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Do chatbots establish "humanness" in the customer purchase journey? An investigation through explanatory sequential design

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Abstract

Chatbots incorporate various behavioral and psychological marketing elements to satisfy customers at various stages of their purchase journey. This research follows the foundations of the Elaboration Likelihood Model (ELM) and examines how cognitive and peripheral cues impact experiential dimensions, leading to chatbot user recommendation intentions. The study introduced warmth and competence as mediating variables in both the purchase and postpurchase stages, utilizing a robust explanatory sequential mixed-method research design. The researchers tested and validated the proposed conceptual model using a 3 × 3 factorial design, collecting 354 responses in the purchase stage and 286 responses in the postpurchase stage. In the second stage, they conducted in-depth qualitative interviews (Study 2) to gain further insights into the validity of the experimental research (Study 1). The results obtained from Study 1 revealed that "cognitive cues" and "competence" significantly influence recommendation intentions among chatbot users. On the other hand, "peripheral cues" and warmth significantly contribute to positive experiences encountered during the purchase stage. The researchers further identified 69 thematic codes through exploratory research, providing a deeper understanding of the variables. Theoretically, this study extends the ELM by introducing new dimensions to human-machine interactions at the heart of digital transformation. From a managerial standpoint, the study emphasizes the significance of adding a "humanness" element in chatbot development to create more engaging and positive customer experiences actively.

KEYWORDS

AI humanness, chatbots, customer journey, elaboration likelihood model (ELM), marketing automation, recommendation intention

1 | INTRODUCTION

Artificial intelligence (AI) has progressed in leaps and bounds, transforming the very foundations of marketing and business practice (Belk, 2021; Puntoni et al., 2021). Natural Language Processing chatbots and allied digital technologies (Quach et al., 2022) are among the most common domains of service dominant logic, experiencing growing AI influence and altered value chain perceptions (Balakrishnan & Dwivedi, 2021a; Flavián et al., 2021; Moriuchi, 2019). Balakrishnan and Dwivedi (2021a, p3) describe chatbots as "a computer program that conducts a conversation in natural language and sends a response based on business rules and data tuned by the organization." According to an emerging stream of research in this discipline, chatbots are gradually replacing human-led service interaction spaces, in addition to other tangible aspects of marketing functionalities, e.g., online food delivery complaints, product inquiries, product delivery status inquiries, and purchase inquiries. Chatbot-based applications have also been noted to be seamlessly integrated across different stages of the customer purchase funnel, making them an integral and impactful part of every stage of the consumer journey (Grewal & Roggeveen, 2020). Despite the considerable expansion of AI-based chatbots in contemporary marketing practice, the majority of research directions in this domain are overly fixated on experimental methods (Balakrishnan & Dwivedi, 2021b; Kar & Kushwaha, 2021). Significant effort has been directed towards investigating the adoption and consumption behavior related to AI-based voice and chat agents (Blut et al., 2021). Tueanrat et al. (2021) were the first to emphasize the need to examine the impact of technology on different types of customer journeys. However, there is still limited research understanding the underlying factors behind user intention toward recommending chatbots. Despite select advancements within the field, there is a clear lack of conceptual and empirical development in exploring cognitive and peripheral cues users encounter with marketing chatbots during the purchase and postpurchase stages (Mishra et al., 2021).

The scope of activities involved in chatbot interaction varies across the customer purchase journey, relative to customer expectations. Previous studies indicated that successful purchase journeys can lead to positive customer intentions toward recommending goods and services within peer networks (Kaur et al., 2020). However, there is a clear data-driven knowledge gap in conceptualizing how customers develop recommendation intentions after using chatbot technology during service encounters. Chatbots' algorithmic information processing systems can incorporate cognitive and peripheral cues (Shin, 2021), similar to advertisements (Van den Broeck et al., 2019). These underlying cognitive and peripheral cues can also impact user perception of specific chatbot functionalities (Shin, 2021). For example, AI-driven chatbots can simulate human voices and respond to user statements like a human, changing the overall nature of human-computer interaction (Belanche et al., 2020). Previous research has investigated various human behavioral characteristics to simulate chatbot conversations (such as voice modulations, gender tuning, contextual replies, etc.) with the aim to generate a more human-like experience (Hill et al., 2015). However, the selective progress made within the field is largely fixated on investigating chatbot conversations from a verbal and auditory perspective (Chang et al., 2018; Hu, Lu, & Gong, 2021). There is a lack of empirical, data-driven robust conceptual or theoretical framework development initiated to understand the "humanness" perception developed by the users of AI-based chatbots, predominantly from a cognitive and peripheral cue perspective, that can subsequently impact user recommendation intentions for selected service experiences. This study offers pioneering thoughts within the field by exploring the relationship between these psychological cues within the customer purchase journey process. In this context, we particularly refer to Yoganathan et al. (2021) work, as the authors emphasized the importance of imparting warmth and competence as key variables for measuring humanness perceptions as part of social cognitive models.

After a thorough review of key academic literature within this area of research development, we highlight three critical knowledge and information gaps: (i) cognitive and peripheral cues of chatbots and their impact on user experience and recommendation intention, (ii) the intervening effect of perceived "humanness" and the relationship of cognitive and peripheral cues in chatbots toward user experience and recommendations, (iii) the impact of these critical psychological cues on the purchase and postpurchase stages of customer journeys and user experience. We strongly believe that investigating these conceptual and empirical gaps can provide much-needed insight into the underlying psychological influences dictating chatbot encounters and perceived humanness in customer journeys.

Based on these identified knowledge gaps, this paper attempts to investigate the impact of cognitive and peripheral cues on chatbot experience, with intended mediation through the psychology of humanness perceptions. Our proposed conceptual framework builds on the theoretical foundations of the Elaboration Likelihood Model (ELM) (Petty & Cacioppo, 1986), psychological experience theories (Hassenzahl & Tractinsky, 2006; Hoffman & Novak, 1996), and humanness perception theories (Belanche et al., 2021a; 2021b). To further explain, the ELM consists of two pathways (central and peripheral) that illustrate how a person's attitude evolves after receiving and processing a message through a communications platform. While the ELM has been primarily applied in advertising studies, recent studies have shown interest in applying this concept to technology-based marketing (Dwivedi et al., 2021; Shahab et al., 2021). Chatbots can be designed to deliver persuasive messages and influence user attitudes, behaviors, and beliefs (Moriuchi et al., 2021). Therefore, we argue that the ELM can provide a valuable framework for developing and investigating behavioral and psychological impacts of persuasive chatbots tailored to users' level of involvement and motivation; such chatbots are likely to be effective in changing user attitude and behavior (Nguyen et al., 2022). Thus, the ELM was integrated as the foundational theoretical framework of this research. The ELM encompasses cognitive and emotional appeals to persuade consumers in decision-making processes. However, previous research has also revealed that the human cognitive load can mediate the process of ELM persuasion to attend to various messages (Chang & Thorson, 2023). In the context of AI-based chatbots, selected human characteristics present in the robotic environment can indirectly influence a user's behavioral perception and persuasion decisions. Therefore, in this research, we conceptualized humanness perceptions with two significant dimensions: competence and warmth (Belanche et al., 2021a), to understand its mediating effect on the components of the ELM, service experience, and user recommendation intentions. We further propose to validate and rationalize our results, alongside our conceptual model, through an additional explanatory study. Based on these cumulative discussions and proposed knowledge gaps, we formulate the following research questions.

RQ1 *How do chatbots' cognitive and peripheral cues build experience and recommendation intention within the purchase and postpurchase stages of customer journey?*

RQ2 *How effective is the mediating role of warmth and competence in relation to cognitive and peripheral cues of experience and recommendation intention?*

RQ3 *What attributes define experience, warmth, competence, and recommendation intention within the relationships proposed in RQ1 and RQ2?*

To examine these research questions, we propose a sequential explanatory mixed-method research design, in which the initial two research questions were investigated through a 3 × 3 *factorial survey design* (*Study* 1), *followed by an investigation of the third research question using an explanatory qualitative analysis* (*Study* 2). *By investigating the two primary research questions, our study extends the ELM* (*Petty & Cacioppo*, 1986), *incorporating psychological experience theories* (*Hassenzahl & Tractinsky*, 2006; *Hoffman & Novak*, 1996), *and humanness perception theories* (*Belanche et al*., 2021b) *within the emerging contextual realms of AI, chatbots, and the future of marketing practice. Previous research within the field made no clear and conscious efforts to integrate the ELM with the humanness theory. We propose a new horizon for this theoretical integration to fill the void. Our conceptual model and empirical work develop a pathway towards applying leading psychological-based theoretical lenses in validating contemporary marketing practices. Our empirical work not only provides deep insight into contrasting psychological cues in the purchase and postpurchase stage, but the design of Study* 2 (*explanatory qualitative study*) *also adds further nuance by offering in-depth analysis of the relationships between the proposed theoretical frameworks in a more exploratory fashion. We believe that the contributions from this study will encourage further development of human-chatbot interaction research incorporating behavioral, psychology, and social science literature. In addition, the contributions of this study also lay down important managerial implications that are vital to an organization's Digital Transformation strategy. The following sequential format was followed in designing and conducting the study:* (*i*) *Integrating the theoretical domains of the ELM and humanness theories*, (*ii*) *Developing a conceptual model leading to Study* 1 *and Study* 2, (*iii*) *Study* 1 *operationalisation—hypothetical model, methodology, analysis, and results* (*iv*) *Study* 2 *operationalisation—methodology construction and analyses*, (*v*) *results discussion* (*vi*) *theoretical and managerial implications*, (*vii*) *concluding remarks*.

2 | THEORETICAL BACKGROUND

2.1 | Elaboration likelihood model

The ELM, proposed by Petty and Cacioppo in 1986, delineates the functions of central and peripheral routes in elucidating human attitudes. The central route reflects an individual's change in attitude and decision-making based on the argumentative information provided, which represents the cognitive way of processing information. On the other hand, the peripheral route pertains to the enticing cues that shift an individual's attitude, requiring less cognitive effort for information processing.

According to Petty and Cacioppo (1986), an individual elaborates on information or stimuli based on their inherent motivation and ability to process information. Thus, an individual's thought process intensifies the message from a cognitive or peripheral cue. Most research has established an understanding of the central route from the perspectives of information (Zha et al., 2018) and intelligence (Chen et al., 2022). Similarly, the literature has utilized design and geometric cues to study peripheral effects (Lu & Dosher, 2000). The current research applies information and intelligence to delineate the central route in terms of cognitive cues and employs static and dynamic designs of chatbots to characterize peripheral cues (Hill et al., 2015).

Over the years, application of the ELM has expanded to various research domains, including advertising (Areni, 2003; Kerr et al., 2015), tourism (Balakrishnan et al., 2021; Yoo et al., 2017), healthcare (Cao et al., 2017), retailing (Yang et al., 2006), social media (Dwivedi et al., 2021; Lee & Hong, 2016), knowledge transfer (Fadel et al., 2009), and online behavior (Lu et al., 2019). Despite the broad use of the ELM across various fields and disciplines, it is primarily leveraged in marketing research to understand and reveal varying levels of consumer interest.

Most studies conceptualize the ELM as a conduit for driving persuasion, attitude formation, and change. Prior research posits that attitude formation is an ongoing evaluation process that bifurcates into utilitarian and hedonic attitudes (Mishra et al., 2022). Therefore, the persuasive potential of the ELM can extend to affect a hedonistic attitude, culminating in a richer experience. The ELM can amplify hedonistic attitudes in service automation, contributing to an improved flow of experience. These implicit and explicit attitude tendencies also extend to service robots such as chatbots (Akdim et al., 2023). Moreover, it is crucial to acknowledge that these experiences and underlying attitudes towards service robots can vary across generations X, Y, and Z (Ayyildiz et al., 2022).

Consumers are often attracted by cognitive and peripheral cues (Lu et al., 2019). Marketers skillfully utilize this strategy to appeal to consumers based on the marketing scenario, aligned to consumer motivation and interest (Chang et al., 2019). Current research on the ELM primarily focuses on examining online content formats and their persuasive influence on users (Shahab et al., 2021).

