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How do system and user characteristics, along with anthropomorphism, impact cognitive absorption of chatbots – Introducing SUCCAST through a mixed methods study

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ABSTRACT

Chatbots are radically redefining the customer service landscape. With the advent of AI-enabled chatbots, like ChatGPT, organizations are adopting chatbots to provide better customer services; however, the user experience has been given less attention. Building on IS success model and cognitive absorption theory, we posit that system and user characteristics enhance cognitive absorption amongst users, such that the relationship varies between anthropomorphic (e.g., human-like) and non-anthropomorphic chatbots. We undertook a cross-sectional comparative study, which was analyzed using PLS-SEM and fsQCA. Where PLS-SEM provided limited inferential insights about the differences between anthropomorphic and non-anthropomorphic chatbots, the FsQCA analysis resulted in three configurations of attributes for non-anthropomorphic and two configurations for anthropomorphic chatbots, which lead to higher cognitive absorption. The findings extend the existing literature, suggesting that anthropomorphic and non-anthropomorphic chatbots impact cognitive absorption through separate system and user characteristics configurations.

1. Introduction

Chatbots have been used increasingly for customer interaction in the last few decades. Chatbots are defined as "Chatbots as machine conversation systems which use natural conversational language to interact with the users" [1] (p. 489). The web of information is an essential platform for accessing information and communication, and chatbots use this platform as knowledge sources while interacting with users. Recently, a new version of ChatGPT developed by OpenAI has gained immense popularity amongst early adopters and is viewed as disruptive [2]. For example, the ChatGPT is based on a transformer-based deep learning framework that uses language models for interacting with individual users in a way that closely resembles the natural intelligence of experts whose knowledge is captured through a large corpus of publicly available documents that has been used for training the model. Chatbots have tremendously improved customer experience regarding interaction flow, service quality, customer satisfaction, telepresence, interactive speed, and sensory appeal [3].

Artificial Intelligence (AI) chatbots are virtual assistants to users who simulate human conversations through text or voice commands [4]. AI simulates human conversations using Natural Language Processing (NLP) [5]. Developing indistinguishable chatbots from people has been a long-term goal [6]. Human-like texts can be produced and comprehended by ChatGPT with the support of NLP [2]. As conversational agents, chatbots aim to simulate interactions and furnish pertinent responses to user inquiries, while generative AI focuses on producing human-like content, such as text or speech [7]. For chatbots that appear human-like in their interactions, generative AI algorithms must be equipped with advanced natural language processing capabilities [8]. Investigating chatbots in the context of generative AI is crucial to understanding and advancing anthropomorphic qualities in human-computer interactions. The configurations of design elements of chatbots with sophisticated generative AI models contribute to exploring anthropomorphism in artificial systems, enabling us to develop more realistic and effective conversational agents.

In the era of Generative AI, chatbots have enabled technology to improve service automation for customer support and service tasks. Chatbots respond timely and efficiently to typical user inquiries [9]. In

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the case of financial services, Generative AI helps by processing data, recognizing patterns, predicting trends, and automating tasks [10]. Further, the healthcare industry employs generative AI to diagnose disease, personalize treatment, and analyze medical data [11]. Furthermore, generative AI optimizes the supply chain by demand forecasting inventory management, reduces disruptions, and enhances logistics [12].

In the case of chatbots, anthropomorphism is when people believe the chatbot to be a human or subconsciously expect human-like behavior from the chatbot [13]. The anthropomorphic chatbot can be deployed by using multiple cues such as a human name, photorealistic human avatar, artificial reading, typing delays, typing indicators, use of emojis, and verbal cues where the chatbot attempts to mimic human language patterns [13]. Using human-like cues in a chatbot is not to convince users they are talking to a human when they are not but to make them feel that the conversation is natural and comfortable [13]. Prior studies attested that customer experience could be enhanced using anthropomorphized chatbots. It helps build social connections, simulating emotional connections with anthropomorphized objects [13]. Anthropomorphism represents human personification, which helps the users perceive the technology intimately [14].

