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Customer trust and willingness to use shopping assistant humanoid chatbot

顾客信任与使用购物助手机器人聊天的意愿

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ABSTRACT
In the digital age, brands use chatbots to address customer queries promptly. However, more research is needed on factors that build customer trust in chatbots, which is crucial for their willingness to use them. This study explores two main aspects of understanding this trust: customer perceptions of new technology acceptance (ease of use and usefulness) and the humanoid attributes of chatbots (anthropomorphism, emotional intelligence, and Personalization). Survey data from 363 Chinese online shoppers were analyzed using structural equation modeling. The results show that customer perceptions and humanoid attributes significantly influence customer trust, positively impacting their willingness to use chatbots. Additionally, customer trust mediates the relationship between these factors and the desire to use chatbots. These findings offer valuable insights for brands and chatbot developers on fostering customer trust and enhancing chatbot usage in online shopping.

摘要
在数字时代，品牌使用聊天机器人及时解决顾客的疑问。然而，很少有研究涉及建立顾客对聊天机器人信任的因素，而这对他们使用聊天机器人的意愿至关重要。本研究探讨了影响顾客信任的两个主要方面：客户对新技术接受度的感知（易用性和有用性）和聊天机器人的类人属性（拟人化、情商和个性化）。对363名中国网上购物者的调查数据进行了结构方程建模分析。结果表明，客户对新技术接受度的感知和聊天机器人的类人属性都显著影响顾客信任，顾客信任相应地积极影响他们使用聊天机器人的意愿。此外，顾客信任在这些因素和使用聊天机器人的意愿之间起着中介作用。研究结果为品牌和聊天机器人开发商致力于培养客户信任，提高聊天机器人在网上购物中的使用率提供了宝贵的建议

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关键词
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性

1. Introduction

Text-based online chat has historically served as the primary method for human conversational personal assistants to deliver information, guidance, and suggestions to clients in

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e-commerce. Latest developments in AI and IT, new types of virtual assistants have emerged, such as chatbots, digital conversational agents, online shopping assistants, and virtual customer care agents. Companies' online customer assistance has been dramatically impacted by these technologies, which attempt to improve customer-support relationships. Software programs that can understand and respond to users' natural language input and output are virtual conversational assistants (Huang et al., 2024; Zhu et al., 2023).

According to Sonntag et al. (2023), chatbots utilize AI technology to assimilate knowledge from user interactions, resulting in progressively precise and pertinent responses as time progresses. Particularly in the fiercely competitive online environment, AI-chatbot usage has skyrocketed in China's fast-expanding e-commerce sector as businesses strive to improve service efficiency, build consumer trust, and increase customer experiences (Fu et al., 2023; Klein & Martinez, 2023). China's online luxury market has grown robust due to a rising middle class and increased digital adoption. Within this market, luxury brand consumers demonstrate a notable openness to AI-enabled tools, such as chatbots, as these tools align with their demand for convenience and premium customer support. Considering these characteristics and examining the types of establishments frequented by the sampled individuals provides context to the dynamics between luxury consumers and their trust in AI-based technologies.

Live chat interfaces are becoming more popular among internet businesses to provide customers with real-time customer assistance. Customers' reluctance to interact with bots is why they have not used this technology (Chen et al., 2021). Trust is essential in human-machine interactions, influencing attitudes and behaviors toward technology (Morosan & Dursun-Cengizci, 2024; Pitardi & Marriott, 2021). Existing research confirms a positive relationship between trust and behavioral intentions to adopt technologies like service robots (Tussyadiah et al., 2020) and AI-based chatbots in hospitality (Pillai & Sivathanu, 2020). Studies also indicate that trust in AI-based agents impacts user attitudes, with positive attitudes fostering higher engagement with these interactive technologies (Moriuchi et al., 2021). Despite this, consumer acceptance of chatbots remains low, underscoring the critical role of trust in enhancing chatbot adoption. While there are few studies on the role of trust in chatbots, it is evident that consumers have a low level of acceptability towards them. We must conduct additional empirical research on consumers' trust in chatbots to enhance our limited understanding of it (Chung et al., 2020).

Despite chatbots' increasing integration, more research is needed on factors that influence customer trust in these interactions, particularly in luxury e-commerce contexts. This study addresses this gap by examining the role of customer perceptions of technology (perceived ease of use and usefulness) and chatbots' humanoid characteristics (such as anthropomorphism, emotional intelligence, and Personalization) in building trust. By grounding our research in the computers as social actors (CASA) theory, which suggests that users apply human-like social expectations to AI interactions, this study explores how these factors influence trust and, ultimately, the willingness to engage with chatbots. Although many researchers (Dekkal et al., 2023; Jiang et al., 2023; Konya-Baumbach et al., 2023) have focused on the humanoid attributes of chatbots to build customer trust in shopping assistant chatbots, this area of research is in initial stage and there is need of thorough investigation about humanoid attributes of chatbots and customers perceptions about this new technology. Thus, considering these two essential aspects, this study first explores customer perceptions about new technology, such as perceived ease of use (PEOU) and perceived usefulness (PU), to build customer trust in shopping assistant chatbots. Secondly, I will elaborate on the humanoid traits of these shopping assistant chatbots, such as anthropomorphism, emotional intelligence, and Personalization, and their role in developing customer trust in these chatbots. Finally, to explore the mediating role of customer trust between these aspects to enhance the willingness of customers to use this new technology. Therefore, this research seeks to answer the following questions:

> RQ1: How do customer perceptions of new technology acceptance (ease of use and usefulness) and humanoid characteristics of chatbots affect customer trust?

> RQ2: How does customer trust influence customers' willingness to use chatbots in online shopping?

This paper provides some valuable contributions for both academicians and marketers. First, it satisfies the growing need for research into consumer communication that uses cutting-edge technology like AI (Ameen et al., 2021). Second, this research is one of the first to fill gaps in our knowledge of online customer trust in shopping assistant chatbots. Our suggested model sheds light on the consumer experience with chatbots in the online purchasing context by emphasizing the importance of user perceptions in driving trust in AI-based technology. The results of this study will offer overall guidance and tactics to firms that intend to create an enhanced and more sophisticated customer experience using AI technology. Furthermore, this study expands the computer as social actors (CASA) theory by incorporating the influence of chatbots' humanoid characteristics on fostering customer trust. This study will shed light on the effectiveness of utilizing AI-based technology to engage in humanoid conversations and support customers in online shopping. The following sections present the theoretical background and literature review, followed by the research methodology. Afterward, we discuss the data analysis and results, concluding with the research implications and limitations.

