Computers in Human Behavior Reports 22 (2026) 101017

Contents lists available at ScienceDirect

Computers in Human Behavior Reports

journal homepage: www.sciencedirect.com/journal/computers-in-human-behavior-reports

How AI-driven chatbots shape customer satisfaction and loyalty to chatbot usage in digital service experience

Paulo Rita [*], Celeste Vong, Catarina Correia

NOVA Information Management School (NOVA IMS), Universidade Nova de Lisboa, Campus de Campolide, Lisboa, 1070-312, Portugal

A R T I C L E I N F O

Keywords:
Chatbots
Consumer–brand interaction
Customer service/satisfaction
Anthropomorphism
Artificial intelligence
Humanness

A B S T R A C T

This research investigates the impact of AI-driven chatbots on customer satisfaction, loyalty to chatbot usage, and purchasing intentions in digital service environments. While chatbots enhance efficiency and provide 24/7 availability, their ability to meet consumer expectations and drive engagement remains a topic of debate. Drawing on a survey of 282 respondents and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM), this study identifies the chatbot attributes that drive customer satisfaction. The results reveal that information quality, problem-solving capability, and understanding of humanness significantly enhance satisfaction. In contrast, perceived contingency, response humanness, and anthropomorphic cues have no impact on satisfaction, underscoring the importance of designing chatbots that excel in providing accurate information and resolving customer issues efficiently. These insights contribute to a deeper understanding of how AI technologies can be leveraged to meet consumers' evolving needs in digital environments.

1. Introduction

In today's dynamic landscape of customer-firm interactions, the infusion of technological advancements, particularly Artificial Intelligence (AI), has emerged as a transformative force reshaping how firms design and manage customer relationships across diverse sectors (Chung et al., 2020; Kaplan and Haenlein, 2018). As defined by Haenlein and Kaplan (2019), AI embodies a system's capacity to interpret data, learn dynamically, and adapt, thereby fostering real-time interactions and rendering technology-based engagements more human and customer-centric.

Within the world of AI applications, chatbots have experienced significant growth, becoming integral components of customer service strategies (Adamopoulou & Moussiades, 2020; Diederich et al., 2022; Sands et al., 2021). Operating as internet-based software systems, chatbots engage users in simulated conversations, automating processes in education, health, and customer support to ensure 24/7 availability, enhance efficiency, and minimize support costs (Følstad & Brandtzaeg, 2020; Janssen et al., 2021).

On the verge of the ongoing shift from face-to-face to virtual interactions, exacerbated by the pandemic, chatbots have emerged as invaluable tools for brands to engage directly with consumers (Tsai et al., 2021). The volume of consumer-chatbot service interactions is escalating, necessitating a deeper exploration of how chatbots should communicate to ensure positive customer service experiences and satisfaction. Brands are progressively integrating chatbots into their service interactions, with as many as one-third of online interactions involving these automated assistants. (Hollebeek et al., 2021; Shumanov & Johnson, 2021).

Despite their growing adoption, the effectiveness of chatbots in fostering positive customer experiences remains a topic of debate. While AI-driven chatbots offer numerous benefits, consumer skepticism and reluctance persist, underscoring the importance of understanding and addressing user concerns (Hildebrand and Bergner, 2021). Existing research has examined how specific chatbot attributes, such as anthropomorphic visual and verbal cues, identity disclosure, conversational cues and skill, and the expression of positive emotion, shape consumer attitudes and behaviors, typically by influencing perceptions such as social presence, homophily, knowledge and empathy, emotional contagion, and expectation–disconfirmation (Araujo, 2018; Go & Sundar, 2019; Han et al., 2023; Luo et al., 2019; Popescu, 2020). However, this body of work generally examines only a few attributes in isolation. It does not systematically compare the relative contributions of multiple functional (e.g., information quality, problem-solving) and social attributes to customers' satisfaction with actual chatbot interactions (Castillo, Canhoto, & Said, 2021). The present study addresses this gap

* Corresponding author.
E-mail address: prita@novaims.unl.pt (P. Rita).

https://doi.org/10.1016/j.chbr.2026.101017
Received 31 July 2025; Received in revised form 9 March 2026; Accepted 13 March 2026
Available online 19 March 2026

by using survey data from consumers with prior experience of customer service chatbots to investigate key questions such as: "Do users end up having their problems solved after interacting with a chatbot?", "How do users perceive new chatbots, and what factors influence their emotional reactions during chatbot interactions?". Given the potential limitations of chatbots' impersonal nature, it is crucial to better understand how such technologies are accepted and used (Chaves & Gerosa, 2021), as this can inform the development of more efficient and gratifying solutions that address both customers' instrumental and emotional needs. Building on the Expectation–Confirmation Model (ECM; Bhattacherjee & Sanford, 2006), we treat the functional and social chatbot attributes as perceived performance cues that shape users' post-use satisfaction, which in turn is expected to influence their loyalty to continue using the chatbot for customer service and their future purchase intention.

2. Literature review

2.1. Customer service chatbots

A chatbot is a computer program created primarily for entertainment or information retrieval, mimicking human conversation using synthesized text or audio (Dahiya, 2017). Chatbots are now widely used in e-commerce applications, such as financial consultations and customer support, thanks to recent developments in AI technology, particularly in natural language processing, which have enabled them to engage in more complex conversations with people (Heo & Lee & Nass, 2010). To provide adequate online customer support, chatbot applications are often integrated into e-commerce websites in modern contexts, whether on desktop or mobile devices. Prominent firms have successfully implemented these applications. E-commerce businesses often utilize chatbots on landing pages, where they interact with clients and provide answers to their questions, much like human customer service personnel (Følstad et al., 2018; Sheehan et al., 2020). Chatbots should be designed to match the type of client problems they are intended to solve. Less complex chatbots should handle simpler jobs, while more complex interactions should utilize AI's natural language understanding and contextual analysis skills. These sophisticated chatbots can converse informally and engage in small talk, making users feel more comfortable (Dahiya, 2017).

2.2. Expectation–Confirmation Model (ECM) and customer satisfaction

Customer satisfaction is commonly understood as the outcome of an evaluative process in which consumers compare their prior expectations about a product or service with its perceived performance after use (Linina et al., 2022; Ueltschy, Laroche, Rita, & Bocaranda, 2008). The Expectation–Confirmation Model (ECM) in the field of information systems domain posits that users form initial expectations, experience the system, and then assess the extent to which performance confirms or disconfirms those expectations; this evaluation shapes satisfaction, which in turn is a central predictor of continuance intentions

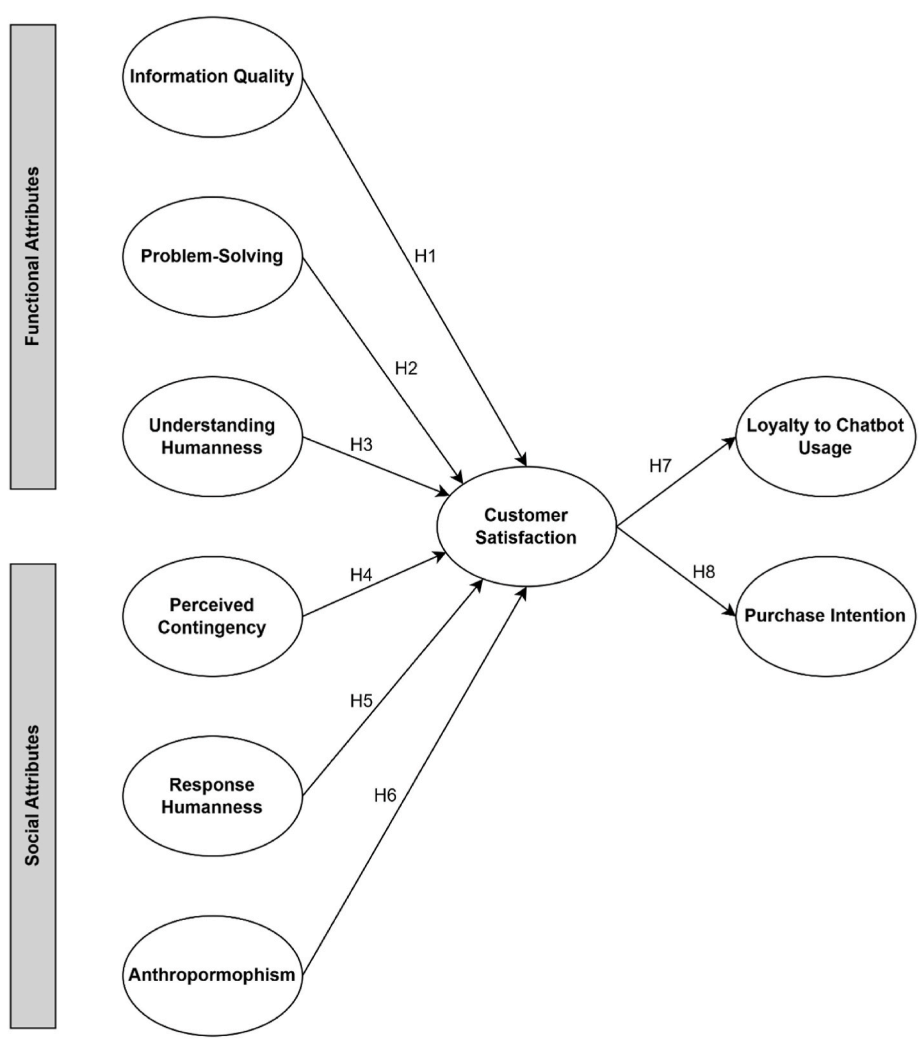

Fig. 1. Conceptual Model.