Chatbots represent advanced human-machine interaction frameworks, instigating a new revolution in online content-based interaction. While chatbots mainly focus on providing requisite information to users, recent research emphasizes optimizing chatbots based on design and appeals to enhance conversation quality and improve service quality (Mogaji et al., 2021; Youn & Jin, 2021).

Chatbots can be optimized to deliver high-quality information with enhanced intelligence without compromising on design. However, the real impact of information and design in chatbots necessitates a thorough investigation to unravel their effects on customer experience and recommendations (Kushwaha & Kumar, & Kar, 2021; Rapp et al., 2021). Most research supports the incorporation of human-like qualities in chatbots to improve conversation quality (Youn & Jin, 2021). Concerning human perception, the ELM can elucidate how people perceive others as 'more or less human.' When people are motivated and capable of processing information carefully, they are more likely to perceive others as complex individuals with thoughts, feelings, and motivations (Loureiro et al., 2022). They are less inclined to rely on stereotypes and prejudices and more likely to consider the unique experiences and perspectives of others.

Within the traditional ELM, the central route function is described as cognitive cues, considering the role of stimuli proposed in chatbots. Likewise, the peripheral route is considered as peripheral cues, based on the design and appeal changes employed as stimuli in this research. Prior research has used analogous terms to describe these theoretical variables. For example, Schepers et al. (2022) introduced three AI types, namely mechanical, thinking, and feeling. Similarly, Huang and Rust (2021) have utilized utilitarian and hedonic thinking AI to better characterize the study variables. This research aims to uncover chatbot functionalities from the cognitive and peripheral cue perspectives.

2.2 | Humanness perception

The Theory of Mind posits that humans interpret their own and others' thought processes to better understand behavior (Baron-Cohen, 1997; Premack & Woodruff, 1978). This principle is integrated into human behavior and the evolutionary learning process to anticipate and attribute humanistic approaches to conversation and social behavior (Apperly, 2012). Research integrating robotic interactions into human life recommends including humanistic characteristics in robots or other AI-based conversations to reduce complexity (e.g., Lazzeri et al., 2018; Sridevi & Suganthi, 2022). Keeping this theory in mind, researchers have advocated for the implementation of human-like characteristics in AI-based interactions (Martini et al., 2016; Söderlund and Oikarinen, 2021). Recently, the concept of humanness has permeated technology and AI studies to understand how machine cognition interacts with the human race (Votto et al., 2021). Chatbots incorporate human-like characteristics such as anthropomorphism (Blut et al., 2021; Sheehan et al., 2020), animacy (Blut et al., 2021), and empathy (Liu & Sundar, 2018). Epley (2018) suggests that by incorporating human elements into a computerized environment, the distinction between human-based and computer-based communication can be better optimized.

Amongst various disciplines studying the notion of "humanness," service research has utilized this concept to understand its impact on service delivery (Belanche et al., 2021a). Although, the recent rise of chatbots and other self-service technologies has raised questions about the humanistic aspects of their service delivery. Previous research has identified warmth and competence as crucial attributes under humanness to enhance service performance (Maar et al., 2022). Competence described as an individual's capacity to adapt to a situation in delivering a service, while warmth refers to an individual's empathy and courtesy in fostering stronger bonds for better service quality (Belanche et al., 2021a). These qualities—competence and warmth—have gained significant attention in AI and chatbot-based communications aiming to elucidate human-like perceptions.

Competence and warmth relate to fundamental principles underpinning the cognitive and affective components of human psychology (Fiske et al., 2007; Huang & Ha, 2020). In an automated environment, humans may expect human-like interactions at both cognitive and affective levels (Bennett & Hill, 2012). At the cognitive level, perceived intelligence in an AI-based environment, when aligned with human-like characteristics, can build more trust and subsequently enhance the perception of AI benefits (Maar et al., 2022). Within the ELM context, when people engage in the central route of processing, they carefully consider the presented information and evaluate it based on its quality and relevance (Chen et al., 2022). This process can lead to a more thoughtful and nuanced understanding of others as fellow human beings with complex thoughts, emotions, and experiences. At the affective level, expectations of human empathy are likely to be met (Bennett & Hill, 2012). Besides the affective level, this research extends the functionality of human-like characteristics to peripheral levels, where peripheral cues refer to attractive features like designs, appeals, colors, and other aspects that can create an initial perception and subsequently translate to consumer interest (Cyr et al., 2018).

However, the roles of competence and warmth in this context—cognitive and peripheral cues—remain unexplored. Notably, the perception of competence and warmth is more subliminal (Crandall et al., 2011), and cannot be directly attributed to cognitive or peripheral cues. Chang and Thorson (2023) further argue that human cognitive load can mediate the ELM persuasion, resulting in altered attitudes and behavior. In the context of AI-based chatbots, the human-like characteristics present within the robotic environment can indirectly influence persuasion. Therefore, in this research, we aim to consider competence and warmth as mediators in the conceptual model to understand their impact and the outcome. Previous research has touched on the role of competence and warmth in communication and how they can lead to greater service satisfaction. We extend this line of argument examining chatbot experience and user recommendation intentions.

3 | RESEARCH DESIGN

This study follows an explanatory sequential mixed-method design to explore and validate a proposed conceptual model, incorporating key foundational theories in a phased manner. First, a 3 × 3 factorial experimental design is employed to investigate the proposed hypothetical model in Study 1. The proposed hypothetical model from Study 1 is then tested across purchase and postpurchase stages with 354 and 286 customers, respectively. Section 4 presents a summary of the model hypotheses, methods, and results obtained from Study 1. In the next stage, Study 2 is conducted to gain an in-depth exploratory understanding of the results obtained from Study 1. Study 2 is devised using in-depth qualitative interviews with 32 customers, equally distributed across purchase and postpurchase stages. Section 5 presents an overview of the study design and results from Study 2.

4 | STUDY 1

Figure 1 represents our conceptual theoretical model, while Figure 2 represents our proposed hypothetical model.

4.1 | Model and hypotheses development

4.1.1 | Cognitive cues in chatbots

The tenet of cognitive psychology primarily revolves around human thought processes and the factors that foster rational thinking. According to cognitive psychology literature, previous studies have revealed that technology-based cognition can stimulate increased engagement among users (Shin, 2018). Similarly, another body of research has underscored that engagement and information shared online can cultivate a positive user experience (Calder et al., 2009). However, the direct relationship between cognitive cues and their impact on experience remains unexplored. Klaus and Maklan (2013, p. 518) defined consumer experience (CX) as "the customers' dynamic, continuous evaluation process of their perceptions and responses to direct and indirect interactions with providers and their social environment." Experience represents a state of flow that delineates an individual's level of immersion. In a technological context, immersion and in-depth interactions can enhance the experience (Dwivedi et al., 2022; Dwivedi et al., 2023a). A chatbot can facilitate cognitive immersion, as outlined in its architecture (Kushwaha & Kar, 2021). Active discussions with a chatbot, particularly in a simulated environment, can foster unique user experiences. Previous literature supports the notion that chatbot

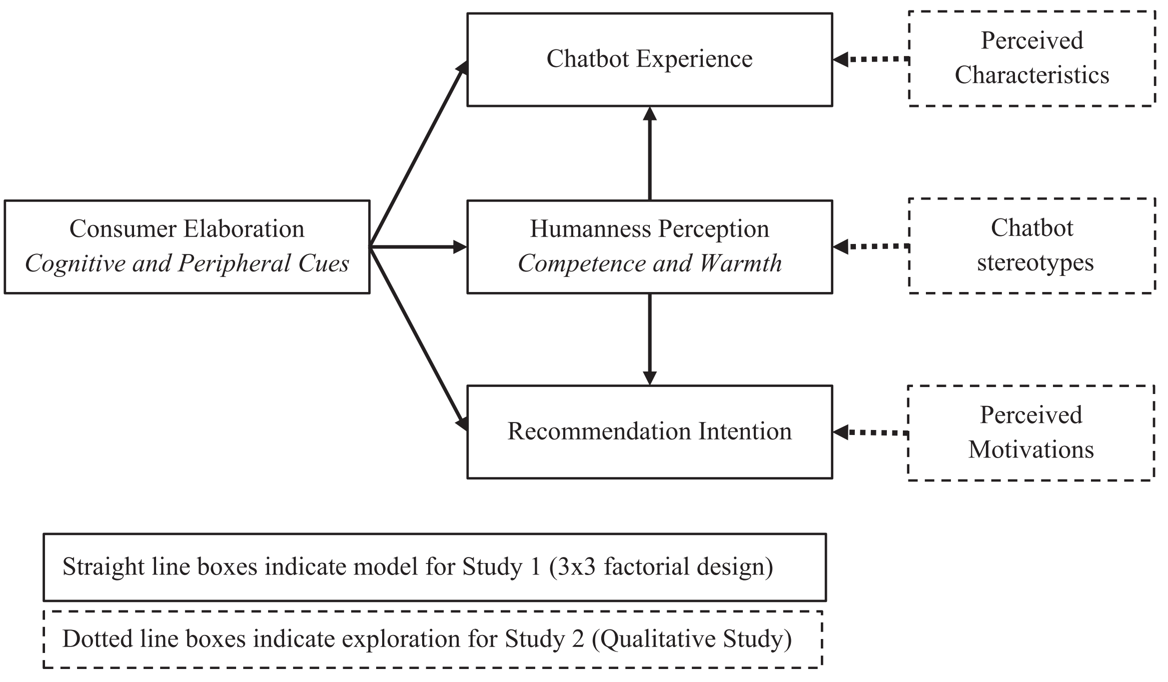

FIGURE 1 Explanatory conceptual framework of the study.

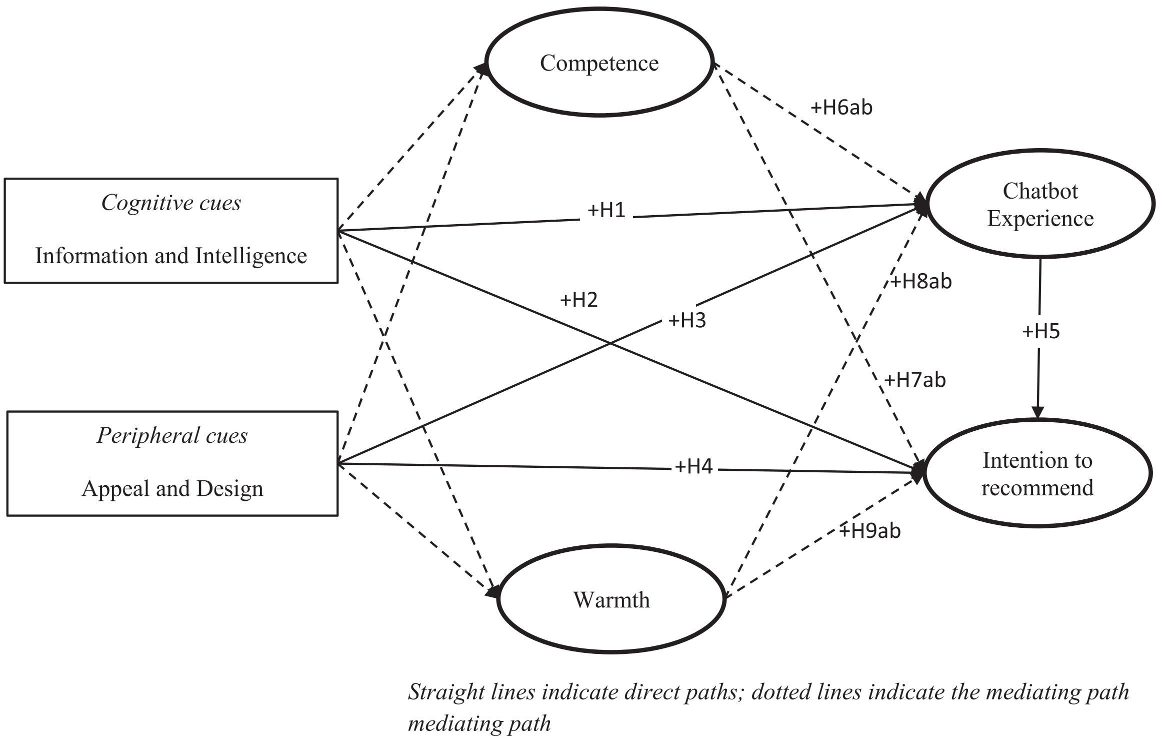

FIGURE 2 The proposed conceptual model for Study 1. Straight lines indicate direct paths; dotted lines indicate the mediating path mediating path.

engagement can cultivate a positive user experience (Moriuchi et al., 2021). Chatbots can incorporate cognitive psychology principles to design user-friendly interfaces, streamline decision-making processes, and create memorable experiences. This study aims to broaden such perspectives from a cognitive engagement standpoint. Drawing from the above discussion, we propose that cognitive cues integrated into chatbots can foster positive user experience during service interaction. The following hypothesis encapsulates our proposed arguments.