2. Theoretical background and literature review

2.1. Computers as social actors (CASA) theory

The theory of computers as social actors (CASA) (Nass et al., 1995; Reeves & Nass, 1996) is highly pertinent to understanding the impact of anthropomorphism, emotional intelligence, Personalization, PU, and PEOU on customer trust and willingness to use chatbots in an online shopping context. While several theories could be applied to study customer interactions with AI-based chatbots, CASA (Computers as Social Actors) theory uniquely explains why users respond positively to human-like traits in technology. Unlike the Technology Acceptance Model (TAM), which focuses primarily on perceived ease of use and usefulness without addressing the social attributes of technology, CASA emphasizes the application of human social norms to AI. This makes CASA particularly relevant for exploring how anthropomorphism, emotional intelligence, and Personalization influence customer trust in chatbots. Additionally, social response theory (SRT) could provide insights into human responses to digital agents, but CASA needs to focus on humanoid characteristics in AI interactions. Thus, CASA theory offers a robust framework for examining the social dynamics of chatbot interactions, particularly in e-commerce settings where trust in human-like AI is essential. The proposed framework is grounded in the CASA theory, which posits that humans apply social rules and attributes to computers and AI-based agents, including chatbots (Nass et al., 1995). In this study, the humanoid characteristics of chatbots, such as anthropomorphism, emotional intelligence, and Personalization, align with CASA's principles by influencing trust and engagement with these technologies. The following hypotheses build on CASA theory alongside additional empirical findings.

2.2. Customer Perceptions to accept new technology

Prior literature has established the link between PEOU, PU, and customers' trust in new technology. According to the technology acceptance model (TAM) developed by Davis (1989), PEOU and PU are significant determinants of technology acceptance. PEOU is the notion that using technology is very easy, reducing the perceived risk and increasing trust since the technology is easily manageable (Choi & Chung, 2013). PU, therefore, is directly related to trust because it guarantees that technology meets the users' needs consistently (Davis, 1989; Gefen et al., 2000). Sonntag et al. (2023) and Nguyen et al. (2023) have shown that PEOU and PU reduce uncertainty and translate into new technology trust. The literature uniformly postures that PEOU and PU play a significant role in establishing customer trust by making technology easy to use and beneficial.

2.2.1. Perceived Ease of Use (PEOU)

User-friendly systems are more likely to earn customers' trust, provided they are designed with this in mind. Depending on the Chatbot's degree of autonomy and the amount of communication it can handle, users will have different impressions of how easy it is to use (Mostafa & Kasamani, 2022). There is strong evidence from multiple studies that consumers are more likely to trust products and services that they see as easy to use, especially regarding the likelihood of adopting or using a personal workstation (Salehan et al., 2018). Consumers are free to choose what they consume; therefore, how easy something is to use will significantly affect whether or not they utilize it. One way to measure the mental effort needed to become proficient with a chatbot is by looking at its ease of use. The perceived benefits of using chatbots grow in proportion to how easy they are to use since the perceived effort and cognitive load decrease as their usefulness grows (Nguyen et al., 2023). Hence, the following hypothesis is proposed:

H1: Perceived ease of use will positively affect customer trust in chatbots

2.2.2. Perceived usefulness (PU)

Customers' trust in chatbots represents the inherent factors influencing their willingness to use them. The level of a customer's adoption and utilization of chatbots reflects how much work they are willing to invest in performing the habit (Izuagbe et al., 2019). Vogelgesang et al. (2021) explained that customer perception about new technology is critical to building customer trust, especially two main elements of customer perceptions: PU and PEOU. PU and willingness to adapt to new technology are positively correlated due to individuals' intention to engage in activities that enhance their online shopping experience (Rehman et al., 2019). The use of shopping assistant chatbots is just one instance of multiple studies that have discovered a positive relationship between PU and willingness to use. The job of PU is anticipated to be crucial in establishing client trust in AI-generated chatbots, given that their utilization is entirely discretionary (Alharbi et al., 2016). Hence, the following hypothesis is proposed:

H2: PU will positively affect customer trust in shopping assistant chatbots

2.3. Humanoid attributes of shopping assistant chatbots

The humanoid elements that impact the utilization of AI-based systems have received less attention than their increasing importance and expected future growth. Not only that, for example, previous research has focused on the effect of only one feature, but other humanoid characteristics have also been left beyond the focus of the investigation. Aoki (2020) focused on the 'humanness' of the chatbots; their study analyzed how 'contingent message exchanges' and 'anthropomorphic interface visual cues' influenced the results. Customers' willingness to accept AI-enabled service delivery systems was investigated by Chen et al. (2022), where three mediating variables were considered, namely, anthropomorphism. The possible benefits of human care providers synchronizing their social presence with automated social presence are unknown, according to Ameen et al. (2021). Investigations by Cameron et al. (2021) identified how enthusiastic customers were to engage social androids in business enterprises that provided hospitality-related services by analyzing customers' perceptions of the robots' empathy. The several humanoid traits of AI systems referred to in prior research are mentioned in the following Table 1. Compared to prior research; this study is comprehensive in that rather than just focusing on the presence or absence of chatbots' humanoid characteristics as previous studies did, this study delves into the impact of three humanoid characteristics of chatbots on trust during online purchases. A concept posits that individuals will exhibit greater faith in technology when it closely resembles human beings. Our study aims to provide professionals and academics with a comprehensive understanding of how various humanoid qualities of AI systems impact customers' trust, considering the significant financial investments firms make in these technologies (Belanche et al., 2024).

2.3.1. Anthropomorphism

Anthropomorphism is the action of attributing emotions, feelings, or sensations to an object of technology (Han, 2021). Anthropomorphism, or attributing human characteristics to chatbots, plays a nuanced role in influencing consumer responses to AI-based agents. Research indicates that the degree of anthropomorphism in service robots can affect customer satisfaction and the likelihood of return after a service failure. For instance, more human-like or 'cute' robots may enhance customer reactions in specific scenarios (Gursoy & Cai, 2024). However, studies also show that highly human-like robots may sometimes trigger negative responses, particularly if customers feel their identities are threatened (Cui & Zhong, 2023; Mende et al., 2019). This complex interplay suggests that anthropomorphism's impact on customer trust is context-dependent, influenced by factors such as corporate reputation and specific service scenarios. The term ''naturalistic'' refers to the most realistic way a machine can engage a human. In the context of the field of study known as Human–Computer Interaction (HCI), dialogue is a core sub-discipline that includes this type of human-machine communication (Klein &

Table 1. Summary of prior literature related to humanoid characteristics of chatbots.