(Bhattacherjee & Sanford, 2006). In the context of AI-driven customer service, chatbot attributes can be regarded as salient performance cues that inform users' satisfaction judgments. Factors such as speed, accuracy, and response quality are central to how consumers evaluate service performance, and firms increasingly deploy chatbots to enhance these dimensions (Mishra et al., 2020). Prior work suggests that chatbots can improve efficiency, reduce service costs, and foster engagement when they deliver timely, relevant, and personalized interactions (Popescu, 2020). Building on ECM, the present study conceptualizes chatbot attributes as perceived performance indicators that shape post-use satisfaction, which in turn drives longer-term outcomes such as loyalty to chatbot usage and future purchase intention. In line with research highlighting instrumental system quality and social or anthropomorphic features (Araujo, 2018; Chung et al., 2020; Go & Sundar, 2019; Han et al., 2023; Popescu, 2020), we group chatbot attributes into functional and social dimensions. Functional attributes capture task-related effectiveness, whereas social and anthropomorphic attributes capture the extent to which the chatbot is experienced as a human-like social actor. Given our focus on these performance-related attributes, confirmation is not modelled as a separate construct; rather, it is reflected in users' overall performance evaluations.

2.3. *Functional chatbot attributes*

Functional chatbot attributes refer to task-related features that enable users to achieve their goals efficiently and effectively (Johari & Nohuddin, 2021). Drawing on the service-quality evaluation that primarily depends on whether the system delivers accurate task content and effective resolution capabilities (Misischia et al., 2022), we focus on information quality and problem-solving as core functional drivers of the customer service outcomes, and include understanding humanness because it captures whether the chatbot's instrumental comprehension capacity required to provide correct, contextually appropriate solutions in goal-directed exchanges (Shams & Kim, 2024).

2.3.1. *Information quality*

Information quality plays a vital role in chatbot interactions, encompassing attributes such as relevance, accuracy, credibility, and usefulness of the information delivered (Chung et al., 2020). Customers expect chatbots to accurately understand their issues and provide suitable solutions, emphasizing the need for chatbots to be viewed as credible, knowledgeable, and competent communicators (Chung et al., 2020). The communicator's role in computer-mediated exchanges remains essential for ensuring high-quality information delivery. To maintain customer satisfaction and protect brand reputation, chatbots must effectively interpret user queries and respond accurately (Chung et al., 2020; Trivedi, 2019). Within the customer experience context, information quality significantly shapes perceptions, as incorrect or outdated responses can create negative impressions of a company and its offerings (Gao et al., 2015). Consequently, organizations should focus on improving chatbot information quality to enhance customer experience. Based on this reasoning, the first hypothesis is proposed:

H1. The information quality provided by chatbots positively impacts customer satisfaction.

2.3.2. *Problem solving*

When assessing service quality, consumers tend to value elements such as personal interaction, physical appearance, company policies, problem resolution, and reliability (Kim et al., 2016). These aspects can shape consumer emotions, and individual shopping patterns may cause customers to emphasize different service dimensions (Kim et al., 2016). Thus, perceptions of quality often differ according to personal preferences and expectations.

It is important to acknowledge that dissatisfied customers may experience negative emotions, such as resentment or humiliation, when their concerns remain unresolved (Chung et al., 2020). Retail brands, therefore, prioritize their employees' ability to address customer issues, complaints, returns, and exchanges promptly and empathetically, as these interactions strongly affect perceived service quality (Chung et al., 2020; Kim et al., 2016; Lee, 2024). Similarly, Popescu (2020) notes that chatbots capable of efficiently handling complex inquiries and delivering rapid responses help reduce user frustration and improve the overall service experience. Furthermore, successful problem resolution tends to enhance users' evaluations of chatbot performance (Huang & Rust, 2021). Accordingly, the following hypothesis is proposed:

H2. The problem-solving capability of chatbots positively influences customer satisfaction.

2.3.3. *Understanding humanness*

The notion of "understanding humanness" in AI chatbots refers to their capacity to accurately interpret and respond to human inputs (Lee & Nass, 2010), which is fundamental in goal-directed customer service exchanges because user's primary objective is to efficiently resolve an issue, making the precise interpretation of intent critical for obtaining correct information and a viable solution (Shams & Kim, 2024). Thus, the technical precision of components underpins this interpretive function (Hsu & Lin, 2023). Effective interaction, therefore, depends not only on accurate intent recognition but also on the delivery of contextually relevant responses, which sustain user trust and facilitate continued engagement (McTear, 2020).

Moreover, advancements in AI have introduced emotional intelligence and adaptive learning, allowing chatbots to detect and respond to users' emotional tones, thereby fostering deeper engagement (Bilquise et al., 2022; Mainardi, 2025). Collectively, accurate comprehension, contextually appropriate responses, and emotional adaptability contribute to a sense of humanness in AI, which enhances user satisfaction and long-term engagement (Luger & Sellen, 2016). Hence, a chatbot's ability to mirror human-like understanding is central to improving user experience and retention.

H3. Understanding humanness positively influences customer satisfaction.

2.4. *Social chatbot attributes*

Social attributes refer to the degree to which users experience the chatbot as a human-like social actor (Nass & Moon, 2000; Nowak & Rauh, 2005). Consistent with the Computers-as-Social-Actors perspective (Stelbotsky & Park, 2024), we conceptualize social chatbot attributes as the user's social-relational experience during interaction and operationalize them through three facets: perceived contingency, response humanness, and perceived anthropomorphism (Go & Sundar, 2019; Hsu & Lin, 2023). These capture the interaction cues and perceptions that shape users' interpersonal impressions of a chatbot.

2.4.1. *Perceived contingency*

Perceived contingency refers to the degree to which each message in a dialogue meaningfully connects with the preceding one, creating a coherent and dynamic exchange (Hsu & Lin, 2023). This concept is key to understanding the human-like nature of communication, especially in chatbot–human interactions. Sundar et al. (2016) explain that message interactivity—where each response depends on and relates to the prior message—enhances perceptions of humanness in conversations. Unlike the "functional view," which centers on basic question-and-answer formats typical of FAQ systems, the "contingency view" highlights the interrelated and fluid nature of dialogue, closely resembling natural human communication (Sundar et al., 2003). In chatbot applications, a high level of perceived contingency fosters greater user engagement by making interactions seem more thoughtful and adaptive rather than rigid or pre-programmed (Sundar et al., 2016). This results in a smoother, more human-like conversational experience, improving chatbot effectiveness and user connection.

H4. High levels of perceived contingency in chatbot interactions positively influence user satisfaction with customer service chatbots.

2.4.2. Response humanness

Response humanness refers to the extent to which chatbot replies sound natural and resemble human communication. The more effectively a chatbot can produce human-like responses, whether through text or voice, the more authentic the interaction feels, thereby enhancing user trust and satisfaction (Schuetzler et al., 2020). This perception of humanness is influenced by factors such as tone, use of conversational fillers (e.g., "um" or "you know"), and sensitivity to emotional nuances in messages (Westerman et al., 2019).

Additionally, response humanness depends not only on linguistic characteristics but also on contextual awareness and personalization. Feine et al. (2019) emphasize that chatbots capable of adapting their replies based on prior user interactions or contextual cues foster stronger emotional connections, as they appear more attentive and empathetic. Such adaptive communication parallels natural human dialogue, where speakers adjust their responses according to conversational cues, thereby reinforcing the perception of humanness.

H5. Response humanness positively influences customer satisfaction.