Hypothesis 1. Integrating cognitive cues in chatbots positively impacts users' chatbot experience during both the purchase and the postpurchase stage.

Information processing through cognitive load and fluency can engender a positive attitude among customers in a retailing format (Fan et al., 2020). Prior research supports that consumers process information cognitively before sharing their ideas with others (Schmeichel et al., 2018). In contrast, consumers who are cognitively engaged during their decision-making process are more likely to develop recommendation behavior regarding products or services (Papadimitriou et al., 2018). Earlier research suggested that cognitive technology interaction can heighten the likelihood of recommending technology usage to others (Tsohou et al., 2015). Chopra et al. (2022) further advocated that the quality and quantity of information can boost electronic word-of-mouth behavior. In case of chatbots, the cognitive architecture of the system can foster deeper interaction, enabling the user to learn more about the product. This paves the way for users to recommend a chatbot system to others. Previous research suggested that informed consumers are well-received among their peers, thus propelling the spread of word-of-mouth communication (Tsohou et al., 2015). Supporting a similar viewpoint, Loureiro et al. (2022) proposed that customer influence and knowledge can foster positive chatbot advocacy. In case of chatbots, customers may tend to recommend a system to others, during both, the purchase and the postpurchase stage, proportion to the level and quality of interaction cues. Drawing from the above discussion, we propose that cognitive cues within chatbots can enhance user recommendation behavior. The following hypothesis encapsulates our proposed arguments.

Hypothesis 2. Integrating cognitive cues in chatbots positively impacts users' recommendation intentions during both the purchase and the postpurchase stage.

4.1.2 | Peripheral cues in chatbots

Social Response Theory (Nass & Moon, 2000) delves into the environmental and social cues inherent within a technology interface. SRT further posits that visual cues in technology-based interactions can cultivate rewarding user experiences (Bolton et al., 2018). Notably, Martin et al. (2011) observed that less involved consumers are more drawn to peripheral designs and cues in online websites, leading to an improved experience. Technology-based interactions are primarily aimed at enhancing usability and fostering greater responsiveness, thereby resulting in a positive overall experience (Chen et al., 2021). Recent research on chatbots underscores the significance of attracting customers by offering visual cues and navigations (Nguyen et al., 2022). Chatbots can be operationalized using dynamic and static interfaces (Loureiro et al., 2022). However, the cues must be adequately defined based on customer expectations and preferences (Blut et al., 2021). As mentioned above, while SRT supports the use of environmental cues in technology-based interactions, its impact on creating a user experience is a less-investigated proposition. Moreover, Clement (2007) suggests that customer proficiency in perceiving peripheral cues can vary at both the purchase and postpurchase stages. Integrating the above points, this research proposes that peripheral cues integrated into chatbots can positively impact chatbot user experience. The following hypothesis encapsulates our proposed arguments.

Hypothesis 3. Integrating peripheral cues in chatbots positively impacts users' chatbot experience during both the purchase and the postpurchase stage.

Much of the research investigating recommendation or word-of-mouth intention has identified attitude and satisfaction as key precursors, fostering recommendation intentions (Zhang et al., 2019). However, earlier studies assert that emotions and cognitive cues can also influence consumer recommendation intentions. Attribution theory explains the process and motivations that enable people to share information with each other (Heung & Gu, 2012; Kelley, 1967). Further research has affirmed that a communication's peripheral cues can also contribute to the attribution of the information shared (Cheung & Thadani, 2012). While various factors that positively affect recommendation intentions have been uncovered, little research has explored the role of peripheral cues in shaping word-of-mouth intentions. In case of chatbots, marketers incorporate various appeals to engage customers (Mogaji et al., 2021). Prior research has implied that appeals present in chatbots can foster a positive attitude towards chatbots, transforming how customers recommend chatbots to others (Go & Sundar, 2019). Based on this discussion, we propose that peripheral cues in chatbots can foster greater user recommendation intentions. The following hypothesis encapsulates our proposed argument.

Hypothesis 4. Integrating peripheral cues in chatbots positively impacts users' recommendation intentions during both the purchase and the postpurchase stage.

4.1.3 | Experience and recommendation intention

Customer experience stems from various underlying cognitive and affective cues, shaping a flow of perceptions and responses. With regard to attribution theory, the transfer of knowledge adjusts to various environmental and personal variables to stimulate recommendation behavior. Weiner's Three-Dimensional Model in attribution theory suggests that higher attribution to a situation will enhance stability, affirming the likelihood of future behavior (Weiner, 1985). Similarly, a successful chatbot experience can foster future behavioral intentions. Within the context of service robots, Belanche et al. (2021a) posited that value expectations in service robots can boost loyalty intentions. Additionally, Belanche et al. (2021b) argued that customer attributions specific to service enhancements could positively result in recommendation intentions for service robots. In recent years, technology-based experience has taken the center stage (Balakrishnan & Dwivedi, 2021a; Dwivedi et al., 2023b; Qin & Jiang, 2019), providing marketers with various potential outcomes. Technology-based experience has been found to foster satisfaction (Djelassi et al., 2018), trust (Glikson & Woolley, 2020), and omnichannel purchases (Shi et al., 2020). In case of chatbots, experience is mostly leveraged by marketers to gain engagement, yielding positive outcomes for customers. Although, little research has sought to understand how technology-based chatbot experience can positively impact recommendation intentions for specific chatbot systems. Bolton et al. (2018) have noted that people using services are inclined to share their experiences with other potential users, thereby sparking recommendation behavior among them. Prior research has also found that experience in the purchase and postpurchase stages can vary based on customer interaction (Shi et al., 2020). Therefore, based on the above discussion, we propose that a chatbot-based experience can positively impact user recommendation intentions to other consumers. The following hypothesis encapsulates our proposed arguments.

Hypothesis 5. Chatbot user experience has a positive impact on user recommendation intentions during both the purchase and the postpurchase stages.

4.1.4 | Mediation effect on humanness perceptions

Research on humanness perception has primarily focused on assessing an individual's humanistic qualities (Belanche et al., 2021a). Recently, literature on technology-based interactions has started to treat humanness perception as a key variable in understanding the humanistic replication in technologies (Hu, Lu, & Gong, 2021). Research in service marketing suggests that competence can be crucial in shaping service value perceptions (Soderlund et al., 2021). While traditionally, competence has been associated with service frontline workers, recent studies have started to examine the competence level of robots and other service agents and their association with service performance. Although competence is an expected trait in a service agent such as a chatbot, the chatbot's competence can only be inherently observed amidst cognitive and peripheral cues. Intelligence (cognitive cues) and designs (peripheral cues) enable chatbot designers to integrate humanness appeals within chatbots.

Therefore, intelligence embedded in chatbot architectures will enhance consumers' competence perceptions, resulting in a more positive experience. A similar logic applies to peripheral cues. Previous research has indicated that consumers expect a human level of competence from robots and other automated agents (Cheng et al., 2022). However, there is no standard benchmark for consumers to measure and compare human versus machine competence. Consumers tend to subconsciously evaluate service offers based on different qualities present in them (Crandall et al., 2011), seeking a fulfilling service consumption experience. Meanwhile, Chang and Thorson (2023) suggested that human cognitive load can mediate the ELM persuasion, affecting the outcome. Thus, competence can mediate the relationship of decisions based on the ELM variables. Therefore, assuming that cognitive and peripheral cues can create superior experiences, an individual service experience can still be enhanced through the humanness competence perceived by consumers. The following hypothesis was synthesized based on the above discussion.

Hypothesis 6. Chatbot competence indirectly impacts the relationship between (a) cognitive cues and experience, and (b) peripheral cues and experience, during both the purchase and postpurchase stages.

In addition to Hypothesis 6, the perception of humanness competence can influence consumer behavior in areas such as satisfaction (Söderlund & Oikarinen, 2021), trust (Hu, Lu, & Gong, 2021), and behavioral intention (Go & Sundar, 2019). Particularly within a technology setup, recommendation intention is an outcome attributed to consumer motivation and ability to share information with others. As proposed in previous hypotheses, recommendation intention can also result from cognitive and peripheral cues in chatbots. Nevertheless, previous literature has supported the notion that perceived competence in chatbots can encourage consumers to recommend goods and services (Konya-Baumbach et al., 2023). As mentioned in the previous hypothesis, designs of chatbots can enhance the sense of humanness perception, thereby providing a greater sense of competence perception. Chatbots can utilize AI and automated architecture to build more competence and capability for the study. Hu, Lu, and Pan, Gong, et al. (2021) highlighted that competence perception promotes individuals' cognitive evaluations, resulting in individuals being engaged in the action and realizing system-based advantages. Such efforts, spending, and realizations (McLean & Osei-Frimpong, 2019) can help to build long-term associative intentions with customers (Hu, Lu & Pan, Gong, et al., 2021). Consumers can perceive the same. However, competence is a reflective component generated from the base of the intelligence and design that a chatbot is composed of. Primarily, the perception of competence can be compared to humans. Based on this discussion, we propose that humanness competence can mediate the relationship between cognitive and peripheral cues and intention to recommend.

Hypothesis 7. Chatbot competence indirectly impacts the relationship between (a) cognitive cues and recommendation intentions, (b) peripheral cues and recommendation intentions, in both the purchase and postpurchase stages.

Beyond competence, warmth is another important humanness characteristic better observed within automated technology interfaces. Like competence, the perception of warmth is traditionally cultivated by frontline service providers to attract consumers (Ren et al., 2018). Previous research has associated competence with different annotations such as courtesy (Babbar & Koufteros, 2008), civility (Kong & Jogaratnam, 2007), benevolence (Sirdeshmukh et al., 2002), or empathy (Parasuraman et al., 1988). Most commonly, warmth can be defined alongside any dimensions underpinning service quality. Borau et al. (2021) have suggested that humanistic aspects of services can provide a memorable experience for consumers in services determined by their gender. Some studies have extended the function of warmth in technology-based interactions and found it can impact various aspects of service-based satisfaction and attitude (Huang & Ha, 2020).

Similarly, warmth can also provide a positive experience during technology interaction. Algorithms used in chatbots are primarily designed to resemble human interaction. Chatbots often incorporate humanistic characters to offer warmth, resulting in a greater experience, especially when various designs are implemented. However, as mentioned in the previous hypotheses, the perception of humanness warmth is more subtly felt during the interaction with chatbots at the cognitive and peripheral cues level. Thus, we propose that humanness warmth in chatbots can indirectly influence the relationship between cognitive and peripheral cues and experience.

Hypothesis 8. Chatbot warmth indirectly impacts the relationship between (a) cognitive cues and user experience, (b) peripheral cues and user experience, in both purchase and postpurchase stages.

As previously noted, perceived warmth in service encounter can lead to various positive outcomes such as satisfaction, continuous usage intentions, and behavioral intentions (Belanche et al., 2021a; Huang & Ha, 2020; Ren et al., 2018). Previous research has supported the idea that recommending services is a significant outcome based on service quality delivery (Huang & Ha, 2020). Warmth is associated with empathy, a major service quality dimension in services research (Bennett & Hill, 2012). Fiske et al. (2007) describe warmth as related to communion involving interactions that build interpersonal relationships. Hu, Lu, and Pan, Gong, et al. (2021) explain that warmth perceptions can build harmonious relationships and develop trust, leading to positive results in postadoption stages of chatbots. Psychological research has posited that interpersonal relationships generally reciprocate altruistic attitudes. In the case of chatbots, warmth felt during an interaction may enable customers to recommend the services to other consumers. The intelligence and designs in chatbot architecture further help consumers perceive warmth. Previous research has applied the role of warmth in both the purchase and postpurchase stages of services (Loupiac &

Goudey, 2019). Given that cognitive and peripheral cues can enable warmth perception, the ability to perceive warmth lies with the customer. Thus, humanness warmth perceived in chatbots can positively mediate the relationship between cognitive and peripheral cues and recommendation intention. Based on this analogy, we synthesize the following hypothesis.