References	Humanoid Characteristics of Chatbots	Context
Pelau et al. (2021)	• Psychological anthropomorphic characteristics • Perceived empathy • Interaction quality	AI devices in the service industry
Fu et al. (2023)	• Anthropomorphism • Empathy • Social Presence	Online Shopping
Fernandes and Oliveira (2021)	• Perceived Humanness • Social Presence	Intelligent digital voice assistants
Roy and Naidoo (2021)	• Anthropomorphism	Online Shopping
Lu et al. (2024)	• Appearance • Communication style	Service recovery in the service sector
Liu et al. (2024)	• Anthropomorphic Profile • Humanoid conversation tone • Contingent Interactivity	Online Health Consultation
Cheng et al. (2022)	• Anthropomorphism	Conversational chatbots
Jiang et al. (2023)	• Social Presence	Conversational chatbots
Yen and Chiang (2021)	• Communication Quality • Human-computer interaction • Human use and gratification	
Janson (2023).	• Personification • Social Orientation communication style • Social Presence	Online social media platforms and University Students

Martinez, 2023). To optimally employ HCI, the artificial intelligence systems should mimic human interaction processes and include other facets of human conduct that allow the ''human user to make social attributions and elicit related feelings and actions. According to Cheng et al. (2022), if artificial intelligence (AI) systems are like people, people will trust them to do their work well. To the best of the author's knowledge, there needs to be more literature on the effects of anthropomorphism on trust towards AI systems. An example of this phenomenon is the work by Cheng et al. (2022), who examined how anthropomorphism affects people's trust in self-driving cars. Cruz-Cárdenas et al.'s (2021) meta-analysis of empirical investigations reveals that the confidence level in the technology is based on the endowment of humanoid qualities to AI. The working assumption proposed in the study is that the consumers would increase their trust in the chatbots if they observed the latter as behaving genuinely empathetically (Fernandes & Oliveira, 2021). Hence, the following hypothesis is proposed:

H3: Anthropomorphism will positively affect customer trust in chatbots

2.3.2. Emotional intelligence

Computers can 'recognize, comprehend, and respond to the thoughts, emotions, actions, and encounters of others.' This concept is called 'emotional intelligence' in the IT industry.

An idea is believed to have cognitive and emotional components, contributing to its multifaceted nature (Tsai et al., 2021). Research suggests that individuals are more inclined to trust chatbots that exhibit emotional intelligence, demonstrated through empathetic and compassionate responses that align with user needs. For instance, emotional intelligence in chatbots enhances user perceptions of warmth and reliability, fostering a greater sense of trust (Magni et al., 2024). These qualities make users feel understood and valued, increasing their willingness to engage with AI-based services in a supportive role. Emotional intelligence is considered crucial for investigating individuals' utilization of AI-based technology (Vatankhah et al., 2024). According to this study, it is hypothesized that individuals are more likely to trust chatbots when they exhibit emotions and behaviors that demonstrate concern for the users' requirements, such as compassion and empathy. Hence, the following hypothesis is proposed:

H4: Emotional intelligence will positively affect customer trust in chatbots

2.3.3. Personalization

Personalization in AI chatbots involves tailoring interactions based on individual user characteristics, such as preferences, browsing history, and purchasing patterns, to enhance engagement and trust. Research indicates personalized experiences foster greater user enjoyment and sustained attention by creating interactions that feel uniquely relevant to each customer (Morosan & Dursun-Cengizci, 2024; Vitezić & Perić, 2024). For instance, when chatbots remember user preferences or suggest products that align with past behavior, customers are more likely to perceive them as attentive and responsive to their needs, which builds trust (Sadiq et al., 2024). This aspect of Personalization extends beyond simple cordiality, emphasizing a customized experience that resonates with users on a deeper level and reinforces their trust in the technology. Mostafa and Kasamani (2022) emphasized that it is associated with Personalization when human engagement occurs through mediated communication and is sensitive, cordial, and personal. Researchers have shown that incorporating personalized welcomes into an IT service enhances the perception of social presence (Huang et al., 2024; Zhu et al., 2023). The acceptability of AI-based systems with sociability and welcoming qualities is influenced by the expectations of users, which in turn enhances human confidence in these systems. Nguyen et al. (2023) asserted that professional agents can cultivate a more personalized approach by eliciting a sense of comfort in their clients. Similarly, consumers will have a greater trust in this AI-driven system if it exhibits humanoid characteristics in its interactions with chatbots (Chi, 2023). Hence, the following hypothesis is proposed:

H5: Personalization will positively affect customer trust in chatbots

2.4. The role of consumer trust in AI chatbot adoption

Consumer trust is critical in determining user engagement with AI-based chatbots. Trust in AI chatbots refers to how users perceive these virtual assistants as reliable, competent, and aligned with their expectations and needs (Ma et al., 2024). Research shows that trust is essential for users to feel comfortable interacting with AI, particularly when these interactions replace human service encounters. Users who trust chatbots are more likely to rely on them for support, recommendations, and other online services, thus increasing their engagement with the technology (Pitardi & Marriott, 2021; Tussyadiah et al., 2020). Factors beyond their anthropomorphic characteristics influence trust in chatbots. Usability and prior user experiences also significantly shape customers' trust and willingness to engage with chatbots. Chatbots that provide intuitive, user-friendly interactions and have previously demonstrated reliability are likelier to foster trust and consistent engagement (Pitardi & Marriott, 2021). Therefore, building and sustaining customer trust requires attention to anthropomorphic traits, the Chatbot's functionality, and users' past interactions with the technology. Studies also indicate that trust in chatbots enhances users' perceptions of ease of use and usefulness, which are critical elements in technology acceptance (Zhou et al., 2024). Trust bridges the gap between the perceived functionalities of chatbots (such as personalized recommendations and proactive assistance) and actual adoption behavior (Morosan & Dursun-Cengizci, 2024). For example, customers who view chatbots as trustworthy are more likely to interpret their responses as authentic and helpful, thus fostering a positive experience and increasing the likelihood of adoption (Vitezić & Perić, 2024).

Furthermore, trust is a mediator between various chatbot characteristics (such as Personalization and emotional intelligence) and user intentions to adopt these technologies. When chatbots are perceived as empathetic and tailored to individual preferences, trust acts as a reinforcing factor, converting positive perceptions into actual usage intentions. Chatbots can encourage sustained engagement and repeated use by establishing reliability and fostering a sense of social presence (Magni et al., 2024). Existing research suggests that consumers are more likely to adopt chatbots when they perceive them as reliable and supportive agents within the online shopping experience. Understanding the pivotal role of trust helps design AI interactions that resonate with user expectations and enhance the adoption of chatbot technology. Given the importance of trust in enhancing chatbot adoption, it is essential to consider usability and prior user experiences as core components in building and sustaining customer trust in AI-based interactions. Hence, the following hypothesis is proposed:

H6: Customer trust in Chatbot will positively influence customer's willingness to use Chatbot

H7: Customer trust in the Chatbot will mediate the relationship between PEOU and the customer's willingness to use a chatbot

H8: Customer trust in the Chatbot will mediate the relationship between PU and the customer's willingness to use a chatbot

In the present digital world, customers can be more satisfied with the humanoid characteristics of AI-generated chatbots (Chen et al., 2021). Three significant factors that can improve customer trust with chatbots include anthropomorphism, emotional intelligence, and Personalization. The rationale behind anthropomorphism is that ascribing human characteristics to a chatbot enhances the customers' experiences and makes them trust the bots more. Chung et al. (2020) suggest that using anthropomorphic characteristics increases the quality of interaction, and people feel more like the product is developed to address their needs, which increases trust and the desire to use it. However, extreme cases of anthropomorphism hinder the 'uncanny valley' effect where chatbots with humanoid characteristics are perceived as uncomfortable, possibly decreasing trust (Cruz-Cárdenas et al., 2021; Han, 2021). Emotional intelligence, when applied to chatbots as the ability to identify and adequately respond to the user's emotions, goes a step further and enhances user experience through empathy, which boosts trust and willingness to use the Chatbot. However, these advantages are sometimes offset by the opposite: several issues that make it difficult to accurately implement emotional intelligence and the aspect of privacy that may lower trust (Fernandes & Oliveira, 2021).