2.4.3. Anthropomorphism

Conversational AI bots have been the subject of extensive research focused on enhancing their human-like qualities (Khatri et al., 2018). Assigning bots human-like characteristics—such as a name, image, and emotional personality—has been shown to strengthen users' perceptions of human resemblance (Følstad & Brandtzaeg, 2020, pp. 194–208). Incorporating visual and verbal cues further fosters rapport between users and bots (Go & Sundar, 2019). Achieving meaningful two-way interaction depends on the bot's ability to interpret natural language and respond in a human-like manner (Foehr & Germelmann, 2020). Using the Input–Process–Output (IPO) model, Hsu & Lin (2023) introduced the second-order formative construct "AI bot conversational quality," comprising three dimensions: understanding humanness (input), perceived contingency (process), and response humanness (output).

Many brands have introduced chatbots with human-like personas, such as Coca-Cola's "Hank" and IKEA's "Anna," complete with human profile images. The Computers as Social Actors (CASA) framework (Nass & Moon, 2000) demonstrates that anthropomorphic design elements encourage users to attribute human traits to computers, making them more receptive to social influence (Nowak & Rauh, 2005). In online retail, consumers perceive websites featuring human representatives as more interactive and socially engaging, thereby increasing trust and purchase intention (Chattaraman et al., 2014). Research on physical robots also highlights that anthropomorphic cues enhance perceived competence and suitability for tasks, improving user acceptance and evaluation (Belanche, Casaló Ariño, Schepers, & Flavián, 2021). The CASA literature further identifies several anthropomorphic features—such as a human-like face, personality traits (e.g., extroversion or introversion), and human-like characters—that prompt users to respond socially to machines (Nass & Moon, 2000; Sundar et al., 2015; Lee & Nass, 2010).

In team-based contexts, Fraune (2020) found that anthropomorphism moderates intergroup effects, making interactions with anthropomorphic robots more closely resemble human group dynamics than those with non-anthropomorphic ones. Similarly, a robot's human-like appearance mitigates users' negative attitudes driven by identity or realistic threats (Huang & Rust, 2018). In chatbot applications, anthropomorphic cues enhance the bot's capacity to meet users' social needs for human-like interaction (Sheehan et al., 2020), reinforcing the importance of perceived social presence. Within the service domain, Blut et al.'s (2021) meta-analysis confirmed that anthropomorphism positively correlates with perceived animacy, intelligence, likability, and social presence in robots.

H6. Anthropomorphic cues enhance user satisfaction.

2.5. Satisfaction to loyalty to chatbot usage

Satisfaction with human–chatbot interactions positively affects loyalty to chatbot usage. Prior research in information systems consistently identifies post-adoption loyalty as a result of satisfaction (Coelho et al., 2018; Limayem & Cheung, 2008). According to the ECM, user satisfaction significantly influences the post-adoption phase and determines the continued use of information technologies. Subsequent studies have reinforced satisfaction's central role in sustaining users' long-term IT engagement (Chiu et al., 2021). In the chatbot domain, empirical evidence similarly shows that satisfaction with chatbot interactions predicts users' continued use and recommendation of the chatbot service (Araujo, 2018; Rossmann et al., 2020). In line with this work, we conceptualize loyalty to chatbot usage as users' intention to continue using the chatbot for future service encounters and recommend the chatbot service to others, and we expect higher satisfaction with chatbot interactions to be associated with stronger loyalty. Thus, we posit that:

H7. An individual's satisfaction positively influences their loyalty to chatbot usage.

2.6. Purchasing intention

Purchase intention refers to the probability that a consumer will buy a product or service based on their attitudes, beliefs, and external factors (Alalwan et al., 2020; Rita et al., 2024). Within chatbot interactions, AI-driven systems can significantly shape purchase intentions by enhancing customer experience, offering personalized recommendations, and enabling smooth, efficient transactions (Ashfaq et al., 2020). Chatbots support purchasing decisions by delivering timely and relevant product information, assisting customers throughout the decision-making process, and resolving inquiries instantly, thereby reducing friction during the buying journey (Alalwan et al., 2020). Research shows that when consumers perceive chatbots as helpful and effective in solving problems, their trust increases, positively influencing purchase intention (Ashfaq et al., 2020). Moreover, personalization features, such as suggesting products based on browsing behavior or preferences, enhance the shopping experience and drive higher conversion rates (Chattaraman et al., 2012). Chatbots that successfully mimic human interaction also generate favorable attitudes toward e-commerce platforms, particularly among older or less tech-savvy users, leading to stronger purchase intentions (Chattaraman et al., 2012).

H8. Customer satisfaction positively influences purchase intention.

The proposed conceptual model of chatbot characteristics influencing customer satisfaction and behavioral outcomes is shown in Figure 1.

3. Methodology

3.1. Data collection and sampling

To understand the influence of chatbot-based services on customer satisfaction, a quantitative data-collection method was employed. Data were collected in November 2024 through an online survey distributed via personal and professional networks, using a convenience sampling method. The final sample consisted of 282 participants, including consumers with prior experience interacting with chatbots in customer service contexts. Participants were asked to rate their experiences on a 5-point Likert scale from "Strongly disagree" to "Strongly Agree", enabling them to indicate the extent to which they agree or disagree with each statement.

Participation in the study was voluntary. Prior to completing the online questionnaire, participants were informed about the purpose of the research and the anonymous nature of the survey. Informed consent was obtained from all participants before they proceeded with the questionnaire. No personally identifiable information was collected, and all responses were treated confidentially and analyzed in aggregate for research purposes only.

3.2. Questionnaire design and measurement

The survey consisted of multi-item scales adapted from established literature to ensure content validity (Table 1). Responses were recorded using a five-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree).

Information quality was assessed using four items derived from Magno and Dossena (2023) to evaluate whether the chatbot provided necessary, sufficient, and helpful information. Understanding humanness was measured using four statements from Hsu & Lin (2023) to evaluate the chatbot's ability to accurately comprehend user inputs and behave in a human-like manner.

Perceived contingency was evaluated using four items from Hsu & Lin (2023) to assess the chatbot's ability to build on previous user inputs and ensure coherent conversations. Response humanness was measured using five statements from Hsu & Lin (2023) to gauge how natural and human-like the chatbot's responses felt. Problem-solving was assessed using four items from Janson (2023) to evaluate the chatbot's effectiveness in resolving customer issues.

Anthropomorphism was measured using four items from Go and Sundar (2019) to determine whether users attributed human-like traits, such as emotions or intentions, to the chatbot. Customer satisfaction was assessed using four items adapted from Magno and Dossena (2023) to gauge users' overall contentment with the chatbot. Purchasing intention was measured using four items from Jiang et al. (2022) to evaluate how chatbot interactions influenced purchase decisions. Finally, loyalty to chatbot usage was assessed with three items from Hsu & Lin (2023) to measure users' intent to continue engaging with the chatbot in the future.

3.3. Data analysis

Quantitative data obtained from the survey was analyzed using Structural Equation Modeling (SEM), specifically employing the Partial Least Squares Structural Equation Modeling (PLS-SEM) technique. PLS-SEM was chosen due to its robustness in handling complex models with multiple constructs and its ability to assess both measurement and structural models. A two-phase approach was adopted for analysis.

In the first phase, the measurement model was evaluated for reliability and validity, ensuring that the constructs and their indicators met essential quality criteria. This included analyzing internal consistency, convergent validity, and discriminant validity. The Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio were applied to assess discriminant validity, while the Variance Inflation Factor (VIF) was calculated to detect multicollinearity issues among predictor variables.

In the second phase, the structural model was assessed to test the hypothesized relationships among variables within the research framework. The direct and indirect effects were analyzed, and hypothesis testing was performed using a bootstrapping procedure with 5000 iterations to estimate the significance of path coefficients. This process ensured that the findings were statistically robust and provided a comprehensive evaluation of the causal relationships outlined in the research model. By following these rigorous data analysis procedures, the study ensured the credibility, reliability, and validity of its results, providing a solid foundation for theoretical and practical contributions.

Table 1
Measurement items by construct with original sources.