Cognitive absorption (CA) can be defined as “a state of deep involvement with the software” [15] (p. 665). CA is considered different from adoption as CA is an essential predictor for IT acceptance behavior, as it is a means to engage an individual in a task [15]. In contrast, adoption pertains to fully utilizing innovation as the most optimal available course of action [16]. Hence, CA involves mental engagement and immersion in a task, while adoption is embracing and integrating novel elements into one’s lifestyle. Regardless of the rapid incorporation of technology into service encounters, research on how user interaction with anthropomorphic chatbots affects CA is limited. CA is defined as “a state of deep involvement with the software” [15] (p. 665). CA is considered an essential predictor of IT acceptance behavior, as it is a means to engage an individual in a task [15].

We examined the salience of anthropomorphic cues in chatbots because organizations have pervasively utilized them to offer exceptional customer service. It provides an improved understanding of human-chatbot interactions that would benefit practitioners utilizing chatbots by assisting developers in enhancing CA.

Therefore, the characteristics identified in our study will help to develop a parsimonious model usable in practice while designing chatbots. The following research questions (RQ) are addressed in our study:

1. How do anthropomorphic and non-anthropomorphic chatbots impact the relationship between user and system characteristics with CA?
2. How do different system and user characteristics configurations influence chatbot users’ CA?

To answer these questions and to extend existing research, we intend to address the literature gaps surrounding (1) the de-conceptualization of the chatbot CA, we propose a model for *System and User Characteristics for Cognitive Absorption of Smart Technologies* (SUCCAST), (2) to examine the effect of anthropomorphic chatbots (compared to traditional non-anthropomorphic chatbots) on the relationship between the system and user characteristics of chatbots that which influence CA, and (3) to identify anthropomorphic chatbot (vs non-anthropomorphic chatbot) specific combinations of systems’ and users’ characteristics that lead to higher CA. Specifically, we draw on IS success model and cognitive absorption theory and examine the effect of an anthropomorphic chatbot consisting of human-like social cues, empathy, and personality on the relationship between system and user characteristics on CA.

The structure of this manuscript is organized in the following order: literature review, model development, research design, and data analysis, followed by discussion and conclusion of the study.

2. Background

We review the literature, divided into two subsections: the anthropomorphism of chatbots and the theoretical lens for the model development. The study has used the information success model and cognitive absorption theory to understand chatbot user CA in the service industry.

2.1. Anthropomorphism of chatbots

Chatbots are innovative customer service methods that provide virtual assistance without human involvement [17]. AI chatbots can outperform humans in different areas of intelligence, such as learning ability, information storage, and computing power [18]. For instance, ChatGPT provides technical customer support and financial advice [2].

Anthropomorphism refers to applying human-like qualities to the systems [19]. Anthropomorphism fulfills two crucial human needs, i.e., social connections and the need to understand and control the environment [20]. Prior research has seen digital agents as social actors, implying that interface designers can use social science ideas that control human-to-human interactions, such as courtesy, emotions, and greetings, to human-machine interactions [21]. Using humanization qualities, such as human-like social cues [22], human-like personality, and human-like empathy, help users consider technologies similar to humans. Human-like social cues include human-like names, avatars, and voices [22]. Human-like empathy highlights how customers perceive chatbots via individualized attention, caring, and understanding [23].

In the study by [24], users displayed significant social responses and viewed high degrees of social presence and anthropomorphism. Over time, researchers have dwelled more profoundly into anthropomorphic-enabled service chatbots’ role in developing users’ excitement and happiness [25]. Users interacting with non-human agents, like ChatGPT and Alexa, ascribe human-like traits to the systems [26]. Table 1 summarizes human-like characteristics associated with technology in general and extensions to chatbots.

2.2. Theoretical lenses on user experience chatbots

Chatbots are increasingly employed for customer service, where it has improved customer assistance methods by replacing human-human interactions with human-computer interactions [14]. Various kinds of research related to human-computer interaction, like psychological reactance due to digital assistants the social cues of conversational agents affect a sense of shared connection by the users [19]. Despite the findings, exploring this aspect has been limited to anthropomorphic chatbot’s impact on system and user characteristics and, subsequently, on chatbot users’ CA. Hence, the study is guided by information systems and human communication lenses to understand system and user characteristics. It helps connect the chatbot’s technical details with its

Table 1
Differences in chatbot’s characteristics.