Personalization, that is, the ability of the Chatbot to customize future interactions based on the user's data and behavior, also significantly affects the customer's trust (Jiang et al., 2023). Customized conversations impact customers by making them feel valued and understood, enhancing satisfaction and trust (Konya-Baumbach et al., 2023). However, when gathering data that will enable Personalization, there is the problem of privacy, which tends to reduce the level of trust. While Personalization is good, going to an extreme may cause discomfort and loss of consumer trust (Tsai et al., 2021). Customer trust is essential in the relationship between these 'humanoid' qualities and the readiness to use chatbots. Trust makes customers perceive fewer risks and thus accept to be served by the chatbots. Therefore, it is essential not to underestimate the importance of trust as one of the aspects that constantly need to be built and sustained due to the presence of other factors that also affect customers' decision to engage with the chatbots, such as usability and prior experiences (Huang et al., 2024). Hence, the following hypotheses are proposed:

> H9: Customer trust in the Chatbot will mediate the relationship between anthropomorphism and the customer's willingness to use a chatbot

> H10: Customer trust in the Chatbot will mediate the relationship between emotional intelligence and the customer's willingness to use a chatbot

> H11: Customer trust in Chatbot will mediate the relationship between Personalization and the customer's willingness to use Chatbot

Following Figure 1 shows the conceptual framework of the study:

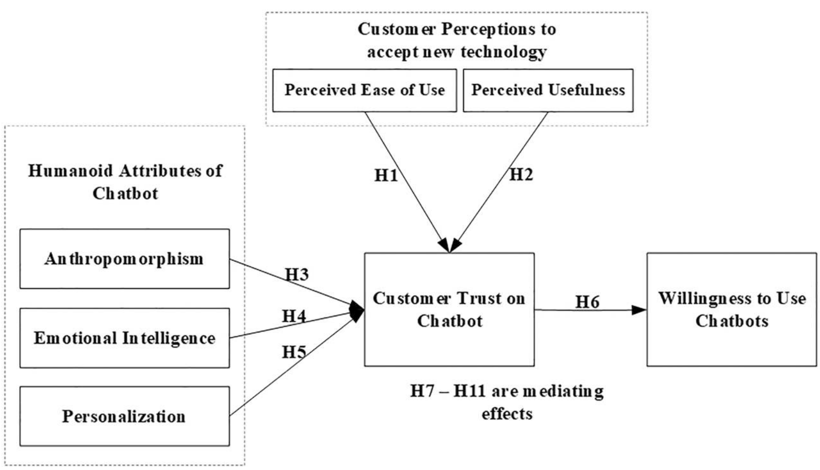

Figure 1. Conceptual framework.

3. Research methodology

3.1. Data collection

In this study, we conducted an online survey to collect data from Chinese customers who have gone through online shopping within the last six months and applied a random sampling technique to recruit such customers. This study specifically focuses on interactions with AI chatbots used by luxury clothing brands. Given the established relationship between brand reputation and consumer trust in AI, studying luxury brands provides valuable context for understanding how brand perception impacts customer interactions with chatbots. For this purpose, we have customer recruitment services, which are famous for respondent recruitment crowdsourcing services in China. Before the start of the survey, we briefly explained the purpose of this study to the respondents and the meaning of chatbots, which are the main focus of this study. After this briefing, we asked the respondents whether they had used these kinds of chatbots during online shopping in the last six months, and those respondents who had used chatbots during online shopping were included in the survey. We invited 2500 respondents, but only 390 respondents showed their agreement to participate in the study and returned our questionnaire after filling it. After receiving the responses from the respondents, we carefully scrutinized the responses. We found some missing items, and some responses were filled without attention and failed to pass the test of verification items, so we excluded these incomplete responses. Now, we have 363 complete and valid responses for the analysis. Data collection for this study was conducted between March and June 2024.

3.2. Measures

We used a five-point Likert scale to collect data from the respondents, where one means 'strongly disagree' and five means 'strongly agree.' Measurement items used in this study were adopted from the prior published studies and were slightly modified according to our research requirements. Dimensions of the TAM model were measured with seven items, PU was measured with four items, perceived ease of use was measured with three items, and the items were adopted from the prior study of Davis (1989). For humanoid characteristics, anthropomorphism was measured with five items adopted from the past study of Fu et al. (2023), emotional intelligence was measured with two items which were adopted from the previous survey of de Kervenoael et al. (2020), and Personalization was measured using five items which were adopted from the past study of Gefen and Straub (2003). Customer trust in chatbots was previously measured through a five-item scale by Fernandes and Oliveira (2021) and Pillai and Sivathanu (2020). Finally, customer willingness to use chatbots was measured through a six-item scale adopted from the prior study of Fernandes and Oliveira (2021) and Gursoy et al. (2019). All the measurement items are presented in Table 3. Additionally included as demographic variables were age, gender, and education level to offset the effect of systematic individual variances, and these groups are essential to study in technology acceptance models (Venkatesh et al., 2003). The questionnaire was initially developed in English and subsequently translated into Chinese using the back-translation method to ensure linguistic and cultural accuracy. A bilingual expert translated the questionnaire into Chinese, and a second bilingual expert translated it back into English. This process aimed to maintain the conceptual equivalence of survey items across languages.

Despite these efforts, potential linguistic nuances may still affect respondents' interpretations, impacting certain items' clarity and perceived relevance (Brislin, 1970).

3.3. Demographic characteristics of respondents

Table 2 presents the demographic characteristics of the respondents, showing that out of 363 respondents, 169 (46.556%) were male, and 194 (53.444%) were female. Moreover, 73 (20.110%) respondents were under the age of 20 years, 82 (22.589%) were between the age group of 20–30 years, 105 (28.925%) respondents were between the age group of 30–40, 74 (20.386%) were between 40 and 50 years and 19 (05.234%) respondents were above the age of 50 years. According to the age distribution of the respondents' younger customers are more attracted to online shopping and the use of chatbots, and these outcomes are in line with the findings of Fernandes and Oliveira (2021). Finally, 82 (22.590%) respondents have school-level education, 90 (24.793%) respondents have undergraduate, 84 (23.140%) have graduation-level education, and 109 (29.477%) respondents have another type of education.

3.4. Common method bias

Researchers have noted the possible effects of common method bias (CMB) on self-reported measures and have stressed the need for its evaluation, where suggestions from scholars such as Podsakoff have been made. To rectify this problem, different empirical approaches have been described in the literature, among which are the ones presented by Chang. In this study, we used the single source method wanted by Harman (1976), recommended by Podsakoff and Organ (1986), to test for CMB. To achieve this, an exploratory factor analysis and a principal component analysis were run on all the items with an eigenvalue of 1. The first factor identified in the study explained 31 percent of the variance. This amounts to 144% of the total variance, less than the 50% cutoff. This means that none of the factors is highly significant, and hence, we can conclude that CMB is not a problem in this data set. In addition, a collinearity test was carried out using Smart-PLS, which offers more precision and has a solid methodological background, according to Kock (2015). The assessment of collinearity revealed that all the VIF values were below the cutoff of 5, which means that CMB is not an issue in the given model (Kock, 2015).