Constructs	Item	Measurement Item	Reference
Information Quality	Quality_1	Chatbot provided me with the necessary information.	Magno and Dossena (2023)
	Quality_2	Chatbot provided me with responses to queries as I expected.	
	Quality_3	The chatbot provided sufficient information.	
	Quality_4	The information provided by the chatbot was helpful regarding my questions.	
Understanding Humanness	Human_1	The chatbot can accurately comprehend my questions or commands.	Hsu and Lin (2023)
	Human_2	The chatbot can accurately comprehend what I mean.	
	Human_3	The chatbot's understanding ability is similar to that of a human being.	
	Human_4	I consider the chatbot's comprehension ability to be human-like,	
Perceived Contingency	Contigency_1	The chatbot's responses are relevant to my previous input in threaded conversations.	Hsu and Lin (2023)
	Contigency_2	The response from the chatbot depends on my previous inputs.	
	Contigency_3	The chatbot will consider my previous series of inquiries and respond to them.	
	Contigency_4	The responses of the chatbot seem to be interconnected.	
Response Humanness	Response_1	The chatbot's responses feel natural.	Hsu and Lin (2023)
	Response_2	The chatbot has a human-like response.	
	Response_3	The chatbot's responses do not feel machine-like.	
	Response_4	The chatbot reacts in a very human way.	
	Response_5	The chatbot's responses seem human to me.	
Problem Solving	Problem_1	When I have an issue, the chatbot demonstrates a	Janson (2023)

(continued on next page)

Table 1 (*continued*)

Constructs	Item	Measurement Item	Reference
		genuine desire to resolve it	
	Problem_2	The chatbot may promptly and directly answer my complaints.	
	Problem_3	I have confidence in the chatbot's ability to do the task.	
	Problem_4	The chatbot processes returns and exchanges willingly.	
Anthropomorphism	Anthropormophism_1	The chatbot has intentions	(Go & Sundar, 2019)
	Anthropormophism_2	The chatbot has free will.	
	Anthropormophism_3	The chatbot can experience emotion.	
	Anthropormophism_4	The chatbot has consciousness.	
Customer Satisfaction	Satisfaction_1	I am satisfied with the chatbot	Magno and Dossena (2023)
	Satisfaction_2	The chatbot did a good job.	
	Satisfaction_3	The chatbot did what I expected.	
	Satisfaction_4	I am happy with the chatbot.	
Purchasing Intention	Intention_1	I will consider purchasing from the brand associated with this chatbot	Jiang et al. (2022)
	Intention_2	I will love to purchase from the brand associated with this chatbot.	
	Intention_3	I will probably purchase from the brand associated with this chatbot.	
	Intention_4	I am going to purchase from the brand associated with this chatbot.	
Loyalty to Chatbot Usage	Loyalty_1	I intend to keep using this chatbot in the future.	Hsu and Lin (2023)
	Loyalty_2	I would like to continue using this chatbot.	
	Loyalty_3	I would recommend this chatbot to friends.	

Table 2
Demographic characteristics of survey respondents (N = 282).

Gender	Frequency	%
Female	173	61.3
Male	104	36.9
Prefer not to answer	5	1.8
Age		
<20 years	7	2.5
20-29 years	178	63.1
30-39 years	18	6.4
40-49 years	18	6.4
50 + years	61	21.6
Education		
Bachelor's/Master's Degree	215	76.2
Doctoral and other postgraduate Degrees	34	11.1
High School Degree	25	8.9
Middle School Degree	8	2.8
Occupation		
Employed	147	52.1
Self-employed	52	18.5
Student	72	25.5
Unemployed	11	3.9

Source: Authors' own compilation from survey data

4. Results and discussion

4.1. Sample description

The demographic analysis of the 282 participants reveals a diverse sample in terms of gender, age, education, occupation, and sector engagement (see Table 2). The sample leans toward female representation (61.3%), with males constituting 36.9%, and a small proportion (1.8%) preferring not to disclose their gender. Age distribution is predominantly young adults, with 63.1% aged 20-29, while a notable segment (21.6%) is 50 and older, indicating a balance of youth and experience. In terms of education, a majority hold a bachelor's or master's degree (76.2%), with 11.1% holding other postgraduate degrees, showing a well-educated sample. Employment rates are high, with 52.1% of the population employed, 25.5% students, and 18.5% self-employed, indicating a predominantly economically active population. Participants also engage across multiple sectors, with strong representation in technology, telecommunications, and fashion, and frequent cross-sector involvement, suggesting interests in dynamic, consumer-focused industries.

4.2. Assessment of the measurement model

In this study, a two-phase approach was implemented. First, the measurement model was examined for reliability and validity, ensuring that the constructs and their indicators met essential quality criteria. All outer loadings were above 0.7, except for Anthropomorphism_1 (0.664) and Problem_1 (0.690). Consequently, Anthropomorphism_1 and Problem_1 were removed from the model, and the analysis was rerun. In the second phase, the structural model was assessed to evaluate the hypothesized relationships among variables within the model, testing both direct and indirect effects as outlined in the research framework.

4.3. Data analysis

Following the guidelines provided by Hair et al. (2021), internal consistency, convergent validity, and discriminant validity were evaluated, as the model consists solely of reflective constructs. This approach ensured a rigorous assessment of construct reliability and validity, providing insights into the quality and consistency of the data (Table 3). Reliability examines whether the data consistently reflect the intended constructs. At the same time, validity assesses the degree to which the results accurately capture and represent the phenomena being studied, indicating their credibility and acceptability.

The composite reliability values for all constructs were above 0.8, which is considered a valid threshold for ensuring internal consistency. The average variance extracted (AVE) values for all variables exceeded the 0.5 threshold, confirming that the constructs explain sufficient variance in their respective indicators (as shown in Table 3). Lastly, the Cronbach's alpha values for all constructs exceeded the 0.8 threshold, further supporting the reliability of the measurement model.

Discriminant validity was evaluated using the Fornell–Larcker criterion and the Heterotrait–Monotrait ratio (HTMT), following recommended PLS-SEM guidelines. The Fornell–Larcker criterion requires the square root of each construct's AVE to exceed its correlations with other constructs. As shown in Tables 3 and 4, all constructs meet this

Table 3
Construct reliability and validity assessment.

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)	√AVE
Anthropomorphism	0.883	0.885	0.928	0.811	0.900
Perceived Contingency	0.816	0.831	0.878	0.642	0.801
Understanding Humanness	0.856	0.867	0.902	0.697	0.835
Purchase Intention	0.927	0.929	0.948	0.820	0.906
Loyalty to Chatbot Usage	0.918	0.918	0.948	0.859	0.927
Problem-Solving	0.812	0.818	0.888	0.726	0.852
Information Quality	0.889	0.890	0.923	0.750	0.866
Response Humanness	0.906	0.910	0.930	0.728	0.853
Customer Satisfaction	0.922	0.924	0.945	0.812	0.901

Note: All constructs exceed the recommended thresholds: Cronbach's α > 0.7, CR > 0.7, and AVE >0.5, indicating adequate reliability and convergent validity.
Source: Authors' own calculations using SmartPLS.

Table 4
Fornell-Lacker criterion analysis for discrimination validity.

	ANT	PC	UH	PI	LCU	PS	IQ	RH	CS
ANT									
PC	0.458								
UH	0.567	**0.765**							
PI	0.458	0.584	**0.669**						
LCU	0.510	0.643	0.672	**0.759**					
PS	0.514	0.815	0.759	0.705	**0.766**				
IQ	0.439	0.700	0.751	0.565	0.764	**0.814**			
RH	0.680	0.647	0.753	0.575	0.654	0.666	**0.549**		
CS	0.494	0.763	0.798	0.699	0.859	0.900	0.893	**0.608**	

Note. ANT = Anthropomorphism; PC = Perceived Contingency; UH = Understanding Humanness; PI = Purchase Intention; LCU = Loyalty to Chatbot Usage; PS = Problem-Solving; IQ = Information Quality; RH = Response Humanness; CS = Customer Satisfaction. Diagonal elements (in bold) represent the square roots of AVE; off-diagonal elements represent inter-construct correlations.
Source: Authors' own analysis.

requirement, demonstrating that each latent variable captures more variance from its indicators than from other constructs, thus supporting construct distinctiveness. HTMT values were computed as a stringent assessment of discriminant validity (Table 5). All HTMT ratios were below 0.90, supporting discriminant validity and indicating that the constructs capture distinct conceptual domains.

The Variance Inflation Factor (VIF) measures the degree of multicollinearity among predictor variables in a regression model, where multicollinearity occurs when predictor variables are highly correlated, potentially distorting the reliability of regression coefficients. VIF values below 5 indicate acceptable levels of multicollinearity. In this study, all VIF values are below 5, ranging from 1.000 to 2.640 (Table 6), confirming that multicollinearity is not a concern and that the predictors independently contribute to the dependent variables without redundancy or overlap. These results confirm the reliability and robustness of the model, ensuring that the statistical inferences and conclusions drawn from the data are valid.