Hypothesis 9. Chatbot warmth indirectly impacts the relationship between (a) cognitive cues and recommendation intentions, (b) peripheral cues and recommendation intentions, in both purchase and postpurchase stages.

4.2 | Method

4.2.1 | Study design and experimental conditions

This research follows an explanatory sequential mixed design, where Study 1 deploys a 3 × 3 factorial experimental design. The 3 × 3 design signifies cognitive cues (ranging from high-level information and intelligence [3] to low level of information and intelligence [1]) × peripheral cues (from high attractive cues [3] to low attractive cues [1]). We utilized a local e-commerce website to conduct this experiment to optimize the company's top-performing chatbot. The experiment was conducted in two phases: (1) during the purchase stage and (2) during the postpurchase stage. Table 1 provides the experimental conditions and explanations for each condition across these phases. A total of 354 customers participated in the experiment-based survey during Phase 1 (purchase stage), and 286 customers participated in Phase 2 (postpurchase stage). Socio-demographic details of the participating customers indicate that the sample is representative of the general customer population. Further details are provided in Table 2.

We used an established e-commerce company that sells products such as smartphones, laptops, consumer electronic appliances, kitchen appliances, personal care & grooming items, and other accessories to operationalize this experiment. The company, in existence for the last 7 years, receives approximately 1200 visitors per day and records around 350 purchases daily. It offers a range of predominantly high-involvement products and is transitioning to

TABLE 1 Conditions of the two experimental variables.

Cognitive cues (This variable deals with the information provided during the purchase stage)		**Purchase stage (Phase 1)**
High (coded as 3)	In high conditions, chatbots are enabled with important information about their purchase process with payment details and information choices with a faster response level minimizing the effort of the customer	
Medium (coded as 2)	In medium conditions, chatbots are enabled with low information with payment details and information choices with a medium response level minimizing the effort of the customer	
Low (coded as 1)	The low condition, chatbots are enabled with no information about the purchase process but with the payment details with a low response level minimizing the effort of the customer	
Peripheral cues (This variable deals with the attractive features in chatbots during the purchase stage)		
High (coded as 3)	In high condition, the design of the purchase chatbots are optimized with attractive design and color	
Medium (coded as 2)	The medium condition, the design of the purchase chatbots are optimized with attractive color but with a static design	
Low (coded as 1)	The low condition, the design of the purchase chatbots are optimized with static color and design	
Central cues (This variable deals with the information provided during the postpurchase stage)		**Postpurchase stage (Phase 2)**
High (coded as 3)	In high condition, chatbots are provided with more postpurchase options in chatbots namely, feedback/review, tracking information, service interaction, and recommendation information	
Medium (coded as 2)	In medium conditions, chatbots are provided with lesser postpurchase options in chatbots namely, feedback/review and tracking information	
Low (coded as 1)	The low condition, chatbots are provided with only one postpurchase option in chatbots – feedback/review	
Peripheral cues (This variable deals with the attractive features in chatbots during the postpurchase stage)		
High (coded as 3)	In high condition, the design of the purchase chatbots are optimized with attractive design and color according to postpurchase functions	
Medium (coded as 2)	The medium condition, the design of the purchase chatbots is optimized with attractive color but with a static design according to postpurchase functions	
Low (coded as 1)	The low condition, the design of the purchase chatbots is optimized with static color and design according to postpurchase functions	

TABLE 2 Social demographic information about the study participants.

Socio-demographic Variables	Characteristics	Frequency N = 354	Percentage (%)	Frequency N = 286	Percentage (%)
Gender	Male	186	52.54	134	46.85
	Female	168	47.46	152	53.15
Age	Under 30 years	136	38.42	108	37.76
	31–40 years	102	28.81	92	32.17
	41–50 years	74	20.90	48	16.78
	Above 50 years	42	11.86	38	13.29
Occupation	Student	124	35.03	108	37.76
	Working professional	156	44.07	122	42.66
	Others	74	20.90	56	19.58
Product purchased or intended to purchase	Electronics	151	42.66	132	46.15
	Apparels	91	25.71	83	29.02
	Toys	36	10.17	26	9.09
	Cosmetics	43	12.15	33	11.54
	Others	33	9.32	12	4.20
Experience in chatbot interaction	Food delivery	167	47.18	154	53.85
	Telecom	56	15.82	45	15.73
	Booking	62	17.51	51	17.83
	Other services	69	19.49	36	12.59

include a chatbot on its website. The company's technical team integrated an automated chatbot using a third-party tool into the e-commerce website. After subsequent testing, it was incorporated into the company's main website. The deployed chatbot functioned based on an architecture specific to each experimental condition, comprising nine interactive levels. The interactive levels refer to the depth of interaction a user can have with the chatbot. In Phase 1, the chatbot's cognitive cue conditions were developed based on features related to customer purchase interactions, such as product information, payment processing, pricing, delivery, and terms and conditions. These options, designed in the chatbot as clickable options, allowed consumers to engage in any queries related to these topics. All options were framed with information according to the design conditions outlined in Table 1. For example, if a consumer selects "product information," it will provide detailed or less information based on blocks 1–9. These features were chosen based on past customer interactions observed on the company's e-commerce website. During our observation of 25 customers, all either checked one or all of these features: product delivery, payment information, terms and conditions, and price information.

Similarly, the cognitive cues for the chatbot employed in Phase 2 were developed with a focus on customer postpurchase interactive features such as providing feedback, tracking the product, interacting with after-purchase services, and making recommendations to friends. The postpurchase stage conditions were selected based on observations of 30 customers interacting with the store after their purchases. In both phases, the chatbot deployed high cognitive cues featuring more information and higher intelligence, while low cognitive cues involved less information and a less intelligent chatbot. The chatbots were designed to test the peripheral cues with high and low attractiveness, respective to Phases 1 and 2. Table 1 provides the explanations of conditions for Phase 1 (purchase stage) and Phase 2 (postpurchase stage). We consulted nine experts (five from academia and four industry practitioners who manage online stores) to understand the experimental conditions and the simulated chatbot environment's representation in the purchase and postpurchase stages.

4.2.2 | Experimental procedure and manipulations

The experimental procedure was similar for both Phase 1 (purchase stage) and Phase 2 (postpurchase stage). The company's website, equipped with a chatbot, went live with nine blocks (3 × 3) conducted during nine periodic intervals, extending to 28 days for Phase 1 and 35 days for Phase 2. The study considered all consumer interactions, irrespective of product category. After the interaction, each customer was invited to participate in a survey, incentivized with loyalty points that could be redeemed during their next purchase on the company website. This survey was conducted in a multicross-sectional format, with samples collected from two groups: the purchase and postpurchase phases. Among the numerous people who interacted with the chatbot, 386 customers participated in the survey for Phase 1, with 354 eligible data points being used to operationalize the analysis for this phase. In the case of Phase 2, 312 customers participated in the survey, resulting in 286 final data points used for the analysis. Nine manipulations (3 × 3) were implemented separately in Phases 1 and 2. Appendix B provides details on these nine manipulations for both the purchase and postpurchase stages. Customers who participated in the survey were almost equally spread across the nine manipulations. These manipulations were determined by factorially combining each condition of the cognitive and peripheral cues. Consequently, across both phases, a total of 18 manipulations were assigned.

4.2.3 | Experiment validations

The experimental conditions were pretested using 60 samples for both phases. In terms of cognitive cues, the chatbot was pretested across three categories: high information and intelligent interaction levels (3), essential information and automated interaction levels (2), and low information and nonintelligent levels (1). The experimental validation assessed whether the three conditions differed in cognitive cues based on the time consumers spent interacting with the chatbots and the level of their interactions. The analysis of variance (ANOVA) results demonstrated that both the time spent with the chatbots ($F = 15.218$; $df = 2{,}57$, $p < 0.001$) and the level of interaction ($F = 40.397$, $df = 2{,}57$, $p < 0.001$) significantly varied across the three experimental conditions for cognitive cues. Regarding peripheral cues, the chatbots were designed under three conditions: dynamic colorful designs (3), colorful static designs (2), and basic static designs (1). ANOVA results indicated that the time spent with the chatbot ($F = 19.451$; $df = 2{,}57$, $p < 0.001$) and the level of interaction ($F = 18.262$; $df = 2{,}57$, $p < 0.001$) significantly varied across these conditions. The pretesting stage confirmed the variance within the conditions for cognitive and peripheral cues, thus highlighting significant behavioral differences across conditions.

4.2.4 | Questionnaire and measurement

The survey instrument included research disclosure and ethical statements, construct scale and measurements, as well as respondents' socio-demographic information. The scales used in the study were adopted from prior research (Al-Ansi et al., 2019; Balakrishnan & Dwivedi, 2021a; Hu, Lu & Pan, Gong, et al., 2021; Judd et al., 2005; Zhou et al., 2019). Scales for perceived warmth and competence were taken from Hu, Lu, and Pan, Gong, et al. (2021), Zhou et al. (2019), and Judd et al. (2005). The chatbot experience scale was derived from Balakrishnan and Dwivedi (2021a), while the scale for intention to recommend was taken from Al-Ansi et al. (2019). All scales were measured on a 7-point Likert scale, ranging from *very strongly agree* (7) to *very strongly disagree* (1). Detailed scale information is provided in Appendix A.

4.2.5 | Analysis

The study adopted a two-step structural equation modeling (SEM) technique to test the proposed hypotheses across the experimental conditions. Initially, a confirmatory factor analysis was conducted, and upon satisfying the reliability and validity requirements, SEM was employed to test the range of hypotheses. The constructs of competence, warmth, chatbot experience, and recommendation intention were measured using well-defined scales. Given the factorial manipulation, the cognitive and peripheral cues variables were coded from 3 to 1. Thus, continuous data was used as input within the SEM. All analyses were performed using AMOS 28.0 and SPSS 28.0 software. Prior research has applied SEM in experimental studies to investigate proposed hypotheses (Balakrishnan & Dwivedi, 2021a). The two-step SEM process allowed us to test the reliability and validity requirements, which can function as a control for external validity. This can help establish the model's generalizability across different contexts, and thus address the challenges of external validity (Henseler, 2017). The SEM-based direct and indirect paths were estimated using the maximum likelihood method (MLM), renowned as an unbiased estimator that considers extraneous effects (Henseler, 2017). It calculates the actual parameter values that are neither systematically too high nor too low (Smid et al., 2020). Given these causal conditions, MLM was used in this study. The fit indices for both measurement and structural models were also calculated to understand the strength of the model.

4.3 | Results

4.3.1 | Measurement model and common method bias (CMB)

The results of the confirmatory factor analysis demonstrated the reliability and validity requirements. The Cronbach alpha for all the constructs exceeded 0.750, which confirms the data is reliable and free from measurement error. Additionally, content, convergent, and discriminant validity requirements were also satisfied, ensuring extended validity. The factor loadings of all the constructs exceeded 0.600, satisfying the requirement for content validity (Nunnally, 1978; Portney & Watkins, 2000). The average variance extracted (AVE) values surpassed 0.500, confirming the convergent validity requirements (Fornell & Larcker, 1981). Table 3 displays the range of factor loadings and the AVE values. Table 4 presents the intercorrelation values and the square root of AVE. As illustrated in Table 4, the intercorrelation values are lower than the corresponding square root of AVE values, which affirms the discriminant validity requirements (Fornell & Larcker, 1981). The CFA satisfies the basic requirements regarding content validity, as well as convergent and discriminant

TABLE 3 Measurement model.

