technologies, and how will this impact their engagement-based resource investments in their role-related tasks? ○ (How) does AI-based CE, and/or its nomological network, develop over time?

Abbreviations: AI, artificial intelligence; CE, consumer engagement.

offers significant value for further researchers in this multidisciplinary field. For example, while the attained acumen of AI-based CE's antecedents facilitates assessments of how to cultivate the concept, its identified consequences help warrant its strategic value (e.g., given AI-based CE's demonstrated effect on key firm performance indicators like customer retention/lifetime value; Maslowska et al., 2022).

5.2 | Managerial implications

Our analyses also raise pertinent managerial implications. First, our initial theme of *increasingly accurate service provision through AI-based CE* suggests that the ability of AI technologies to learn or to reduce human error benefits service accuracy and -quality (Hollebeek et al., 2021; Huang & Rust, 2021). We, therefore, advise managers to scan their firms for relevant AI implementation opportunities, which we anticipate to raise long-term service quality, while reducing service issues and failure, in turn boosting organizational performance (Chen, Gong, et al., 2022). However, as not all tasks may be equally suited to AI adoption (e.g., in some cases, customers may prefer talking to a real person; Longoni & Cian, 2022), we advise managers to carefully assess those firm priority areas in which to adopt AI technology.

Second, our theme of the *capacity of AI-based CE to (co)create consumer-perceived value* suggests AI-based CE's ability to (co)create consumer-perceived value (Hollebeek, Sharma, et al., 2022). Specifically, AI technologies may help reduce perceived cost (e.g., by saving consumers time or effort in their task execution), or they may offer more convenient access, communication, or personalization options (Hari et al., 2022; Jiang et al., 2022), boosting consumer-perceived (co)creation (Vargo & Lusch, 2016). We, therefore, advise managers to conduct upfront (e.g., scoping) research with their target audiences to pinpoint those areas in which they would most value engaging with AI technologies. At the same time, we also caution against potential AI-based (e.g., privacy or security) risks (Bertrandias et al., 2021).

Third, our final theme of *AI-based CE's reduced consumer effort in their task execution* proposes that AI-based CE reduces consumers' required effort in executing their role-related activities (e.g., by automating routine tasks), which we expect to, in many cases, raise their service (quality) assessments (Hollebeek et al., 2021; Leung et al., 2018). Correspondingly, we recommend managers to implement consumer-perceived effort-reducing AI technologies, given their predicted beneficial impact on users' service assessments (Sampson, 2021).

5.3 | Limitations and further research

Notwithstanding its contribution, this study also has limitations. First, we relied on the Scopus database to identify relevant AI-based CE articles in English, thus excluding articles published in non-Scopus

journals. Future researchers could, therefore, consult other or related databases (e.g., Web of Science/Google Scholar) to source their data and include non-English works in their further reviews of AI-based CE.

Second, though we adopted a broad range of search keywords, AI's rapid innovation and evolution may spark new (future) AI-related terminology that is not covered in our analysis. We, therefore, recommend scholars to carefully scrutinize the emerging AI discourse, and assess its potential impact on or implications for CE, as well as for other stakeholders' (e.g., employees' or suppliers') engagement (Hollebeek, Kumar, et al., 2022). In other words, the emergence of new AI (or CE)-based insight may generate a need to revisit, test, validate, or refine the proposed AI-based CE themes. Relatedly, while *AI washing*—claimed AI deployment when this is not the case (Leffrang & Mueller, 2023)—may aim to raise engagement, consumers learning about this falsehood may, in fact, lower their engagement, thus also meriting further scrutiny.

Third, though the emerging subfield of AI-based CE remains relatively nascent to-date, our sample, nevertheless, contains 89 articles, revealing the vibrant research activity in this area. We, however, expect AI-based CE research to proliferate in the coming years, offering opportunities for further (e.g., bibliometric) reviews of AI-based CE to complement our findings. Finally, based on the observed paucity of prior research in specific AI-based CE subareas (e.g., the effect of AI-based CE on human/AI collaboration), we recommend the development of further insight in these areas. For example, what AI attributes are core (vs. less core) in shaping users' engagement with specific AI technologies or with the brand? What is the effect of AI-based automated social presence (Van Doorn et al., 2017) on consumers' (e.g., brand) engagement? How many current or evolving AI technologies (uniquely) affect CE? Providing answers to these questions is pivotal to better understand the interplay between AI and CE in an increasingly automated world.

ACKNOWLEDGMENTS

The authors thank the editor and the review team for their helpful feedback, which has helped us improve the manuscript. The lead author would also like to thank Professor Brett A.S. Martin and Professor Cristiana Lages for a discussion on AI and CE. Finally, the second author would like to thank Pr Amor Djenina, Dr Riyadh Moussaoui, Dr Otmane Atmania, Dr Saif Eddine Guehairia, Dr Adel Khaldi, Dr Fares Gater, Dr Abdelkarim Choukal, Dr Widad Benkirat, and Dr Sara Helimi for their invaluable support and for creating conducive working conditions during the preparation of this article, allowing him to dedicate time to this research.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

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How to cite this article: Hollebeek, L. D., Menidjel, C., Sarstedt, M., Jansson, J., & Urbonavicius, S. (2024). Engaging consumers through artificially intelligent technologies: Systematic review, conceptual model, and further research. *Psychology & Marketing*, 41, 880–898. <https://doi.org/10.1002/mar.21957>