Table 6
Variance Inflation Factor (VIF) for multicollinearity assessment.

	VIF
Anthropomorphism - > Customer Satisfaction	**1.633**
Perceived Contingency - > Customer Satisfaction	**2.237**
Understanding Humanness - > Customer Satisfaction	**2.640**
Problem-Solving > Customer Satisfaction	**2.572**
Information Quality - > Customer Satisfaction	**2.379**
Response Humanness- > Customer Satisfaction	**2.324**
Customer Satisfaction - > Purchasing Intention	**1.000**
Customer Satisfaction- > Loyalty to Chatbot Usage	**1.000**

Source: Authors' own calculations using SmartPLS.

4.4. Structural model and hypothesis testing

In this study, the hypothesis testing was conducted using a bootstrapping procedure with 5000 iterations to assess the significance of the path coefficients at a 0.05 significance level. The path coefficient values ranged from −0.014 to 0.790, providing a comprehensive evaluation of

Table 5
Heterotrait-Monotrait ratio (HTMT) for discriminant validity assessment.

	ANT	PC	UH	PI	LCU	PS	IQ	RH	CS
ANT	-								
PC	0.397	-							
UH	0.485	0.652	-						
PI	0.418	0.510	0.598	-					
LCU	0.459	0.567	0.598	0.701	-				
PS	0.434	0.670	0.639	0.612	0.665	-			
IQ	0.388	0.614	0.666	0.515	0.690	0.699	-		
RH	0.608	0.566	0.655	0.530	0.597	0.573	0.495	-	
CS	0.448	0.675	0.717	0.647	0.790	0.783	0.810	0.559	-

Note. ANT = Anthropomorphism; PC = Perceived Contingency; UH = Understanding Humanness; PI = Purchase Intention; LCU = Loyalty to Chatbot Usage; PS = Problem-Solving; IQ = Information Quality; RH = Response Humanness; CS = Customer Satisfaction.
Source: Authors' own calculations using SmartPLS.

each hypothesized relationship. To further analyze the model, R^2 values were calculated to assess the proportion of variance explained in the dependent variables. Additionally, the bootstrapping outputs, including sample mean, standard deviation, T-values, and P-values, were analyzed to statistically confirm the significance of the relationships (Table 7).

The R-squared values indicate the level of explained variance for the dependent variables. Customer Satisfaction, the primary construct in the model, has an R^2 square value of 0.774, meaning that 77.4% of the variance in Customer Satisfaction is explained by the predictor variables (Information Quality, Understanding Humanness, Perceived Contingency, Response Humanness, Anthropomorphism, and Problem-Solving). Additionally, Loyalty to Chatbot Usage has an R-squared value of 0.624, and Purchasing Intention has an R-squared value of 0.419. Both exceed the minimum threshold, indicating that the model effectively explains the variance in these outcome variables.

The results of this study provide significant insight into the factors that influence customer satisfaction in chatbot-based interactions (see Table 8). The analysis demonstrated that information quality and problem-solving capability are the strongest predictors of customer satisfaction. High-quality information—characterized by relevance, accuracy, and helpfulness—greatly enhances user experience, underscoring the importance of chatbots being not just functional but also competent communicators. Problem-solving capability also plays a critical role, as users highly value the chatbot's efficiency in addressing and resolving issues promptly.

Understanding humanness also emerged as a significant driver of customer satisfaction, as chatbots that accurately comprehend and respond to user inputs create a more seamless and natural conversational flow. This finding suggests that “humanness” in the sense of being understood functions as an instrumental capability that directly supports goal attainment in customer service exchanges (Shams & Kim, 2024).

However, the effects of perceived contingency and response humanness were weaker than expected and not statistically significant. While contingent responses (i.e., replies that build on prior messages) may improve conversational flow, perceived contingency did not significantly predict satisfaction (p = 0.162; Table 7). Likewise, response humanness (natural-sounding, human-like wording) did not significantly increase satisfaction once more utilitarian attributes, particularly problem-solving, were considered, suggesting that in goal-directed customer service interactions, users prioritize effective resolution over stylistic human-likeness. Similarly, perceived anthropomorphism had a limited influence on satisfaction, suggesting that functional performance may outweigh social perceptions in shaping customer evaluations in this context.

The study also found strong links between customer satisfaction, loyalty to chatbot usage, and purchase intention. Users who were satisfied with their chatbot experiences were more likely to engage with the chatbot in future interactions and make purchases. This highlights the importance of designing chatbot systems that not only meet functional requirements but also foster positive emotional connections to drive business outcomes.

Table 7
Bootstrapping results: Path coefficients and significance levels.

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Anthropomorphism - > Customer Satisfaction	0.040	0.039	0.042	0.963	0.336
Perceived Contingency- > Customer Satisfaction	0.092	0.091	0.066	1.399	0.162
Understanding Humanness - > Customer Satisfaction	0.173	0.173	0.067	2.583	0.010
Problem-Solving- > Customer Satisfaction	0.315	0.315	0.074	4.241	0.000
Information Quality - > Customer Satisfaction	0.409	0.409	0.067	6.146	0.000
Response Humanness > Customer Satisfaction	−0.014	−0.011	0.055	0.252	0.801
Customer Satisfaction- > Purchasing Intention	0.647	0.648	0.057	11.340	0.000
Customer Satisfaction - > Loyalty to Chatbot Usage	0.790	0.790	0.033	24.252	0.000

Source: Authors' own calculations using SmartPLS.

Table 8
Summary of hypotheses results.

Hypothesis	Results
H1- The information quality provided by chatbots positively impacts customer satisfaction	Supported
H2- Chatbots' problem-solving capability positively influences customer satisfaction	Supported
H3- Understanding humanness positively impacts customer satisfaction	Supported
H4- High levels of perceived contingency in chatbot interactions positively influence user satisfaction with customer service chatbots	Not supported
H5-Response humanness positively affects customer satisfaction	Not supported
H6- Anthropomorphic cues enhance user satisfaction	Not supported
H7- An individual's sense of satisfaction positively affects his/her loyalty to chatbot usage	Supported
H8- Customer satisfaction positively impacts purchase intention	Supported

Note: Hypotheses were tested using structural equation modeling with a significance level of $p < 0.05$.
Source: Authors' own findings.

4.5. Discussion

The results align with prior studies, such as those by Chiu et al. (2021) and Popescu (2020), in highlighting the importance of information quality and problem-solving capabilities in driving customer satisfaction. Users consistently value chatbots that deliver accurate, relevant, and helpful information while effectively resolving their issues. These attributes are foundational to the perception of chatbot competence and reliability, and in line with the ECM, represent core performance cues that strongly shape post-use satisfaction. However, this study places greater emphasis on the significance of these functional attributes over sociability-related factors.

In contrast to work that attributes comparable importance to functional and anthropomorphic features (e.g., Blut et al., 2021; Go & Sundar, 2019), our findings suggest that in task-oriented interactions, information quality and problem-solving capabilities take precedence. This distinction highlights the practical nature of most chatbot use cases, where users prioritize effective solutions over conversational or emotional rapport. This divergence highlights the importance of tailoring chatbot design to context.

Previous literature, including Nass and Moon (2000) and Sheehan et al. (2020), strongly advocates for the inclusion of anthropomorphic features, such as human-like names, avatars, and personalities, to enhance the social presence of chatbots and foster trust and engagement.

Our results do not contradict the potential value of such features, but indicate that in our setting, anthropomorphic cues have a relatively limited direct impact on satisfaction once functional performance is accounted for. This observation aligns with Araujo's (2018) argument that practical functionality often outweighs social presence in task-oriented interactions. Users seem to value anthropomorphic features primarily in scenarios where emotional engagement is important, such as brand marketing or casual interactions. In contrast, for service-oriented tasks that require efficiency and reliability, these features are less influential.

A similar pattern emerges for perceived contingency and response humanness. Prior work has shown that contingent responses that build coherently on previous messages and natural, context-aware replies foster human-like conversational flow and engagement (Schuetzler et al., 2020; Sundar et al., 2016). In our study, however, these social-conversational attributes do not significantly predict satisfaction when functional attributes are considered simultaneously, suggesting that in largely utilitarian service interactions, users prioritize outcome-oriented performance. Specifically, satisfaction appears to be driven more by whether the chatbot accurately understands user intent and supports effective resolution, whereas human-like expression and contingent conversational flow play a more peripheral role once the interaction delivers an effective outcome. This aligns with prior research suggesting that social cues in chatbot interactions primarily strengthen socio-emotional responses (e.g., social presence, emotional validation) rather than utilitarian evaluations (Araujo, 2018; Go & Sundar, 2019). Accordingly, our non-significant effects for perceived contingency and response humanness imply that these cues may shape affective impressions more than instrumental satisfaction once functional performance is accounted for. Overall, this pattern clarifies the anthropomorphism debate by indicating that human-like design features are context-dependent in their impact and are likely to matter less for satisfaction when task performance is strong and users' goals are primarily instrumental.