Phase	Constructs	No. of items	Mean (standard deviation)	Standardized factor loadings (range)	Cronbach alpha
Phase 1 (purchase stage) $N = 354$	Perceived competence	5	3.68 (1.26)	0.721***–0.811***	0.789
	Perceived warmth	5	4.08 (0.98)	0.763***–0.832***	0.792
	Experience	6	4.22 (0.96)	0.812***–0.901***	0.901
	Recommendation Intention	3	4.28 (1.02)	0.886***–0.911***	0.812
Phase 2 (postpurchase stage) $N = 286$	Perceived competence	5	3.54 (1.04)	0.768***–0.809***	0.782
	Perceived warmth	5	3.85 (1.01)	0.809***–0.826***	0.762
	Experience	6	4.02 (1.08)	0.786***–0.848***	0.924
	Recommendation Intention	3	3.96 (1.12)	0.856***–0.923***	0.856

Note: ***indicate values significant at 99% confidence level.

TABLE 4 Inter-construct correlations and AVE value.

	CR	AVE	1	2	3	4	Phase 1 (purchase stage)
1. Competence	0.778	0.620	**0.787**				
2. Warmth	0.788	0.626	0.436	**0.791**			
3. Chatbot experience	0.898	0.748	0.367	0.637	**0.864**		
4. Recommendation intention	0.812	0.711	0.564	0.512	0.712	**0.843**	
	CR	**AVE**	**1**	**2**	**3**	**4**	**Phase 2 (postpurchase stage)**
1. Competence	0.782	0.608	**0.779**				
2. Warmth	0.762	0.628	0.386	**0.792**			
3. Chatbot experience	0.924	0.768	0.288	0.522	**0.876**		
4. Recommendation intention	0.856	0.687	0.657	0.324	0.576	**0.828**	

Note: **1**. AVE represents average variance extracted; **2**. CR represents composite reliability; **3**. Square root of AVEs are presented in the diagonal for each construct in bold format; **4**. All values in the correlation matrix are significant at 99% confidence level.

validity, thereby confirming the validity of the constructs and measurements as suggested by Bagozzi et al. (1991) and Fornell and Larcker (1981). The fit indices of the measurement model exhibited an excellent fit, and these indices are presented in Table 5. The overall results of the confirmatory factor analysis met the requirements necessary to analyze the structural model.

The CMB was evaluated as part of the confirmatory factor analysis. CMB is important in confirmatory factor analysis to assess the common variance shared by the constructs. Previous research has suggested that Harmon's one-factor model is more conservative with complex data; hence the common latent factor (CLF; Podsakoff et al., 2003) method was used to assess the CMB. In the CLF model, a common factor is introduced with a path extending to each construct item, with “1” set as a constraint for each path connected with the common construct. The estimates of the CLF model are then combined with the non-CLF model to check the deviation in the standardized estimates. As per previous literature, a deviation of 0.05 is permissible between the estimates. Any item with a difference exceeding 0.05 among the estimates is deemed to introduce method bias into the model. In this study, the CLF and non-CLF models were compared to check for CMB issues. The difference in their estimates ranged from 0.012 to 0.038, thus confirming that the measurement is free from CMB issues and that the constructs may enhance predictability in the model (MacKenzie & Podsakoff, 2012).

4.3.2 | Structural model

The structural model evaluated five direct paths and eight indirect effects paths. It was estimated using the maximum likelihood model, with significance measured at a 95% confidence level. Hypothesis 1 investigated the relationship between cognitive cues and the chatbot experience. In the purchase stage, the hypothesis was significant ($\beta = 0.244$). However, during the postpurchase stage, the hypothesis was not significant ($\beta = 0.082$) at a 95% confidence level. Hypothesis 2 demonstrated that the relationship between central cues and recommendation intention was significant during both the purchase ($\beta = 0.187$) and postpurchase ($\beta = 0.311$) stages. The coefficient

TABLE 5 Fit indices of the measurement and structure model.

Fit indices	Measurement model: Purchase stage	Measurement model: Postpurchase stage	Structural model: Purchase stage	Structural model: Postpurchase stage	Recommended value	Reference
χ^2/df	2.134	2.425	2.475	2.678	≤3.00	Bentler (1990) and Hu and Bentler (1998)
GFI	0.945	0.924	0.921	0.911	≥0.900	
NFI	0.936	0.910	0.932	0.911	≥0.900	
CFI	0.954	0.936	0.942	0.921	≥0.900	
RMR	0.072	0.088	0.082	0.086	≤ 0.100	
RMSEA	0.042	0.047	0.068	0.071	≤ 0.080	

related to the postpurchase stage was higher than the purchase stage. Hypothesis 3 revealed that the relationship between peripheral cues and the chatbot experience was highly significant at both the purchase ($\beta = 0.348$) and postpurchase ($\beta = 0.312$) stages. Notably, the coefficients of both paths showed a minimal coefficient difference. Hypothesis 4 indicated that the relationship between peripheral cues and recommendation intention was not significant at the purchase stage ($\beta = 0.056$) but was significant at the postpurchase ($\beta = 0.126$) stage. The results of Hypothesis 4 (peripheral cues to intention to recommend) were relatively weak compared to Hypothesis 3 (cognitive cues to intention to recommend). Finally, Hypothesis 5 demonstrated that chatbot experience could significantly affect recommendation intention. The model fit indices for the structural model, displayed in Table 5, showed a good fit. This also supports the robustness of the model. The variance explained (R^2) is depicted in Figure 3, which shows better results.

The mediation results are displayed in Table 6. These results indicate that competence could significantly mediate the relationship between cognitive cues and chatbot experience, thus supporting Hypothesis 6a in both the purchase and postpurchase stages. However, the relationship of 6a exhibited partial mediation in the purchase stage and full mediation in the postpurchase stage. In Hypothesis 6b, which explored the mediating effect of competence in the relationship between peripheral cues and experience, competence failed to create a significant indirect effect in the purchase stage. However, competence did create a significant partial mediation effect in the postpurchase phase. Additionally, competence significantly mediated the relationship of cognitive cues to recommendation intention in both the purchase and postpurchase stages (Hypothesis 7a). Also, Hypothesis 7a exhibited partial mediation for both stages.

However, Hypothesis 7b indicated that competence could partially mediate the relationship between the peripheral route and recommendation intention in the postpurchase stage. However, it failed to create a significant indirect effect in the purchase stage. Hypotheses 8a and 8b investigated the mediating effects of warmth. Warmth significantly indirectly affected the relationships between cognitive cues and chatbot experience (Hypothesis 8a), and between the peripheral route and chatbot experience (Hypothesis 8b) in both the purchase and postpurchase stages. However, the relationship in Hypothesis 8a exhibited full mediation during the postpurchase stage, while the remaining paths associated with Hypotheses 8a and 8b showed partial mediation. The results differed for Hypothesis 9a, in which warmth did not significantly mediate the relationship between cognitive cues and recommendation intention in the postpurchase stage but did partially mediate this relationship during the purchase stage. Hypothesis 9b demonstrated that warmth significantly mediated the relationship between peripheral cues and recommendation intention during both the purchase and postpurchase stages. The purchase stage was found to be fully mediated, while the postpurchase stages were partially mediated.

5 | THEMATIC EXPLORATION (STUDY 2)

Study 2 offers an in-depth thematic and exploratory insight into the results obtained from Study 1, further enriching the conceptual and empirical meaning of the model proposed in Figure 1.

5.1 | Study design

As part of Study 2, we conducted in-depth interviews with 32 consumers, evenly distributed across the purchase and postpurchase stages. These interviews were designed to uncover inherent ideas embedded within the behavioral and psychological relationships derived from foundational theories, leading to comprehensive validation of the conceptual model presented in Figure 1. The exploratory dimension added through the qualitative study follows an explanatory sequential research design to confirm, extend, and validate the results obtained during the initial stage. Walker and Baxter (2019) advocated the importance of such an explanatory sequence for pairing quantitative research with qualitative analysis to better understand and validate conceptual models through extended analysis and results. Interviews were conducted with customers of the company who participated in Study 1. Of these, 16 customers were engaged with the purchase stage chatbot. Eight customers encountered the chatbot's high cognitive cues, while the other eight experienced the high peripheral cues offered by the chatbot. The remaining 16 customers interacted with the postpurchase stage

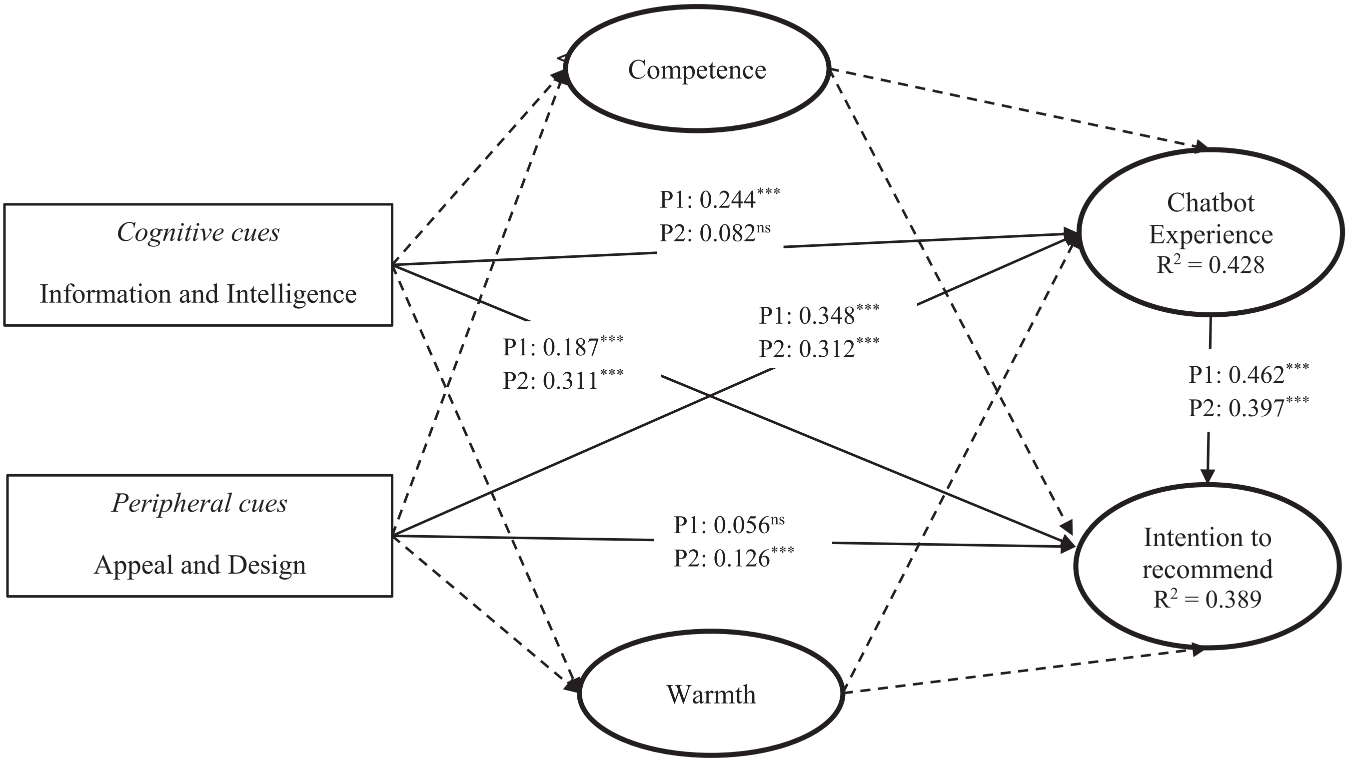

FIGURE 3 Results from Study 1. Note 1: Straight lines indicate direct paths; dotted lines indicate the mediating path. Note 2: The mediation effects are shown in Table 6. Note 3: ***indicate values significant at 95% confidence level; nsindicate values not significant. P1 refers to standardized coefficient values of the path at purchase stage, and P2 refers to the values corresponding to postpurchase stage.

chatbot, where eight of them experienced the high cognitive cues, while the other eight experienced the high peripheral cues of the chatbot. Conditions tuned for high-cognitive and high-peripheral cues are provided in Table 1.