Table 2. Demographic profile of respondents.

Characteristics	Frequency	Percent
Gender		
Male	169	46.556%
Female	194	53.444%
Age (Years)		
<20	73	20.110%
20–30	82	22.589%
30–40	105	28.925%
40–50	74	20.386%
>50	19	05.234%
Education		
College Level	82	22.590%
Undergraduate	90	24.793%
Graduation	84	23.140%
Others	107	29.477%

4. Data analysis and results

Partial Least Squares Structural Equation Modeling (PLS-SEM) is an effective statistical method in behavioral and social science research because of the characteristics of modeling complexity, prediction, theory creation, and low demands for data distribution. It is beneficial for exploratory research, which aims to identify crucial variables and forecast outcomes, which is critical in these disciplines characterized by the constant appearance of new theories and models (Hair et al., 2014; Hair et al., 2017). PLS-SEM implemented through Smart PLS 4, is particularly useful in research contexts requiring robust prediction and analysis of latent constructs (Hair & Alamer, 2022). Studies such as Wang have demonstrated the software's intuitive interface, user-friendly options, and powerful visualization capabilities, which enhance clarity in model interpretation and increase accessibility for researchers. Smart PLS 4 also addresses multicollinearity concerns and handles small sample sizes effectively, making it a valuable tool for behavioral and social sciences research (Hair et al., 2019). It is possible to model both formative and reflective constructs in PLS-SEM; the software is suitable for research with small sample sizes and has no problems with multicollinearity. Also, user-friendly software and clear guidelines for the assessment of measurement and structural models enhance the application of this tool in the investigation of consumer behavior, organizational behavior, education, health psychology, and social psychology (Hair et al., 2019). In this context, the application of the PLS-SEM approach through Smart PLS 4 is exceptionally reasonable because of the availability of numerous options for model assessment, the software's intuitive interface, and the powerful data visualization tools that help to provide a detailed analysis and a clear interpretation of the results, thus providing a high level of research relevance and significance.

4.1. Measurement model results

Table 3 and Figure 2 present the reliability and validity results for the constructs examined in the study. These constructs include Anthropomorphism, Emotional Intelligence, Personalization, PU, PEOU, Customer Trust, and Willingness to Use Chatbots. The item loadings for all constructs are above the acceptable threshold of 0.60, indicating that the items are reliable indicators of their respective constructs (Hair et al., 2014). The Cronbach's alpha (Cα) values for all constructs are above the recommended threshold of 0.70, demonstrating good internal consistency reliability. Specifically, Anthropomorphism (Cα = 0.829), Emotional Intelligence (Cα = 0.752), Personalization (Cα = 0.763), PU (Cα = 0.803), PEOU (Cα = 0.788), Customer Trust (Cα = 0.882), and Willingness to Use Chatbot (Cα = 0.799) all show good internal consistency reliability (Hair et al., 2016). The rho_a values, which should also be above 0.70, further confirm the reliability of the constructs. Moreover, each construct's composite reliability (rho_c) exceeds the threshold of 0.70, indicating good internal consistency. For instance, Anthropomorphism (rho_c = 0.887), Emotional Intelligence (rho_c = 0.890), Personalization (rho_c = 0.848), PU (rho_c = 0.871), PEOU (rho_c = 0.876), Customer Trust (rho_c = 0.919), and Willingness to Use Chatbot (rho_c = 0.866) all demonstrate reliable measurement (Hair et al., 2019). Additionally, each construct's average variance extracted (AVE) surpasses the 0.50 threshold, signifying adequate convergent validity. Specifically, Anthropomorphism (AVE = 0.666), Emotional Intelligence (AVE = 0.801), Personalization (AVE

Table 3. Reliability and validity results.

Items		Loadings	VIF	Cα	rho_a	rho_c	AVE
Anthropomorphism				0.829	0.874	0.887	0.666
ANT1	When it comes to online shopping, chatbots can be independent.	0.850	2.219				
ANT2	Chatbots exhibit consciousness during online shopping	0.888	2.816				
ANT3	Chatbots used in online stores are autonomous.	0.871	2.081				
ANT4	Chatbots feel emotions during online shopping.	0.626	1.305				
ANT5	Intentions are a feature of artificially intelligent technologies like robots.	Removed					
Emotional Intelligence				0.752	0.754	0.890	0.801
EI1	During the online shopping process, chatbots typically focus on the emotions and needs of the customers	0.901	1.570				
EI2	Online shoppers often receive personalized service from chatbots.	0.889	1.570				
Personalization				0.763	0.792	0.848	0.583
PER1	Talking to a chatbot is like having a conversation with a natural person.	0.720	1.364				
PER2	Interacting with chatbots makes me feel more intimate.	0.753	1.533				
PER3	Engaging in conversation with chatbots brings a friendly vibe.	0.841	1.630				
PER4	Talking to a chatbot makes me feel more human.	0.734	1.471				
PER5	Interacting with chatbots makes you feel like you are talking to a natural person.	Removed					
Perceived Usefulness				0.803	0.820	0.871	0.629
PU1	Using chatbots makes shopping online better for me.	0.848	1.846				
PU2	Before making a purchase decision, talking to Chatbot about product features is very beneficial	0.837	1.844				
PU3	I can make a good purchase decision with the help of Chatbot	0.763	1.602				
PU4	I got proper information from Chatbot before online shopping	0.717	1.395				
Perceived Ease of Use				0.788	0.791	0.876	0.702
PEU1	To talk with Chatbot is very easy	0.821	1.468				
PEU2	I can get the required information from Chatbot very easily	0.840	1.792				
PEU3	When I need to, I can talk to Chatbot very easily	0.851	1.919				
Customer Trust				0.882	0.884	0.919	0.739
CTC1	Chatbots provide accurate and authentic information during online shopping.	0.867	2.265				
CTC2	Chatbots provide clear and valuable opinions during online shopping, which can be trusted	0.823	1.960				
CTC3	Chatbots provide trustworthy information during online shopping.	0.891	2.956				
CTC4	I can trust the recommendations which are provided by the chatbots during online shopping	0.857	2.564				
CTC5	Information provided by chatbots during online shopping is accurate and up-to-date.	Removed					

(*Continued*)

Table 3. Continued.