5. Conclusions

This study has provided valuable insights into the factors influencing customer satisfaction in chatbot interactions, highlighting the primacy of functional attributes including information quality, problem-solving capabilities, and the importance of understanding human aspects. While the findings highlight the potential of chatbots to enhance customer experiences and foster user loyalty, several hypotheses regarding social and anthropomorphic attributes namely perceived contingency, response humanness, and anthropomorphism, were not supported. Although previous studies have reported positive effects of human-like design features and conversational qualities on user evaluations, our results suggest that these attributes have a limited direct impact on satisfaction once core functional performance is taken into account. Rather than contradicting prior findings outright, this pattern helps clarify their boundary conditions. In routine, utilitarian customer service interactions where users are primarily focused on getting problems solved, functional performance appears to outweigh human-like cues in driving satisfaction, whereas anthropomorphic and conversational features may play a more central role in hedonic, relational, or branding-oriented contexts. These results suggest that functionality and efficiency often outweigh sociability in task-oriented interactions.

The insights from this study underline the importance of prioritizing chatbots' ability to deliver accurate, relevant, and personalized responses while addressing user concerns promptly. By investing in technologies that enhance natural language understanding and emotional intelligence, organizations can bridge the gap between human and machine interactions, fostering trust and loyalty to chatbot usage.

As organizations continue to integrate AI-driven chatbots into their service strategies, the findings of this study serve as a roadmap for developing user-centric systems. By addressing the identified limitations and pursuing the proposed future research directions, scholars and practitioners can unlock the full potential of chatbots, ensuring they not only meet functional requirements but also create meaningful and satisfying user experiences.

Ultimately, this research reinforces the idea that while technology continues to evolve, its success will always hinge on its ability to connect with users.

5.1. Theoretical implications

While prior research has broadly highlighted the potential of AI in enhancing customer experiences (e.g., Araujo, 2018; Chung et al., 2020), this study advances the literature by empirically testing how attributes such as information quality, problem-solving capabilities, and understanding of humanness influence satisfaction, loyalty to chatbot usage, and purchase intention.

Our findings reinforce prior work emphasizing the centrality of high-quality information in service evaluations (Chung et al., 2020; Gao et al., 2015), but differ in the extent to which anthropomorphic features influence outcomes. Although social cues have been linked to enhanced user experiences via social presence and related socio-emotional mechanisms (e.g., Blut et al., 2021; Sheehan et al., 2020; Sundar et al., 2016), our results indicate that these effects may be mitigated in utilitarian customer service contexts where users prioritize efficient problem resolution.

Importantly, the study refines the discussion of humanness by distinguishing between competence-oriented humanness (understanding humanness) and expression-oriented humanness (response humanness). While both are "human-related," they do not predict satisfaction equivalently. Understanding humanness, which reflects accurate intent comprehension, shows stronger explanatory power, whereas stylistic human-likeness (including contingent conversational flow and response humanness) appears weaker or more conditional once instrumental performance is jointly evaluated (Sundar et al., 2016; Hsu & Lin, 2023). Overall, these findings suggest that the impact of social attributes depends on the evaluative goal of the interaction and may contribute less to satisfaction when functional performance is already strong.

5.2. Managerial implications

By focusing on elements such as information quality, problem-solving capabilities, and the thoughtful deployment of human-like attributes, managers can create more effective user experiences, foster user loyalty, and drive positive business outcomes. Organizations should prioritize ensuring their chatbots deliver relevant, accurate, and valuable information promptly. Enhancing the chatbot's ability to solve complex queries is essential, as users primarily seek efficient resolutions to their issues.

Companies must also invest in improving the chatbot's comprehension of natural language and emotional cues, enabling it to provide empathetic and contextually appropriate responses. This fosters a sense of trust and reliability, enhancing the user's overall experience. While human-like personas such as avatars and names have a limited impact on overall satisfaction, they can still serve a supportive role in non-critical interactions or as a means of brand differentiation. These features should be deployed strategically, focusing on contexts where social engagement is valued over efficiency, such as casual conversations or brand marketing initiatives.

Finally, the study underscores the strong relationship between satisfaction, loyalty to chatbot usage, and purchase intention, highlighting the importance of continuously measuring these outcomes. Enhancing satisfaction not only improves immediate service interactions but also fosters long-term loyalty to chatbot usage and encourages repeat purchases.

By adopting these strategies, organizations can better position their chatbots to meet user expectations, maximize customer satisfaction, and achieve meaningful business outcomes.

5.3. Limitations and future research

This research offers valuable insights into the factors influencing customer satisfaction in chatbot interactions. However, certain limitations need to be addressed to enhance the robustness and applicability of the findings across diverse contexts.

First, the sample composition predominantly consisted of younger, tech-savvy individuals, particularly those aged 20–29. This demographic is more likely to engage with chatbot-based services, which may limit the generalizability of the findings to older adults or individuals with less technological proficiency. Different age groups or levels of technological competence may have varying perceptions of chatbot performance; future studies should incorporate a more diverse and representative sample to enhance external validity.

Second, the study employed a convenience sampling method, relying on personal networks for data collection. While practical, this approach inherently limited the diversity of respondents and introduced potential bias. Consequently, the findings may not fully reflect the broader population of chatbot users, particularly those from varied cultural, economic, or geographic backgrounds. Future research should consider random or stratified sampling techniques to improve the robustness and applicability of the results.

Third, at the time of data collection, most customer service chatbots in use by firms relied on rule-based or narrowly trained AI architectures, rather than on large-scale generative models. The rapid diffusion of Generative AI-based conversational agents, which can offer more flexible and context-aware interactions (Oni, 2025), is likely to raise users' expectations and may change the relative salience of specific attributes. Nevertheless, our results provide a useful baseline by showing that, in routine task-oriented service interactions, functional performance dominates social and anthropomorphic cues in shaping satisfaction; future research should examine whether this pattern persists, or whether more advanced generative capabilities increase the weight of social and anthropomorphic attributes in Generative AI-enabled chatbots.

Lastly, the research primarily focused on customer service chatbots within the technology, telecommunications, and fashion industries. These sectors often attract digitally fluent customers, and the findings may not apply directly to other contexts, such as healthcare, education, or non-profit organizations, where user expectations and needs differ significantly. Expanding research to these fields could uncover industry-specific challenges and opportunities, providing deeper insights into chatbot design and implementation across diverse service settings.

Beyond addressing these limitations, future research should explore additional dimensions of chatbot interactions. A key area of investigation is the emotional and psychological aspects of chatbot use. While this study focused on functional attributes such as information quality and problem-solving, further research could employ qualitative methods, such as interviews or focus groups, to explore users' emotional responses, trust formation, and overall engagement with chatbots.

Additionally, as chatbots increasingly handle sensitive customer data, future research should examine the ethical and privacy concerns surrounding AI-driven customer interactions and investigating how transparency, data security, and regulatory compliance impact user trust and acceptance would provide valuable insights for businesses and policymakers.

By addressing these areas, future studies can further enhance our understanding of how chatbot interactions influence consumer behavior across diverse demographics, industries, and ethical landscapes.

CRediT authorship contribution statement

Paulo Rita: Writing – original draft, Investigation, Conceptualization. **Celeste Vong:** Writing – original draft, Investigation, Conceptualization. **Catarina Correia:** Writing – original draft, Investigation, Conceptualization.

Ethics statement

The study followed established ethical guidelines for research involving human participants. Data was collected through an anonymous online questionnaire, and participation was entirely voluntary. Participants were informed about the purpose of the study and provided informed consent before completing the survey. No personally identifiable information was collected, and all data was analyzed in aggregate to ensure confidentiality and privacy.

Declaration of AI use

The authors declare that no generative AI or AI-assisted technologies were used in the writing, analysis, or preparation of this manuscript.

Funding source(s)

This work was supported by national funds through FCT (Fundação para a Ciência e a Tecnologia), under the project - UID/04152/2025 - Centro de Investigação em Gestão de Informação (MagIC)/NOVA IMS - https://doi.org/10.54499/UID/04152/2025 (2025-01-01/2028-12-31).

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data presented in this study are available on request from the corresponding author. The data are not publicly available due to privacy restrictions.