Characteristics	General Technology	Chatbot-specific	Reference
Intelligence	Artificial Intelligence (AI)	AI-driven chatbot with NLP capabilities	[19]
Personalization	Customization for users	Understanding user needs and customizing response	[27]
Emotional response	Not inherently present	Simulated emotional response	[13]
Personality	Not inherently present	Simulated personality traits	[13]
Error recognition and recovery	Error handling mechanism	Identifying and correcting errors	[28]
Communication	Data transmission	Conversational abilities	[19]
Memory	Data storage	Remembering user preferences	[13]

behavioral aspects.

The proposed *SUCCAST model* is developed on the tenets of the information success model and cognitive absorption theory to explain chatbot user experience in the service industry. The model provides a comprehensive and multidimensional perspective to assess the success and impact of smart technologies. By examining system characteristics (IS success model) and user characteristics (cognitive absorption theory), researchers can gain a more holistic understanding of the effectiveness of smart technologies. The model is built upon system characteristics, which include information quality (IQ), system quality (SYQ), and service quality (SEQ), and user characteristics, including self-efficacy (SE) and personal innovativeness in the domain of information technology (PIIT). Its subsequent effect on CA on smart technologies.

Utilizing the IS success model and cognitive absorption theory in the context of smart technologies offers a unique and comprehensive approach to exploring these advanced systems' effectiveness, user experience, and psychological engagement. By combining these theoretical frameworks, researchers can better assess and design smart technologies that meet user needs and expectations, contributing to advancing these innovative solutions as done in previous literature (Table 2).

2.2.1. IS success model

The information systems success model comprised IQ, SYQ, user satisfaction, use, and individual and organizational impact as dependent variables [29]. Later, the model was updated, combining individual and organizational effects as a net benefit and introducing SEq. [30]. IQ and site design are critical for developing a satisfying customer experience [31]. Further, IQ, SEQ, and SYQ are inseparable in the context of AI chatbots [18]. It provides guidelines for system use and quality perspective. They have highlighted that the essential quality dimension is a pre-condition for user satisfaction, which is a narrow concept [32]. Hence, it is necessary to consider a user experience that considers a comprehensive approach.

2.2.2. Cognitive absorption theory

CA is a multidimensional construct synthesized from the psychological and social psychological dimensions [33]. It is referred to as an information technology's holistic experience. Five dimensions of CA: (1) focused immersion, (2) control, (3) curiosity, (4) temporal disassociation, and (5) focused immersion [15]. CA is a type of intrinsic motivator that simulates a feeling of gratification and pleasure [14]. SE and PIIT are individual characteristics that determine CA [33]. CA has gained much attention in recent years in exploring a user's technology adoption behavior. As a result, this study aims to broaden our understanding of CA in the context of human and system characteristics influencing chatbot CA in the service business.

Table 2
Domain-specific theoretical understanding.

Theory	Domain	Articles	Contribution
IS Success Model	Conversation Agent	[17]	• Integrates TAM and IS success model for investigating chatbot customer service
		[3]	• Service quality significantly impacts customer satisfaction • A customer looks towards IQ and its link with customer queries
		[34]	• Hedonic and utility gratification from virtual assistants
Cognitive Absorption Theory	Chatbots	[14]	• Human-machine interaction model • CA is a significant predictor of technology continuation intention
	IT usage	[32]	• CA positively affects utilitarian performance, hedonistic performance, expectation disconfirmation, and satisfaction
	Online Recommendation Agents	[35]	• Examines the design of recommendation agents for an online shopping experience

3. Model development

3.1. Chatbot type and IS success

IQ is essential for information system success [36]; AI chatbots provide relevant and accurate information to customers [3]. However, outdated, erroneous, or irrelevant information can negatively affect user experience [37]. The IQ impacts decision-making satisfaction [38]. SYQ includes adaptability, availability, usability, and reliability, which measure the service's technical success [29]. It is a system performance evaluation by the users during information delivery and satisfying user needs [39]. From a cognitive standpoint, information and SYQ positively relate to technology adoption [40].