Items		Loadings	VIF	Cα	rho_a	rho_c	AVE
Willingness to Use Chatbot				0.799	0.821	0.866	0.617
WUC1	In the future, I will prefer to use chatbots during online shopping	Removed					
WUC2	I will always use chatbots for online shopping	0.831	1.599				
WUC3	My intentions are clear to use chatbots for online shopping	0.788	2.050				
WUC4	In the future, when I have the option to use chatbots, my priority will be chatbots	0.763	1.959				
WUC5	I will be delighted to use chatbots for online shopping	0.759	1.395				
WUC6	I will indeed adopt Chatbot for online shopping	Removed					

= 0.583), PU (AVE = 0.629), PEOU (AVE = 0.702), Customer Trust (AVE = 0.739), and Willingness to Use Chatbot (AVE = 0.617) all exhibit adequate convergent validity (Hair et al., 2016). Therefore, the constructs' reliability and validity support their use in further analyses (Figure 3).

The discriminant validity of the constructs was assessed by the Heterotrait-Monotrait (HTMT) ratio and Fornell-Larcker criterion. HTMT ratios of all the construct pairs were below 0. 85 (Henseler et al., 2015), meaning that the used constructs are not only different but also not significantly related to each other, each of them reflecting a specific aspect of the theoretical model (see Table 4). Further, the Fornell-Larcker criterion involved the comparison of the square root of the average variance extracted (AVE) of

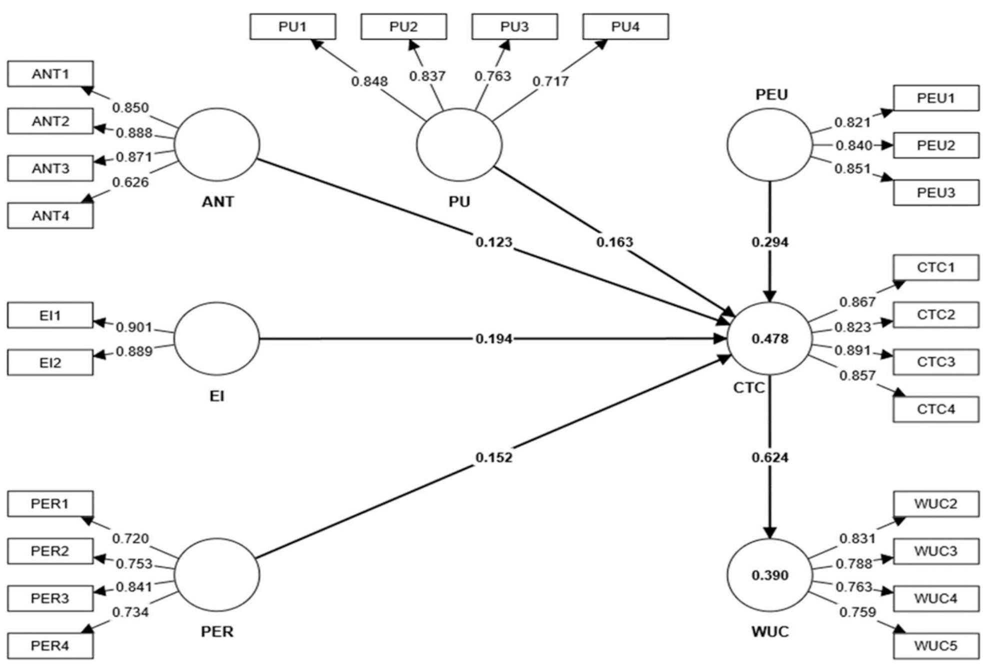

Figure 2. Measurement model.

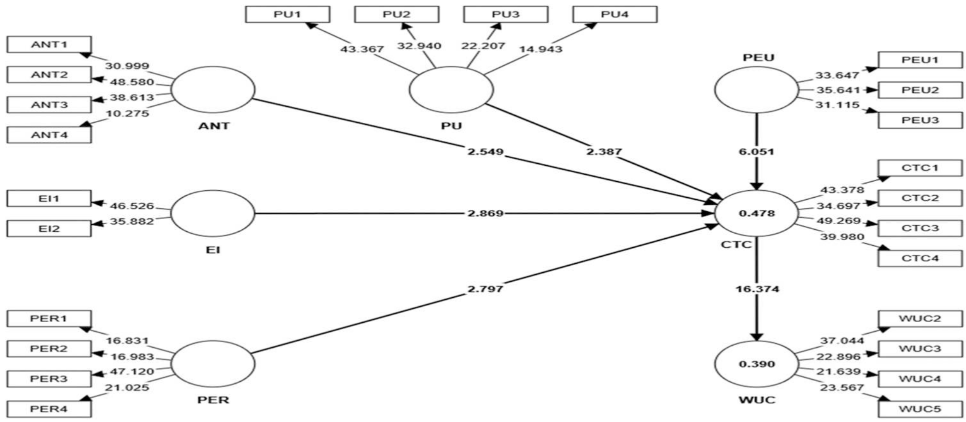

Figure 3. Structural model.

Table 4. Hertrotrait monotrait ratio.

Constructs	ANT	CTC	EI	PER	PEU	PU	WUC
ANT							
CTC	0.455						
EI	0.419	0.650					
PER	0.341	0.584	0.622				
PEU	0.366	0.652	0.551	0.526			
PU	0.589	0.645	0.761	0.720	0.547		
WUC	0.574	0.707	0.623	0.583	0.584	0.813	

Table 5. Fornell larcker criterion.

Constructs	ANT	CTC	EI	PER	PEU	PU	WUC
ANT	0.816						
CTC	0.401	0.860					
EI	0.341	0.529	0.895				
PER	0.281	0.494	0.474	0.763			
PEU	0.309	0.549	0.426	0.416	0.838		
PU	0.479	0.550	0.589	0.572	0.433	0.793	
WUC	0.469	0.624	0.507	0.474	0.482	0.661	0.786

each construct with the construct's correlations with other constructs. Table 5 also indicated that the square root of the AVE for each construct was higher than the maximum coefficient value of the construct with the other constructs, which also supported discriminant validity. These results prove that the constructs are indices of different theoretical constructs that have made the measurement model more credible (Fornell & Larcker, 1981). Such strong discriminant validity helps analyze and interpret the data within the context of the research framework.

4.2. Predictive relevance

Table 6 shows the predictive relevance of the two independent variables, CTC and WUC, in the research model. The R-square and the adjusted R-square are significant measures

Table 6. Predictive relevance.

	Coefficient of determination		Blindfolding		
	R-square	R-square adjusted	SSO	SSE	Q^2 (=1-SSE/SSO)
CTC	0.478	0.471	1456.000	957.209	0.343
WUC	0.390	0.388	1456.000	1135.122	0.220

that help understand the proportion of the total variation accounted for by the predictors in the model. For CTC, the value of the R-square is 0. 478, and for the adjusted R-squared, it is 0. 471, meaning that the proportion of patients with these diseases is roughly 47 percent. The model accounts for 1% of the variation in Customer Trust. Correspondingly, for WUC, the R-square value is equal to zero. 390, and for the adjusted R-square value, it equals 0. 388; this means that the model explains 38 percent of the variation in the dependent variable. Thus, the test results show that Attitude has a moderate positive impact on Willingness to Use Chatbot, explaining 8% of the variance.