References

Adamopoulou, E., & Moussiades, L. (2020). An overview of chatbot technology. In *Proceedings of the IFIP international conference on artificial intelligence applications and innovations*. https://doi.org/10.1007/978-3-030-49186-4_31

Alalwan, A. A., Algharabat, R. S., Baabdullah, A. M., Rana, N. P., Qasem, Z., & Dwivedi, Y. K. (2020). Examining the impact of mobile interactivity on customer engagement in the context of mobile shopping. *Journal of Enterprise Information Management, 33*(3), 627–653. https://doi.org/10.1108/JEIM-07-2019-0194

Araujo, T. (2018). Living up to the chatbot hype: The influence of anthropomorphic design cues and communicative agency framing on conversational agent and company perceptions. *Computers in Human Behavior, 85*, 183–189. https://doi.org/10.1016/j.chb.2018.03.051

Ashfaq, M., Yun, J., Yu, S., & Loureiro, S. M. C. (2020). I, chatbot: Modeling the determinants of users' satisfaction and continuance intention of AI-powered service agents. *Telematics and Informatics, 54*, Article 101473. https://doi.org/10.1016/j.tele.2020.101473

Belanche, D., Casaló, L. V., Schepers, J., & Flavián, C. (2021). Examining the effects of robots' physical appearance, warmth, and competence in frontline services: The humanness-value-loyalty model. *Psychology and Marketing, 38*(12), 2357–2376. https://doi.org/10.1002/mar.21532

Bhattacherjee, A., & Sanford, C. (2006). Influence processes for information technology acceptance: An elaboration likelihood model. *MIS Quarterly, 30*(4), 805–825. https://doi.org/10.2307/25148755

Bilquise, G., Ibrahim, S., & Shaalan, K. (2022). Emotionally intelligent chatbots: A systematic literature review. *Human Behavior and Emerging Technologies, 1*, 9601630. https://doi.org/10.1155/2022/9601630.

Blut, M., Wang, C., Wünderlich, N. V., & Brock, C. (2021). Understanding anthropomorphism in service provision: A meta-analysis of physical robots, chatbots, and other AI. *Journal of the Academy of Marketing Science, 49*(4), 632–658. https://doi.org/10.1007/s11747-020-00762-y

Castillo, D., Canhoto, A. I., & Said, E. (2021). The dark side of AI-powered service interactions: Exploring the process of co-destruction from the customer perspective. *Service Industries Journal, 41*(13-14), 900–925. https://doi.org/10.1080/02642069.2020.1787993

Chattaraman, V., Kwon, W.-S., & Gilbert, J. E. (2012). Virtual agents in retail websites: Benefits of simulated social interaction for older users. *Computers in Human Behavior, 28*(6), 2055–2066. https://doi.org/10.1016/j.chb.2012.06.009

Chattaraman, V., Kwon, W.-S., Gilbert, J. E., & Li, Y. (2014). Virtual shopping agents: Persona effects for older users. *The Journal of Research in Indian Medicine, 8*(2), 144–162. https://doi.org/10.1108/JRIM-08-2013-0054

Chaves, A. P., & Gerosa, M. A. (2021). How should my chatbot interact? A survey on social characteristics in human–chatbot interaction design. *International Journal of Human-Computer Interaction, 37*(8), 729–758. https://doi.org/10.1080/10447318.2020.1841438

Chiu, W., Cho, H., & Chi, C. G. (2021). Consumers' continuance intention to use fitness and health apps: An integration of the expectation–confirmation model and investment model. *Information Technology & People, 34*(3), 978–998. https://doi.org/10.1108/ITP-09-2019-0463

Chung, M., Ko, E., Joung, H., & Kim, S. J. (2020). Chatbot e-service and customer satisfaction regarding luxury brands. *Journal of Business Research, 117*, 587–596. https://doi.org/10.1016/j.jbusres.2018.10.004

Coelho, P. S., Rita, P., & Santos, Z. R. (2018). On the relationship between consumer-brand identification, brand community, and brand loyalty. *Journal of Retailing and Consumer Services, 43*, 101–110. https://doi.org/10.1016/j.jretconser.2018.03.011

Dahiya, M. (2017). A tool of conversation: Chatbot. *International Journal of Computer Sciences and Engineering, 5*(5), 158–161.

Diederich, S., Brendel, A., Morana, S., & Kolbe, L. M. (2022). On the design of and interaction with conversational agents: An organizing and assessing review of human-computer interaction research. *Journal of the Association for Information Systems*. https://doi.org/10.17705/1jais.00724

Feine, J., Gnewuch, U., Morana, S., & Maedche, A. (2019). A taxonomy of social cues for conversational agents. *International Journal of Human-Computer Studies, 132*, 138–161. https://doi.org/10.1016/j.ijhcs.2019.07.009

Foehr, J., & Germelmann, C. C. (2020). Alexa, can I trust you? Exploring consumer paths to trust in smart voice-interaction technologies. *Journal of the Association for Consumer Research, 5*(2), 181–205. https://doi.org/10.1086/707731

Følstad, A., & Brandtzaeg, P. B. (2020). Users' experiences with chatbots: Findings from a questionnaire study. *Quality and User Experience, 5*(1), 1–14. https://doi.org/10.1007/s41233-020-00033-2

Følstad, A., Nordheim, C. B., & Bjørkli, C. A. (2018). What makes users trust a chatbot for customer service? An exploratory interview study. *International conference on internet science*. https://doi.org/10.1007/978-3-030-01437-7_16

Fraune, M. R. (2020). Our robots, our team: Robot anthropomorphism moderates group effects in human–robot teams. *Frontiers in Psychology, 11*, 1275. https://doi.org/10.3389/fpsyg.2020.01275.

Gao, L., Waechter, K. A., & Bai, X. (2015). Understanding consumers' continuance intention towards mobile purchase: A theoretical framework and empirical study. *A case of China. Computers in Human Behavior, 53*, 249–262. https://doi.org/10.1016/j.chb.2015.07.014

Go, E., & Sundar, S. S. (2019). Humanizing chatbots: The effects of visual, identity, and conversational cues on humanness perceptions. *Computers in Human Behavior, 97*, 304–316. https://doi.org/10.1016/j.chb.2019.01.020

Haenlein, M., & Kaplan, A. (2019). A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. *California Management Review, 61*(4), 5–14. https://doi.org/10.1177/0008125619864925.

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial least squares structural equation modeling (PLS-SEM) using R: A workbook*. Springer International Publishing. https://doi.org/10.1007/978-3-030-80519-7

Han, E., Yin, D., & Zhang, H. (2023). Bots with feelings: Should AI agents express positive emotion in customer service? *Information Systems Research, 34*(3), 1296–1311. https://doi.org/10.1287/isre.2022.1179

Heo, M., & Lee, K. J. (2018). Chatbot as a new business communication tool: The case of naver TalkTalk. *Business Communication Research and Practice, 1*(1), 41–45. https://doi.org/10.22682/bcrp.2018.1.1.41

Hildebrand, C., & Bergner, A. (2021). Conversational robo advisors as surrogates of trust: Onboarding experience, firm perception, and consumer financial decision making. *Journal of the Academy of Marketing Science, 49*(4), 659–676. https://doi.org/10.1007/s11747-020-00753-z

Hollebeek, L. D., Sprott, D. E., & Brady, M. K. (2021). Rise of the machines? Customer engagement in automated service interactions. *Journal of Service Research, 24*(1), 3–8. https://doi.org/10.1177/1094670520975110

Hsu, C.-L., & Lin, J. C.-C. (2023). Understanding the user satisfaction and loyalty of customer service chatbots. *Journal of Retailing and Consumer Services, 71*, Article 103211. https://doi.org/10.1016/j.jretconser.2022.103211

Huang, M. H., & Rust, R. T. (2018). Artificial intelligence in service. *Journal of Service Research, 21*(2), 155–172. https://doi.org/10.1177/1094670517752459

Huang, M. H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. *Journal of the Academy of Marketing Science, 49*(1), 30–50. https://doi.org/10.1007/s11747-020-00749-9.

Janson, A. (2023). How to leverage anthropomorphism for chatbot service interfaces: The interplay of communication style and personification. *Computers in Human Behavior, 149*, Article 107954. https://doi.org/10.1016/j.chb.2023.107954

Janssen, A. H. A., Grützner, L., & Breitner, M. H. (2021). Why do chatbots fail? A critical success factors analysis. In *In proceedings of the 42nd international conference on information systems (ICIS)*.