5.1.1 | Sampling and operationalisation

Customers who participated in Study 2 had prior experience using chatbots ranging from 1 to 4 years (mean = 2.267; *SD* = 0.785). These customers were almost equally divided by gender, with 17 males and 15 females. The duration of the interviews with these customers lasted between 28 and 76 min (mean = 52.133; *SD* = 12.328). Since the customers who participated in the qualitative study were also part of Study 1, they already had a sound understanding of the rationale for their participation in the second study and what influenced their perceptions and certain behaviors during Study 1. To regain momentum, the participants were once again asked to interact with the chatbots before the interview process. This projective technique was designed to help the participants reinvigorate their earlier memories just before the interview process. Participants were carefully selected based on their recorded responses from Study 1. This selection criteria facilitated an understanding of the rationale behind the results proposed in Figure 1. Selected participants provided their opinions in response to a list of formulated questions, leading to thematization and triangulation of results with greater nuance and validity. Appendix C provides the list of questions asked during the interview process.

5.1.2 | Data analysis

We adhered to a five-step process to record, transcribe, and analyze the interview data verbatim (Braun & Clarke, 2006; McCrudden & McTigue, 2019). A code-driven thematic analysis was carried out to understand latent conceptual development without imposing any individual ideas or personal biases. Initially, all the transcripts were thoroughly read to gain a holistic overview of the interview data, ensuring the collected data adhered to the principles of triangulation and met research objectives. During the second stage, descriptive

TABLE 6 Mediation effects present in the structural model.

Hypotheses	Total effect (lower bound, upper bound) Phase 1 N = 354	Phase 2 N = 286	Direct effect (lower bound, upper bound) Phase 1 N = 354	Phase 2 N = 286	Indirect effect (lower bound, upper bound) Phase 1 N = 354	Phase 2 N = 286
Hypothesis 6a	0.368***	0.216***	0.256***	0.078ns	0.111***	0.138***
CC->COMP->EXP	(0.263, 0.586)	(0.093, 0.356)	(0.124, 0.386)	(−0.086, 0.189)	(−0.026, 0.287)	(−0.012, 0.301)
Hypothesis 6b	0.392***	0.413***	0.348***	0.312***	0.042^{ns}	0.101***
PC->COMP->EXP	(0.191, 0.575)	(0.214, 0.591)	(0.181, 0.553)	(0.176, 0.542)	(−0.098, 0.174)	(−0.012, 0.311)
Hypothesis 7a	0.282***	0.437***	0.186***	0.311***	0.099***	0.126***
CC->COMP->RI	(0.111, 0.412)	(0.292, 0.660)	(0.043, 0.322)	(0.111, 0.509)	(−0.101, 0.232)	(0.001, 0.303)
Hypothesis 7b	0.097 ^{ns}	0.222***	0.056^{ns}	0.124***	0.031^{ns}	0.098***
PC->COMP->RI	(−0.099, 0.214)	(0.064, 0.413)	(−0.112, 0.216)	(0.002, 0.286)	(−0.132, 0.196)	(−0.109, 0.312)
Hypothesis 8a	0.381***	0.232***	0.256***	0.078^{ns}	0.124***	0.154***
CC->WARM->EXP	(0.192, 0.536)	(0.064, 0.412)	(0.124, 0.386)	(−0.086, 0.189)	(−0.009, 0.312)	(−0.014, 0.286)
Hypothesis 8b	0.560***	0.440***	0.348***	0.312***	0.215***	0.128***
PC->WARM->EXP	(0.412, 0.712)	(0.312, 0.557)	(0.181, 0.553)	(0.176, 0.542)	(0.042, 0.413)	(−0.011, 0.312)
Hypothesis 9a	0.297***	0.342***	0.186***	0.311***	0.111***	0.031^{ns}
CC->WARM->RI	(0.101, 0.423)	(0.126, 0.465)	(0.043, 0.322)	(0.111, 0.509)	(−0.032, 0.268)	(−0.145, 0.191)
Hypothesis 9b	0.148***	0.236***	0.056^{ns}	0.124***	0.092***	0.112***
PC->WARM->RI	(0.002, 0.345)	(0.058, 0.379)	(−0.112, 0.216)	(−0.028, 0.311)	(−0.098, 0.216)	(−0.079, 0.299)

Note 1: All the estimates are standardized and significant at the 95% level: bootstrap iterations = 5000 through the bias-corrected percentile bootstrap method. *** indicates $p < 0.05$, and ^{ns} indicate not significant. Phase 1 corresponds to the purchase stage, and phase 2 corresponds to the postpurchase stage.

Note 2: CC denotes Cognitive Cues; COMP denotes Competence; EXP denotes Chatbot Experience; PC denotes Peripheral Cues; RI denotes Recommendation Intention; WARM denotes Warmth.

quotes from the interviews were classified and open-coded for thematization. For example, "My experience with the chatbot is more involved in the interaction" (P18), "I would recommend my friends and family to use a chatbot for better performance in the future" (P3), "During a long interaction, I forgot it's technology that I am interacting with" (P2), and "Chatbots have more courtesy in responding, and the key is its patience to respond " (P24). In the third stage, open codes were systematically amalgamated to develop an axial coding system. For example, P18's statement above was coded as "Functional Involvement", and P3's statement above was coded as "Performance and Recommendation Intention". In the end, 69 labels were created based on the phrases identified during this stage. Following the principles of selective coding, the axial coding labels were further grouped into categories during the fourth stage, based on thematic congruence. For instance, the codes "Functional Involvement" and "Easy to Use Chatbot" were grouped into "Functional Flow" based on the conversational context. Finally, during the fifth stage, selective codes and categories were compared to gain a holistic understanding of research results and their conceptual fit into the model presented in Figure 1. The entire process was conducted using two qualitative analysis software programs.

5.2 | Results of Study 2

From a holistic perspective, customer interviews complemented and confirmed the results from Study 1. Study 2 served its purpose by facilitating the understanding of explanatory insights related to (i) user experience characteristics, (ii) chatbot stereotypes (humanness perception stereotypes), and (iii) user recommendation intention motives. The following sections elucidate participants' perspectives on certain behavioral actions while they were subjected to cognitive and peripheral cues at the purchase and postpurchase stages. Tables 7 and 8 present the results from Study 2.

5.2.1 | Chatbot experience

The interview transcripts revealed two characteristics of participants' chatbot experiences, illuminating their relationship with chatbot recommendation intentions. Apart from this associative relationship, results convey a more holistic understanding of how customers experience chatbots at both cognitive and peripheral levels during different stages of the journey process. In both the purchase and postpurchase stages, customers assigned more importance to the

TABLE 7 The categories and codes for the purchase stage (n = 16).

Cognitive cues (n = 8)					
Chatbot experience characteristics	***n***	**Chatbot stereotypes**	***n***	**Recommendation intention motivations**	***N***
Functional		***Competence stereotype***		***Patronage***	
Features (+)	5	Ability (+)	6	Social support (+)	6
Interactive (+)	3	Conformance (+)	5	Recognition (+)	6
Accessibility (+)	2	Information (+)	5	Technology support (+)	4
Task-based (+)	2	Task and Roles (+)	4	Credibility (+)	2
Difficulty (–)	2	Vocational talent (+)	3	Technology risk (-)	1
		Accuracy (+)	2		
Emotional		***Warmth stereotype***		***Altruism***	
Excitement (+)	5	Empathy (+)	4	Reciprocation (+)	5
		Patience (+)	3	Considerate (+)	4
		Responsive (+)	2	Offering (+)	2
		Lack of human feel (–)	1		
Peripheral cues (n = 8)					
Chatbot experience characteristics	***n***	**Chatbot stereotypes**	***n***	**Recommendation Intention Motivations**	***N***
Functional		***Competence stereotype***		***Patronage***	
Accessibility (+)	6	Quality (+)	5	Belongingness (+)	4
Interactive (+)	3	Ability (+)	4	Credibility (+)	3
Usability (+)	3	Conformance (+)	3	Association (+)	2
		Information (+)	3		
Emotional		***Warmth stereotype***		***Altruism***	
Excitement (+)	6	Contrast (+)	5	Self-value (+)	3
Joy (+)	4	Feel (+)	5	Positivity (+)	4
Pleasure (+)	3	Empathy (+)	4		
Arousal (+)	2	Response (+)	4		
		Transparency (+)	3		
		Tangibility (+)	3		

functional experience than to the emotional experience. Twelve labels were identified under functional experience, while nine were pinpointed under emotional experience. The distribution of these labels across the purchase and postpurchase stages is presented in Tables 7 and 8, respectively.

The final results indicate that "accessibility" holds more significance than the other labels. Accessibility, a key aspect encapsulating both the cognitive and peripheral states, relates to the functional characteristics of the chatbot as perceived by the customers. Significantly, accessibility is a crucial variable that defines experience at both the purchase and postpurchase stages.

> *P3 stated, "The chatbot is accessible across devices, and the contents are more assistive. It was a new, fruitful experience for me using the chatbot."*

Within the emotional category, "excitement" was identified as a critical variable related to the chatbot experience. Although excitement is part of both cognitive and peripheral interactions, this variable was predominantly present only in the purchase stage. This suggests a diminishing effect of excitement when customers use chatbots during the postpurchase phase.

> *P11 stated, "I am more excited to use chatbots; the design and interface usage is a new key to me which provides an exciting experience."*

Apart from accessibility and excitement, pleasure, interactive, and response quality were also identified as more weighted labels that shared meaning with the chatbot experience in creating positive recommendation intention.

TABLE 8 The categories and codes for the postpurchase stage ($n = 16$).

Postpurchase stage (n = 16)					
		Cognitive cues (n = 8)			
Chatbot experience characteristics	***n***	**Chatbot stereotypes**	***n***	**Recommendation intention motivations**	***n***
Functional		***Competence stereotype***		***Patronage***	
Response quality (+)	6	Problem solving (+)	5	Service support (+)	5
Accessibility (+)	4	Skill (+)	4	Service quality (+)	4
Task-based (+)	2	Accuracy (+)	4	Technology support (+)	3
Interface (+)	2	Task and roles (+)	3	Credibility (+)	1
Intelligence (+)	2	Intelligence (+)	1	Operational difficulty (−)	1
Emotional	***n***	***Warmth stereotype***	***n***	***Altruism***	***n***
Pleasure (+)	5	Empathy (+)	6	Empathize (+)	4
Anxiety (−)	2	Assurance (+)	5	Considerate (+)	3
		Trust (+)	3	Clemency (+)	1
		Responsive (+)	2		
Peripheral cues (n = 8)					
Chatbot experience characteristics	***n***	**Chatbot stereotypes**	***n***	**Recommendation intention motivations**	***n***
Functional		***Competence stereotype***		***Patronage***	
Assistance (+)	4	Innovative (+)	4	Time saving (+)	4
Design (+)	3	Skill (+)	2	Value (+)	3
Intelligence (+)	2	Conversation (+)	2	Reputation (+)	2
Accessibility (+)	2	Assertive (+)	2		
Personalization (+)	1				
Emotional		***Warmth stereotype***		***Altruism***	
Vividness (+)	2	Design (+)	4	Social sharing (+)	4
Colorful (+)	2	Facilitation (+)	3	Positivity (+)	2
Sensation (+)	2	Friendly (+)	2	Considerate (+)	2
Anger (−)	1	Responsive (+)	2		

> P8 stated, "It is a pleasure interacting with a chatbot, the interactiveness and features are highly rememberable, and I would be happy to share this experience with others too".

5.2.2 | Chatbot stereotypes

While examining the responses related to perceived humanness characteristics, the transcripts outlined participants' perceived stereotypes of chatbots. Most of the responses reaffirmed the results identified in Study 1. Furthermore, the stereotypes that customers perceived aligned with the two humanness variables identified in this study: competence and warmth. We identified 28 labels across these categories, spread across cognitive and peripheral cues at both the purchase and postpurchase stages. Tables 7 and 8 present these weights and labels. The weights were comparatively higher for the purchase stage than the postpurchase stage.

Empathy was the most highly perceived attribute of the chatbot at both the purchase and postpurchase stages. We categorized empathy under warmth, as the conversation codings expressed a similar viewpoint. Notably, empathy was found to be higher at the peripheral cue compared to the cognitive cue. Ability was also identified as the next most significant factor, marking it as one of the important competences of chatbots. Six participants exposed to cognitive cues and four exposed to peripheral cues at the purchase stage indicated that the chatbot's ability and performance were the major reasons compelling them to recommend it to others within their peer network.