Moreover, the extent of predictive relevance of the model was tested further by applying the blindfolding procedure; particularly, the Stone-Geisser's Q^2. Q^2 values greater than zero indicate that the model has predictive relevance (Geisser, 1974). The Q^2 value for CTC is 0.343, derived from the SSO (sum of squares total) of 1456.000 and SSE (sum of squares error) of 957.209. This value indicates a substantial predictive relevance for Customer Trust. For WUC, the Q^2 value is 0.220, with an SSO of 1456.000 and SSE of 1135.122, suggesting a moderate predictive relevance for Willingness to Use Chatbot.

4.3. Hypotheses results

The results of the hypothesis testing in Table 7 revealed significant relationships among the constructs in the proposed model. Hypothesis H1 posited that PEU has a positive effect on CTC, and this hypothesis was supported, as indicated by a significant path coefficient ($\beta = 0.294$, $p < 0.001$) with a *T* statistic of 6.051 and an effect size (f^2) of 0.121. Hypothesis H2 suggested that PU positively influences CTC, and this hypothesis was supported ($\beta = 0.163$, $p = 0.017$) with a T statistic of 2.387 and an effect size of 0.024.

The proposed hypothesis H3 stated that ANT positively impacts CTC, supported by the results ($\beta = 0.123$, $p = 0.011$) with a T statistic of 2.549 and an effect size of 0.022.

Table 7. Hypotheses results.

Hypotheses	Statistical Path	β	STDEV	*T* statistics	*P* values	*f*-square	2.5%	97.5%	Conclusion
H1	PEU → CTC	0.294	0.049	6.051	0.000	0.121	0.203	0.392	Supported
H2	PU → CTC	0.163	0.068	2.387	0.017	0.024	0.033	0.295	Supported
H3	ANT → CTC	0.123	0.048	2.549	0.011	0.022	0.030	0.218	Supported
H4	EI → CTC	0.194	0.068	2.869	0.004	0.043	0.068	0.334	Supported
H5	PER → CTC	0.152	0.054	2.797	0.005	0.027	0.044	0.259	Supported
H6	CTC → WUC	0.624	0.038	16.374	0.000	0.639	0.551	0.700	Supported
H7	PEU → CTC → WUC	0.184	0.033	5.599	0.000		0.125	0.254	Supported
H8	PU → CTC → WUC	0.102	0.045	2.263	0.024		0.020	0.191	Supported
H9	ANT → CTC → WUC	0.077	0.030	2.560	0.010		0.019	0.137	Supported
H10	EI → CTC → WUC	0.121	0.043	2.792	0.005		0.042	0.213	Supported
H11	PER → CTC → WUC	0.095	0.034	2.775	0.006		0.028	0.162	Supported

Hypothesis H4 suggested that EI positively affects CTC, which was supported ($\beta = 0.194$, $p = 0.004$) with a T statistic of 2.869 and an effect size of 0.043. Hypothesis H5 asserted that PER positively affected CTC, which was supported ($\beta = 0.152$, $p = 0.005$) with a T statistic of 2.797 and an effect size of 0.027. Hypothesis H6 tested the effect of CTC on WUC. This hypothesis was strongly supported, as indicated by a significant path coefficient ($\beta = 0.624$, $p < 0.001$) with a T statistic of 16.374 and an effect size of 0.639.

Moreover, the mediation hypotheses were also tested. Hypothesis H7 posited that CTC mediates the relationship between PEU and WUC, supported ($\beta = 0.184$, $p < 0.001$) with a T statistic 5.599. Hypothesis H8 proposed that CTC mediates the relationship between PU and WUC, which was supported ($\beta = 0.102$, $p = 0.024$) with a T statistic of 2.263.

Hypothesis H9 proposed that CTC mediates the relationship between ANT and WUC, and the results supported this hypothesis ($\beta = 0.077$, $p = 0.010$) with a T statistic of 2.560. Hypothesis H10 posited that CTC mediates the relationship between EI and WUC, and this hypothesis was supported ($\beta = 0.121$, $p = 0.005$) with a T statistic of 2.792. Lastly, Hypothesis H11 suggested that CTC mediates the relationship between PER and WUC, which was also supported ($\beta = 0.095$, $p = 0.006$) with a T statistic of 2.775. These results provide robust evidence for the hypothesized relationships, demonstrating the significant role of CTC as a partial mediator in the proposed model.

4.4. Discussion

This study has developed a framework based on the theory of computers as social actors (CASA). CASA theory robustly supports the proposed research model by providing a framework that explains why users respond positively to humanoid traits in chatbots. It highlights the importance of these factors in fostering trust and encouraging usage in online shopping environments. Customers are more likely to use chatbots while making online purchases since their trust in this AI-powered technology is enhanced.

First, this study found that customer perceptions, i.e. perceived ease of use ($\beta = 0.294$, $p < 0.001$) and PU ($\beta = 0.163$, $p = 0.017$), positively influence customer trust in chatbots, which support H1 and H2. These findings show that PEOU positively impacts customer trust in chatbots. When users find the interaction effortless and intuitive, they are more likely to feel confident and comfortable, fostering trust. PU enhances customer trust as users are more inclined to rely on chatbots that effectively assist them and improve their online shopping experience, reinforcing their belief in the Chatbot's reliability and value. Prior studies have also concluded similar findings that PEOU and PU are essential indicators of developing customer trust in chatbots. For example, Yen and Chiang (2021) show that PEOU and PU positively enhance students' trust in chatbots.

Second, this study found that humanoid characteristics of chatbots, i.e. anthropomorphism ($\beta = 0.123$, $p = 0.011$), emotional intelligence ($\beta = 0.194$, $p = 0.004$), and personalization ($\beta = 0.152$, $p = 0.005$) have a positive and significant impact on customer trust on chatbots in the context of online shopping and these findings support H3, H4, and H5. These findings indicate that humanoid characteristics such as anthropomorphism, emotional intelligence, and Personalization positively impact customer trust in chatbots because they make interactions feel more natural and relatable, similar to engaging with a human. When chatbots exhibit these traits, users perceive them as more empathetic and attentive to their needs, which enhances their trust. Personalized and emotionally intelligent responses reinforce the Chatbot's reliability and understanding, increasing user confidence and trust. Past studies have also reported similar findings that humanoid characteristics of chatbots positively influence customer trust in chatbots. For example, Roy and Naidoo (2021) presented that it is a valuable construct to develop customer trust in chatbots in an online shopping context, and Janson (2023) shows that Personalization and emotional intelligence positively and significantly enhance customer trust in chatbots. On the other hand, Fu et al. (2023) reported contradicting results that anthropomorphism has no effect on customer trust in chatbots.

Third, this study found that customers' willingness to use chatbots for online shopping is exactly influenced by their degree of trust in them ($\beta = 0.624$, $p < 0.001$), and this finding supports H6. This finding suggests that consumers will reject the application of this technology in the online business framework should they view chatbots as unreliable. Encouraging a positive view of chatbots will probably help reduce customer anxiety about this technology. Previous studies have similarly shown that trust influences user behavior favorably when adopting new technologies. For example, Dhagarra et al. (2020) found that patients' desire to use chatbots in the context of healthcare services is directly related to trust. In line with this, Cheng et al. (2022) found that customers' trust in chatbots on e-commerce platforms will likely diminish their desire to switch from bots to human representatives.