Jiang, K., Qin, M., & Li, S. (2022). Chatbots in retail: How do they affect the continued use and purchase intentions of Chinese consumers? *Journal of Consumer Behaviour, 21*(4), 756–772. https://doi.org/10.1002/cb.2034

Johari, N. M., & Nohuddin, P. N. (2021). Quality attributes for a good chatbot: A literature review. *International Journal of Electrical Engineering and Technology (IJEET), 12*(7), 109–119.

Kaplan, A., & Haenlein, M. (2018). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons, 62*(1), 15–25. https://doi.org/10.1016/j.bushor.2018.08.004

Khatri, C., Venkatesh, A., Hedayatnia, B., Gabriel, R., Ram, A., & Prasad, R. (2018). Alexa prize-state of the art in conversational AI. *AI Magazine, 39*(3), 40–55. https://doi.org/10.1609/aimag.v39i3.2810

Kim, S., Park, G., Lee, Y., & Choi, S. (2016). Customer emotions and their triggers in luxury retail: Understanding the effects of customer emotions before and after entering a luxury shop. *Journal of Business Research, 69*(12), 5809–5818. https://doi.org/10.1016/j.jbusres.2016.04.178

Lee, W. J. (2024). Service failure by human, service recovery by AI chatbot: The impact of justice, AI efficacy on recovery effort. *Virtual Economics, 7*(4), 48–63. https://doi.org/10.34021/ve.2024.07.043

Lee, J. R., & Nass, C. I. (2010). Trust in computers: The computers-are-social-actors (CASA) paradigm and trustworthiness perception in human-computer communication. In J.-E. R. Lee, & C. I. Nass (Eds.), *Trust and technology in a ubiquitous modern environment: Theoretical and methodological perspectives* (pp. 1–15). IGI Global. https://doi.org/10.4018/978-1-61520-901-9.ch001.

Limayem, M., & Cheung, C. M. K. (2008). Understanding information systems continuance: The case of internet-based learning technologies. *Information & Management, 45*(4), 227–232. https://doi.org/10.1016/j.im.2008.02.005

Linina, I., Zvirgzdina, R., & Vevere, V. (2022). *Ensuring consumer satisfaction with chatbots in the Baltic states, 2022* pp. 512–520). Business and Management. https://doi.org/10.3846/bm.2022.855

Luger, E., & Sellen, A. (2016). "Like having a really bad PA": The gulf between user expectation and experience of conversational agents. *CHI Conference on Human Factors in Computing Systems*, 5286–5297. https://doi.org/10.1145/2858036.2858288

Luo, X., Tong, S., Fang, Z., & Qu, Z. (2019). Frontiers: Machines vs. humans: The impact of artificial intelligence chatbot disclosure on customer purchases. *Marketing Science, 38*(6), 937–947. https://doi.org/10.1287/mksc.2019.1192

Magno, F., & Dossena, G. (2023). The effects of chatbots' attributes on customer relationships with brands: PLS-SEM and importance–performance map analysis. *The TQM Journal, 35*(5), 1156–1169. https://doi.org/10.1108/TQM-02-2022-0080

Mainardi, I. (2025). Change management: Artificial intelligence (AI) at the service of public administrations. *AI & Society, 40*(5), 3953–3981. https://doi.org/10.1007/s00146-024-02136-2

McTear, M. (2020). Conversational AI: Dialogue systems, conversational agents, and chatbots. *Synthesis Lectures on Human Language Technologies, 13*(3), 1–251. https://doi.org/10.2200/S01060ED1V01Y202010HLT049

Mishra, N., Kaipu, K., & Prasad, Y. (2020). The role of chatbots in enhancing staff productivity of network service providers in Bengaluru. *IUP Journal of Organizational Behavior, 19*(4), 7–21.

Misischia, C. V., Poecze, F., & Strauss, C. (2022). Chatbots in customer service: Their relevance and impact on service quality. *Procedia Computer Science, 201*, 421–428. https://doi.org/10.1016/j.procs.2022.03.055

Nass, C., & Moon, Y. (2000). Machines and mindlessness: Social responses to computers. *Journal of Social Issues, 56*(1), 81–103. https://doi.org/10.1111/0022-4537.00153

Nowak, K. L., & Rauh, C. (2005). The influence of the avatar on online perceptions of anthropomorphism, androgyny, credibility, homophily, and attraction. *Journal of Computer-Mediated Communication, 11*(1), 153–178. https://doi.org/10.1111/j.1083-6101.2006.tb00308.x

Oni, O. (2025). Memory-enhanced conversational AI: A generative approach for context-aware and personalized chatbots. *Communication In Physical Sciences, 12*(2), 649–657. https://doi.org/10.4314/g4280q29

Popescu, C.-A. (2020). Chatbots as marketing communication tool. *FAIMA Business & Management Journal, 8*(3), 62–75.

Rita, P., Guerreiro, J., Ramos, R., & Caetano, R. G. (2024). The role of microtransactions in impulse buying and purchase intention in the video game market. *Entertainment Computing, 50*, Article 100693. https://doi.org/10.1016/j.entcom.2024.100693

Rossmann, A., Zimmermann, A., & Hertweck, D. (2020). The impact of chatbots on customer service performance. In *In advances in intelligent systems and computing* (pp. 237–243). Springer. https://doi.org/10.1007/978-3-030-51057-2_33

Sands, S., Ferraro, C., Campbell, C., & Tsao, H.-Y. (2021). Managing the human–chatbot divide: How service scripts influence service experience. *Journal of Service Management, 32*(2), 246–264. https://doi.org/10.1108/JOSM-06-2019-0203

Schuetzler, R. M., Grimes, G. M., & Scott Giboney, J. (2020). The impact of chatbot conversational skill on engagement and perceived humanness. *Journal of Management Information Systems, 37*(3), 875–900. https://doi.org/10.1080/07421222.2020.1790204

Shams, G., & Kim, K. (2024). Chatbots on the frontline: The imperative shift from a "One-size-fits-all" strategy through conversational cues and dialogue designs. *Journal of Hospitality & Tourism Research, 50*(1), 5–19. https://doi.org/10.1177/10963480241280991

Sheehan, B., Jin, H. S., & Gottlieb, U. (2020). Customer service chatbots: Anthropomorphism and adoption. *Journal of Business Research, 115*, 14–24. https://doi.org/10.1016/j.jbusres.2020.04.030

Shumanov, M., & Johnson, L. (2021). Making conversations with chatbots more personalized. *Computers in Human Behavior, 117*, Article 106627. https://doi.org/10.1016/j.chb.2020.106627

Stelbotsky, B., & Park, S. (2024). Can chatbots represent? Examining the potential for symbolic representation in automated service agents. *Public Management Review*, 1–21. https://doi.org/10.1080/14719037.2024.2443064

Sundar, S. S., Bellur, S., Oh, J., Jia, H., & Kim, H. S. (2016). Theoretical importance of contingency in human-computer interaction: Effects of message interactivity on user engagement. *Communication Research, 43*(5), 595–625. https://doi.org/10.1177/0093650214534962

Sundar, S. S., Jia, H., Waddell, T. F., & Huang, Y. (2015). *Toward a theory of interactive media effects (TIME) four models for explaining how interface features affect user psychology. The handbook of the psychology of communication technology* (pp. 47–86). https://doi.org/10.1002/9781118426456.

Sundar, S. S., Kalyanaraman, S., & Brown, J. (2003). Explicating website interactivity: Impression formation effects in political campaign sites. *Communication Research, 30*(1), 30–59. https://doi.org/10.1177/0093650202239025

Trivedi, J. (2019). Examining the customer experience of using banking chatbots and its impact on brand love: The moderating role of perceived risk. *Journal of Internet Commerce, 18*(1), 91–111. https://doi.org/10.1080/15332861.2019.1567188

Tsai, W.-H. S., Liu, Y., & Chuan, C.-H. (2021). How chatbots' social presence communication enhances consumer engagement: The mediating role of parasocial interaction and dialogue. *The Journal of Research in Indian Medicine, 15*(3), 460–482. https://doi.org/10.1108/JRIM-12-2019-0200

Ueltschy, L. C., Laroche, M., Rita, P., & Bocaranda, C. (2008). A pan-european approach to customer satisfaction: An optimal strategy? *Multinational Business Review, 16*(3), 41–72. https://doi.org/10.1108/1525383X200800013

Westerman, D., Cross, A. C., & Lindmark, P. G. (2019). I believe in a thing called bot: Perceptions of the humanness of “chatbots”. *Communication Studies, 70*(3), 295–312. https://doi.org/10.1080/10510974.2018.1557233