> *P19 stated, "I am surprised that a technology (chatbot) can express empathy through emoji and words. This is a new experience for me. My friends and I recently discussed how these chatbots are empathetic by understanding human feelings. Technology developers should be credited for these developments."*

> *P6 stated, "I feel the chatbots are highly competent. Their ability to answer the queries is a new experience for me. I would be happy to recommend this to others so that they can also benefit from this".*

Besides empathy and ability, conformance and information were also notably identified as important nodes within the competence category, acting as stereotypes of chatbots, by the respondents. However, most of the emphasis given to these two categories corresponded to the purchase stage, with very limited emphasis observed within the postpurchase stage.

5.2.3 | Recommendation intention

Twenty-two labels were discovered while analysing participant interviews related to their intentions of recommending chatbots to others. The identified 22 labels across the cognitive and peripheral cues exhibited two categories, namely, patronage and altruism. Patronage here stands for loyal support extended to others based on various factors observed in chatbots. Meanwhile, altruism refers to a phenomenon where customers recommend chatbots without any self-interest.

Consideration was found to be a highly weighted node, observed as an altruistic attribute emphasized at the cognitive level. Unlike other variables, consideration was given substantial importance in both purchase and postpurchase stages. In addition to consideration, technology support was also identified as a highly emphasized node in purchase and postpurchase stages. Technology support was extensively highlighted under patronage within cognitive cues.

> *P26 stated, "I consider recommending chatbot to others given the functionalities and experience it can provide customers."*

> *P31 stated, "The technology support of the chatbot is a standout in the services provided. I hope they will extend and develop more support to enhance the services. I will be happy to recommend the chatbot to others".*

Apart from the terms consideration and technology support, other variables such as credibility, reciprocation, and positivity were also identified as main drivers of the recommendation intention for chatbots. Compared to altruism, patronage had more substantial emphasis.

> *P28 stated, "I wish to recommend the chatbot to others. It is a kind of reciprocation that I extend to my well-wishers."*

6 | DISCUSSION

Study 1 explored the influence of cognitive and peripheral cues on user chatbot experience, with recommendation intention being analyzed through the mediators of "humanness," "competence," and "warmth." This model was scrutinized during both the purchase and postpurchase stages of the customer journey, labeled as Phase 1 and Phase 2, respectively. Thirteen hypotheses concerning direct and indirect effects were tested using structural equation modeling. Study 2 was subsequently designed and implemented to further examine the rationale and reinforce the results.

6.1 | Discussion on the Study 1 results

The fit indices yielded a satisfactory fit for both measurement and structural models, with solid R^2 values demonstrating the robustness of the entire model. Hypothesis 1 examined the relationship between cognitive cues and the chatbot experience in the purchase and postpurchase stages. The results were significant for the purchase stage and insignificant for the postpurchase stage, a finding that became interesting when comparing both stages. Research concerning technology interactions predominantly asserts that cognitive cues can enhance the chatbot experience (Chen et al., 2021). Fan et al. (2023) echoed this by asserting that efficient chatbots can enrich user experience. However, this was not supported during the postpurchase stage. Prior research has also discovered that when individuals fully engage with cognitive cues, they evaluate all aspects rationally, which may interfere with their experience or flow (Fan et al., 2020). Balakrishnan and Dwivedi (2021a) likewise supported the notion that cognitive absorption can foster understanding. Therefore, customers are more engaged in cognitive interaction during the postpurchase stage compared to the purchase stage.

Hypothesis 2 suggested that cognitive cues can stimulate recommendation intention in both the purchase and postpurchase stages. However, the coefficients were relatively higher for the postpurchase stage, underscoring the role of cognitive cues in this phase. Research has endorsed a similar viewpoint that cognitive interactions can lead to the attribution of recommending information to others (Hu, Lu & Pan, Gong, et al., 2021). Grewal and Roggeveen (2020) also confirmed that cognitive exposures significantly influence postpurchase decisions.

Hypothesis 3 demonstrated similar results for the purchase and postpurchase stages, showing the role of peripheral cues in shaping the chatbot experience. These findings underscore the importance of peripheral cues in chatbots at both stages. Prior research has ardently advocated that peripheral attraction can enhance the experience and flow in technology usage (Balakrishnan & Dwivedi, 2021a). Peripheral cues, being more connected with emotional responses and high perceptual flow, can cultivate the flow of experience with technology (Bolton et al., 2018). Hence, the results of Hypothesis 3 are justified.

Hypothesis 4 presented a fragile effect on the postpurchase stage and an insignificant impact during the purchase stage, thus explaining the role of peripheral cues in recommendation intention. Although people's experiences improve with peripheral cues, the same is not accurately reflected in recommendation intention. As mentioned above, customers may engage more rationally in the postpurchase stage, enabling them to identify minimal cognitive aspects even under the influence of peripheral cues. This would have subsequently built a weak yet significant coefficient in the postpurchase stage, although it might not have influenced the purchase stage.

Hypothesis 5 explains the positive relationship between the chatbot experience and recommendation intention. Previous research has shown similar outcomes in online purchase scenarios (Djelassi et al., 2018). Recommendation is the sharing of knowledge and experiences with others (Kelley, 1967). This research affirms that the flow of experience can motivate others to recommend.

Hypotheses 6ab, 7ab, 8ab, and 9ab examined the indirect relationship between perceived humanness, competence, and warmth in the proposed relationships. Out of the 16 indirect relationships for both purchase and postpurchase stages, 13 hypotheses were found to be significant, while three were not. Competence significantly mediated the relationship between a central cue, experience, and recommendation intention. This result illustrates how competence can augment cognitive connection positively. Prior research has explained that competence can indirectly influence rational thinking and generate positive outcomes (Todd & Gigerenzer, 2003). Pizzi et al. (2023) found that warmth and competence can significantly mediate the relationship between anthropomorphism and gaze direction and future intentions with chatbots. These research results support the earlier findings of Pizzi et al. (2023).

On the other hand, competence did not influence the relationship of peripheral cues to experience and recommendation intention in the purchase stage, although it did affect the postpurchase stage indirectly. Barta et al. (2023) argue that competence tendencies will process through a central route, suggesting that the peripheral impacts may be limited in generating positive intentions. Earlier studies have found that customers tend to make rational decisions postpurchase (Shi et al., 2020). Similar results confirm that anthropomorphic humanness characteristics will be more effective in cognitive cues than peripheral cues (Blut et al., 2021). Wang et al. (2023) found that human interactions offer a better emotional experience than chatbots. Businesses should take these results as cues to enrich their chatbot architecture with more human-like elements.

As for the humanness warmth, the results indicate that Hypotheses 8a, 8b, and 9b are significant at both the purchase and postpurchase stages. Relative to cognitive cues, warmth was able to indirectly influence peripheral relationships significantly. Zhang (1996) states that when the need for cognition is low, consumers tend to be attracted to emotional cues to make a decision. This research implies users expect human-like warmth in technology-level conversations. However, Hypothesis 9a was found to be insignificant, suggesting that warmth failed to indirectly impact the relationship of cognitive cues to recommendation intention in the postpurchase stage. Such results also indirectly reflect high consumer cognition during the postpurchase stages, reiterating that customers in the postpurchase stage are more attentive towards cognitive cues than affective ones. Thus, competence and warmth are crucial in accelerating a cognitive or peripheral-focused experience in the chatbot. Also, it can be ascertained that cognitive cues play a pivotal role in the postpurchase stage among customers.

6.2 | Discussion on the Study 2 results

Tables 7 and 8 show the results of Study 2. These results reaffirm the findings obtained from Study 1, but with greater detail. This study also underscores that customers experience chatbots from both functional and emotional perspectives. In line with previous research, our study illuminates how functional and emotional attributes of the flow can drive a positive experience in technology adaptation (Pinochet et al., 2018). Furthermore, our study identified accessibility and excitement as positive drivers of chatbot experience. Earlier research indicated that accessibility is a vital attribute in technology usage that can enhance user experience. Our research supports and extends this idea, contextualizing it in chatbot adoption. We also found that excitement with technology can accelerate the flow of experience, depending on the context of usage. Overall, the findings from Study 2 largely align with the selected literature from psychology, marketing, and behavioral science, as they explain the rationale behind chatbot usage experience, summarized in Figure 4.

The issue of humanness was examined through 28 stereotypes associated with chatbot usage. These stereotypes were categorized under competence and warmth, helping us to gain a better understanding of the empirical work's results. Empathy emerged as a dominant stereotype associated with chatbots. Prior research suggests that empathy in technology-based services is necessary to drive a positive user experience and positive intentions (de Kervenoael et al., 2020); our research supports this view and uncovers the components of empathy essential for a positive experience and positive word-of-mouth. While most of the variables were weighted higher under warmth, competence had a larger combined weightage when considered holistically. This finding confirms that competence plays a significant role in defining the humanness variable within chatbots, along with its intervening effects. The stereotypes discovered in Study 2 encompass both human and technology-based attributes, validating the overall characteristics of chatbots.

Recommendation intentions were captured under 22 labels categorized as patronage and altruism. Previous literature has associated patronage with long-term associations typically connected with the brand (Bian & Haque, 2020), or the features (Banik, 2021). Some studies have linked patronage with loyalty towards the product and brand. We categorized labels describing the features, benefits, and other company-oriented attributes under patronage. On the other hand, participants expressed altruistic comments about their rationale to recommend the chatbot to others. Notably, customers who consider themselves considerate are more likely to recommend chatbots to others. Past research supports the idea that human characteristics and patronage behavior significantly influence how customers recommend products to others. Our study extends these views with greater detail, exploring chatbot recommendation behavior.

6.3 | Theoretical contribution of Studies 1 and 2

Discussion from the study presents new ideas that can provide valuable insights to various theories and enhance existing knowledge in key theoretical areas. (1) this study has explored the conditions of the ELM through an experimental design, linking it with user experience and recommendation intentions. This unique contribution can extend the scope of the ELM within the context of AI and technology adoption. (2) Minimal literature on technology-based conversation has incorporated the aspect of exploring recommendation intentions or behavior among consumers. This study fills that gap, thereby contributing to the theory of attribution and marketing literature. (3) While most research has focused on the chatbot's role

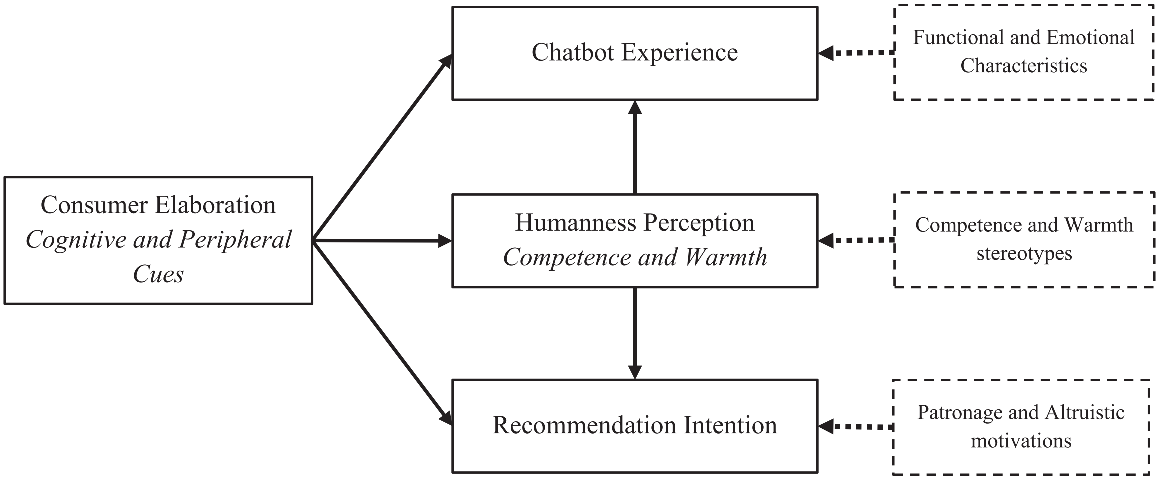

FIGURE 4 Appended conceptual model of the study.

in individual parts of the customer purchase journey, our study contrasts the differences between the purchase and postpurchase stages in relation to chatbot usage. (4) Prior studies have confirmed that expectations of humanness exist within technology interactions (Hu, Lu, & Gong, 2021) and have employed competence and warmth as significant variables to understand their direct impact on the conversation outcome. In contrast, our research utilizes perceived warmth and competence to understand their indirect influence on experience and recommendation intentions. (5) Literature on chatbots is abundant with various studies investigating anthropomorphism (Sheehan et al., 2020), animacy (Go & Sundar, 2019), design (Nguyen et al., 2022), and cognitive interface (Nguyen et al., 2022) separately. However, this study aids in comparing cognitive and peripheral cues together within a holistic framework. (6) Importantly, the contributions mentioned above have been critically assessed through the results of Study 2, adding further value to existing theories and literature.