Fourthly, this study reported that customer trust in chatbots positively mediates the relationship between customer perceptions (PEOU and PU) and willingness to use chatbots, and these findings support H7 and H8. These findings explain that customer trust acts as a crucial intermediary because when users find chatbots easy to use and beneficial, their increased trust in the technology enhances their confidence and willingness to engage with it. This trust bridges the gap between positive perceptions and actual usage, as users are more likely to adopt and rely on chatbots they trust to deliver a seamless and valuable shopping experience. These findings are in line with the findings of prior researchers. For example, Cameron et al. (2021)found that customers' willingness to use new technology is increased if they find it helpful and can easily use it. These perceptions create customer trust in technology, which leads to their willingness to use new technology.

Fifthly, this study elaborates that customer trust in chatbots positively mediates the relationship between humanoid characteristics of chatbots (i.e. anthropomorphism, emotional intelligence, Personalization) and customers' willingness to use chatbots in online shopping, and these findings support H9, H10, and H11. According to these findings, customer trust mediates the relationship between the humanoid characteristics of chatbots and the willingness to use them. Users perceive chatbots as more relatable and reliable when they exhibit anthropomorphism, emotional intelligence, and Personalization. This heightened trust makes users more comfortable and confident in engaging with the chatbots, increasing their willingness to use them for online shopping. Thus, trust transforms positive perceptions of humanoid characteristics into user adoption and sustained usage. Similar findings are also presented by Pelau et al. (2021) and Fu et al. (2023); they also found that customer trust is a positive mediating element between humanoid characteristics and customers willing to use chatbots.

5. Implications

5.1. Theoretical implications

This study contributes to understanding human-AI interactions within the framework of CASA theory by validating the importance of anthropomorphism, emotional intelligence, and Personalization in enhancing customer trust toward chatbots. The findings support the premise of CASA theory that users apply social norms to interactions with AI when human-like qualities are present. This research extends CASA theory by highlighting the characteristics that build trust in e-commerce chatbot interactions, particularly within the luxury market. These insights suggest that CASA theory can effectively explain customer behavior in contexts where trust and social presence are critical. Theoretically, this work has various implications for scholars. First, the present research results significantly contribute to the little-known knowledge of the acceptance of artificial intelligence, especially concerning online buying. This study presents valuable insights into the determinants of consumers' trust in chatbots, encompassing the systems' humanoid attributes and customer perceptions. In the end, these factors affect consumers' willingness to use chatbots. Second, this study uses CASA theory to examine how customers feel about chatbots when shopping online, an area that has yet to be looked into. The present study examined how customers' trust in chatbots is affected by their positive humanoid characteristics. Third, this study is unique in investigating customer perceptions of chatbots in terms of their resemblance to humans. This facilitates our understanding of the factors contributing to customers' trust in this technology. We aim to contribute to the expanding corpus of chatbot research, particularly in investigating the significance of their 'human' attributes. Fourth, this study contributes to understanding interactions between human customers and non-human entities by empirically testing a framework that explores the influence of chatbot characteristics such as anthropomorphism, emotional intelligence, and Personalization on customer trust and engagement (Lin et al., 2022). This study expands on existing theoretical perspectives by validating the significance of these characteristics in fostering trust and encouraging chatbot adoption. Fifth, our research has established that trust in chatbots can be improved through emotional intelligence, Personalization, and anthropomorphism of the chatbots. Prior research has provided conflicting findings concerning the influence of humanoid features in intelligent systems (Chang & Chen, 2021). Dikmen and Burns (2017) pointed out that the anthropomorphism concerning chatbots and the ability to handle emotions play a part in creating a favorable attitude towards chatbots in the context of automated systems. However, Gursoy et al. (2019) have revealed that anthropomorphism and Personalization reduce customer trust in AI technology performance. The results of this study show that customer trust is affected when the chatbots have humanoid characteristics, increasing the customers' willingness to use AI technologies.

5.2. Practical implications

For practitioners, the results emphasize the importance of designing chatbots with human-like qualities to enhance customer engagement. Companies should prioritize chatbot features that embody anthropomorphism and emotional intelligence, as these traits foster user trust and a positive customer experience. Organizations can improve customer satisfaction and retention by ensuring that chatbots are perceived as approachable and responsive. Furthermore, marketing strategies could highlight chatbot advantages, such as availability and efficiency, while addressing concerns around AI interaction to enhance customer comfort with this technology. First, the primary focus of our study is to emphasize the significance of considering the aspects that influence a customer's perception of adopting new technology. Perceptions of a technology's utility and user-friendliness significantly affect individuals' trust in chatbots while online buying. Brands may enhance the user-friendliness of their strategies and increase the usefulness of chatbots by demonstrating the utilization of cutting-edge AI technology through chatbots to assist customers during online shopping. Second, according to our findings, customers are more open to using chatbots when they shop online because they have the human traits necessary to be helpful. When we look at our results, we see that customers trust chatbots more when they act like humans. In addition, our data show that customer trust affects how customers feel about chatbots' humanoid traits and how eager they are to use them. So, developers need to make chatbots that want to build a connection with customers by showing care and having a friendly conversation. This can include warm greetings, short responses, and emotional concerns. Online brands trying to stay in business and get ahead by using new technologies to change how they provide customers will likely find these social exchanges interesting. This is because they work in very competitive markets. Third, online stores can let consumers inquire about their products and services using chatbots. This helps to make the services more readily available and saves consumers time. Chatbots allow consumers to access free, quick, customized services instead of email or live people using their reach 24 h a day, seven days a week. Thus, managers of online store marketing could emphasize the sensitivity and emotional intelligence of humanoid qualities when they discuss the advantages of chatbots in their commercials. Customers will thus be more receptive to this technology. Additionally, while chatbots are widely integrated into customer support, companies could benefit from targeted advertising highlighting specific chatbot features like personalized recommendations, empathy-driven interactions, and enhanced convenience. Such marketing could differentiate chatbots as valuable tools for streamlined, user-centric customer experiences. Emphasizing these attributes may reshape consumer perceptions, positioning chatbots as reliable and approachable customer assistants.

6. Limitations and future research

Although this work has delved into a significant area of research concerning the use of AI in online purchasing, it is crucial to recognize its limitations, as they could lead to chances for future studies. First, further research in other demographic areas is needed to determine the findings' generalizability and understand how customers' trust in chatbots varies across cultures, as this study was only conducted in China. Second, to verify the study model, using the current model in different contexts, such as using chatbots in education and healthcare, is necessary. Additionally, future researchers should investigate the possible influence of aspects like customer satisfaction and communication quality on consumers' trust in chatbots. Third, because chatbot utilization is still in its infancy, it is probable that consumers' perspectives regarding chatbots will evolve. Fourth, this study uses cross-sectional data, which may not present the change of mind of the customers with time; therefore, future researchers could utilize longitudinal data to investigate the consumer's trust in chatbots over an extended period.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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