As chatbots are increasingly becoming more dynamic (Mogaji et al., 2021), the application of cognitive and peripheral cues within the chatbot interface has opened new avenues for discussion about the ELM from a technology perspective. Furthermore, the constructs of the ELM has mostly been investigated alongside behavioral patterns from the perspective of the Theory of Planned Behavior and the Theory of Reasoned Action. By exploring the prospect of the ELM with experience and recommendation intentions, this study has provided an integrated view of the experience-based theory (Shin, 2018) and attribution theory (Kelley, 1967). Additionally, the attributes identified in Study 2 have given us a comprehensive understanding of how cognitive and peripheral cues connect with the chatbot experience, driving user experience towards recommendation intentions.

Previous applications of the ELM have primarily focused on advertising research; this study extends the scope of the framework by exploring and applying the concept within the technology adoption debate involving AI-based consumer chatbot interactions. This theoretical integration lends greater potential to the ELM, helping to understand existing results and frame future research questions. Therefore, researchers aiming to develop similar conceptual frameworks can develop a comprehensive understanding by incorporating this research.

Very few studies have attempted to understand customer behavior across various stages of customer purchase journey. This study provides an overview of how cognitive and peripheral cues, along with subsequent experiences, can differ across the purchase and postpurchase stages. The study further highlights that technology-based interactions will vary between these stages. Notably, direct and indirect effect results showcase the importance of cognitive function in the postpurchase stage; whereas, both cognitive and peripheral cues can impact the purchase stage. Regarding the later, few studies have attempted to investigate customers' postpurchase behavior (Shi et al., 2020). This study provides a comprehensive thematic overview of results along with directions for future research within the field of human-AI interaction from behavioral and psychological perspective.

Humanness characteristics are highly anticipated in services and are emphasized in chatbot conversations (Flavián et al., 2021). However, competence and warmth are seldom explored as mediating variables in technology-based conversations. Specifically, recent literature on chatbots has primarily focused on human-like cues (Jiang et al., 2023). This research adds a precise understanding of these cues from the perspective of competence and warmth. In addition, while studies have found that human-like characteristics build satisfaction, trust, and social presence in chatbots (Chen et al., 2023a), this research extends the outcomes to include experience and recommendation intention. It indicates that the role of humanness expectation can trigger further effects within existing relationships between cognitive and peripheral cues, and experience and recommendation intention.

This strudy furthr challenges the existing studies that have directly measured the various relationships associated with chatbot behavior, questioning whether the indirect role of humanness characteristics may be inherently present. Especially, as the role of competence wass found to indirectly impact the relationships in the postpurchase stage. Thus, chatbot-based conversations predominantly emphasize cognitive cues and competence in the postpurchase stage. In addition, Study 2 provides better interpretations of the 'humanness' attributes in chatbot interaction. Finally, findings related to animacy and anthropomorphism (Balakrishnan & Dwivedi, 2021b) of chatbots can be reconciled by integrating results from Studies 1 and 2.

6.4 | Practical implications

This study offers multiple recommendations for AI and digital marketing practitioners. First, it provides clear directions for technology partners and marketing managers to optimize their chatbots for improved performance, focusing on levels of engagement and "humanness" goals. For example, when managers aim to provide a better experience, they can prioritize more peripheral variables, including static and dynamic cues. Conversely, when they seek to create enhanced touchpoints throughout the customer journey, they should focus on cognitive cues.

From a design theory perspective, the study presents numerous insights into designing chatbots to improve customer experience. Providing better accessibility and interactive features can enhance the user experience. Given that peripheral cues play a pivotal role in the customer experience, managers should design dynamic chatbots to incorporate a warmth condition. AI-driven chatbots should be programmed to express empathy, leading to improved satisfaction and perceived quality of service. In particular, results from the purchase and postpurchase stages will enhance understanding of chatbot usage.

Chatbots come in various formats, including AI, simulated, and those integrating human interaction. Therefore, optimizing chatbots consistently throughout each phase of the customer purchase journey is both difficult and inappropriate. Current research underlines this by offering contrasting results specific to the purchase and postpurchase stages.

Humanness perceptions are integral to any conversation, and this is no different for technology-based interactions. This research unconditionally supports this view. Marketers should aim to incorporate more human-like characteristics into chatbots. While this study has focused on competence and warmth, competence may be inherently present due to the AI engines powering chatbots. However, the most significant challenge lies in understanding how chatbots can convey warmth. Marketers should collaborate with technology developers to create new prototypes that mimic human behavior, particularly when generating affective responses.

Previous research has endorsed the use of gender-based cues (Borau et al., 2021), conversational affection (Chen et al., 2022), courtesy (Liu & Sundar, 2018), and avatars (Cheng et al., 2023b) to evoke stronger affective responses in customers. Marketers can develop future strategies by combining selected ideas from recommended research along with the findings from this study.

With the anticipated exponential growth of chatbots poised to replace human-based services in the coming years, marketers should aim to design chatbots with greater peripherality without neglecting cognitive functions. Peripheral chatbots should prioritize both appeal and design. Overall, marketers can utilize these results to optimize chatbot designs that incorporate appropriate human-like variables, thereby generating superior customer experiences and recommendation intentions.

7 | CONCLUSIONS AND LIMITATIONS

This research designed and deployed a robust explanatory sequential mixed research method consisting of two complementary studies. Study 1 utilized a 3 × 3 factorial experimental design to investigate and validate our proposed hypothetical model, while Study 2 used in-depth qualitative interviews to gain a deeper understanding of the results and the final validated model. Study 1 results revealed that cognitive conversations in chatbots can foster more user recommendation intention, whereas peripheral conversations can create a more positive experience during chatbot interactions. Considering a complete purchase journey, no inherent pattern was observed during the purchase stage. However, cognition and competence play significantly stronger roles in creating experience and recommendation intentions within the postpurchase stage. Study 2 identified 69 labels/nodes that are associated with the investigated variables. Both studies helped extend knowledge and the interdisciplinary application of existing behavioral theories such as the ELM, flow theory, attribution theory, theory of mind, and humanness theories. This study also enriches AI and chatbot literature by providing meaningful behavioral and psychological insights to practitioners.

Future studies in the field should consider a longitudinal design to evaluate and compare between purchase and postpurchase stages for better validation of the results observed (Maier et al., 2023). This study is limited by the cognitive and peripheral designs of the chatbots. Future studies can also deploy a more detailed and robust framework of chatbots to test the cognitive and peripheral routes. This study didn't use any control variables in the model concerning users' technology competence. Future research can employ such variables to control the effects on dependent variables. Future research could also focus on investigating the following avenues: (i) different aspects of experience, such as cognitive, affective, and conative experience, (ii) a prepurchase stage "humanness" evaluation of chatbots could add value to this research stream, allowing researchers to gain a holistic view, (iii) service quality dimensions could be integrated with humanness perception to understand how they can act as indirect variables within the model, (iv) the labels identified in Study 2 should be considered and addressed by future research while framing conceptual models.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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APPENDIX A

Table A1

TABLE A1 Table showing the measurement scales (All scales are measured from 7 to 1).

Constructs	Items	Source
Warmth	I perceive that, this chatbot cares about me while interacting	Hu, Lu, and Pan, Gong, et al. (2021); Judd et al. (2005); Zhou et al. (2019)
	I perceive that, this chatbot cares is kind to me	
	I perceive that, this chatbot is friendly to me during the conversation	
	I perceive that, the conversation with this chatbot is warm	
	I feel this chatbot is sociable	
Competence	I perceive that, this chatbot is intelligent	
	I perceive that, this chatbot is skillfull	
	I perceive that, this chatbot is capable	
	I perceive that, this chatbot is effective	
	I perceive that, this chatbot is efficient	
Chatbot experience	The interaction through chatbots is more appealing	Balakrishnan and Dwivedi (2021a)
	It is easy to navigate through chatbots during interactions	
	The query results are returned promptly	
	The interaction is more personalized	
	The query results are always up to date	
	The query results are always accurate	
Intention to recommend	I will recommend others to use chatbots	Al-Ansi et al. (2019)
	I will say positive things to others about using chatbots	
	I will encourage friends and relatives to use chatbots	

APPENDIX B

Table B1

TABLE B1 Factorial Manipulations.

Blocks	Cognitive cues	Peripheral cues	The explanation for purchase stage	The explanation for postpurchase stage
Block 1 (Wave 1)	High	High	Chatbots are enabled with important information about their purchase process with attractive design and color.	Chatbots are provided with more postpurchase options in chatbots with attractive design and color according to postpurchase functions
Block 2 (Wave 2)	Medium	High	Chatbots are enabled with low information about payment details and information choices with attractive design and color.	Chatbots are provided with lesser postpurchase options in chatbots with attractive design and color according to postpurchase functions
Block 3 (Wave 3)	Low	High	Chatbots are enabled with no information about the purchase process but with attractive design and color.	Chatbots are provided with only one postpurchase option with attractive design and color according to postpurchase functions
Block 4 (Wave 4)	High	Medium	Chatbots are enabled with important information about their purchase process with attractive color but with a static design	Chatbots are provided with more postpurchase options in chatbots with a static design according to postpurchase functions
Block 5 (Wave 5)	Medium	Medium	Chatbots are enabled with low information about payment details and information choices with attractive color but with a static design.	Chatbots are provided with lesser postpurchase options in chatbots with a static design according to postpurchase functions
Block 6 (Wave 6)	Low	Medium	Chatbots are enabled with no information about the purchase process but with attractive color but with a static design.	Chatbots are provided with only one postpurchase option with a static design according to postpurchase functions
Block 7 (Wave 7)	High	Low	Chatbots are enabled with important information about their purchase process with static color and design	Chatbots are provided with more postpurchase options in chatbots with static color and design according to postpurchase functions
Block 8 (Wave 8)	Medium	Low	Chatbots are enabled with low information about payment details and information choices with static color and design	Chatbots are provided with lesser postpurchase options in chatbots with static color and design according to postpurchase functions
Block 9 (Wave 9)	Low	Low	Chatbots are enabled with no information about the purchase process and the payment details with a low response level with static color and design	Chatbots are provided only one postpurchase option with static color and design according to postpurchase functions

APPENDIX C

Indicative questions of in-depth interview (Study 2)

Some indicative questions were asked and discussed during the in-depth conversation in the purchase and postpurchase stages.

1. Can you recall your previous participation in the experiment? (Everyone was able to remember their response in study 1)
2. Have you started using chatbots more nowadays?
3. Which characteristics of chatbot give you more experience in using it?
4. What characteristics do you see in the chatbot that concern and accelerate your experience while using it?
5. Which characteristics connected more with your intention to recommend the chatbot to others?
6. If the chatbot is human, which humanistic stereotype will you associate with it?
7. How will you associate these stereotypes with your experience and intention to recommend chatbots to others?
8. Given that experience and chatbot functions build positive intentions to recommend chatbots to others. However, what are your inherent motivations apart from these that have made a solid intention to recommend chatbots to others?
9. Have you recommended chatbots to others after our study 1? (Everyone answered that they have recommended and spoken about chatbots to others on multiple occasions)

The questions mentioned above had several follow-up questions and conversations aimed at accomplishing the study's objective.