Customer satisfaction is positively impacted by SEQ, leading to mobile value-added services continuance intention [41] and customer loyalty [42]. The studies have highlighted that IQ, SYQ, and SEQ play are crucial antecedents for user experience and system usage but have not explored linkages with the CA [43]. Hence, we hypothesize:

H1. The higher IQ a user perceives of a chatbot, the higher the user's experience of CA.

H2. The higher SYQ a user perceives of a chatbot, the higher the user's experience of CA.

H3. The higher SEQ a user perceives of a chatbot, the higher the user's experience of CA.

3.2. Chatbot type and self-efficacy (SE)

Chatbot features can limit or extend users' abilities, [44] attested that simple technology positively impacts user response. SE is one of the individual traits influencing the CA [33]. Higher SE reduces anxiety and positively influences computer usage [45]; however, lower SE can lead to customers quitting the platform [46]. SE significantly predicts the intention to use technology [47]. Hence, we hypothesized:

H4. SE is positively associated with the CA of the chatbot.

3.3. Chatbot type and personal innovativeness in the domain of information technology (PIIT)

PIIT is an individual's willingness to explore new technology regardless of others' experience [33]. Users desire an immediate and frictionless experience with the technology, where a chatbot can offer speed and convenience to users. Millennials use chatbots for a seamless and innovative digital experience [5]. Consumers with higher technology readiness can better use technology features with humanized experience [48]. Information systems researchers have highlighted that AI artifacts' characteristics like quality, innovativeness, and anthropomorphism can stimulate users' inference of AI artifacts competence perception [49] and can affect the CA [33]. Innovativeness is essential to predict non-user intentions to adopt new technologies [50]. Hence, we posit that:

H5. PIIT is positively associated with the CA of the chatbot.

3.4. Anthropomorphic and non-anthropomorphic Chatbot

Researchers and chatbot designers are striving to refine human-computer interactions.

[51] highlighted that anthropomorphism improves SEQ based on analytical learning, providing complete, objective, and detailed information [52]. Interactive technology stimulates a familiar shopping experience and enhances customer response [53]. Therefore, anthropomorphism is vital in fulfilling the aspiration for human contact during service experience.

The impact of anthropomorphism on CA is not uniform and can vary depending on other factors. For example, a highly anthropomorphic chatbot may evoke a stronger sense of CA in some users who find the human-like qualities appealing and relatable. On the other hand, users with prior experience with chatbots might be more aware of the agent's artificial nature and may not be as affected by anthropomorphism.

As a moderating variable, anthropomorphism interacts with other factors [54] in shaping the user's CA experience. Its influence is contingent upon the user's characteristics, familiarity with AI technologies, and the context in which the conversation occurs [55]. By considering anthropomorphism as a moderating variable, researchers can more accurately assess its impact on CA and better understand the complex interplay of factors contributing to user engagement. In light of the above, we pose the following hypothesizes:

H6. The structural relationship between (a)IQ, (b)SYQ, (c)SEQ, (d) SEQ, and (e) PIIT with CA are stronger for users using anthropomorphic chatbots than for users using non-anthropomorphic chatbots.

From the above hypothesis, we can present the conceptual model as follows (Fig. 1).

4. Complexity theory and research prepositions

Complexity theory postulates that different combinations of variables, routes, or configurations may result in the same result [56]. Additionally, different outcomes may result from combining the same condition of one element with a different condition of another factor. The equifinality principle, which underpins complexity theory, states that "outcomes of interest can equally be explained by alternative sets of causal conditions that combine in sufficient configurations for the outcome" [57].

This configurational method combines various causal circumstances to capture intricate interaction effects rather than isolating single causal factors to forecast a particular event. Therefore, we focus on the configurations of these causative circumstances and the individual causal conditions revealed in earlier hypotheses to forecast the final result variable (i.e., CA). Therefore, we provide the following claim:

P1. Multiple, equally effective configurations of causal factors result in a high level of CA for chatbot users.

5. Research design

The current study demonstrated the relevance of SUCCAST through the effects of anthropomorphic vs. non-anthropomorphic chatbots on the relationship between system and user characteristics on CA through a mixed research design. System and user characteristics are positioned based on the tenets of the information systems success model and cognitive absorption theory, respectively. Experimental research was employed to empirically investigate how anthropomorphic techniques embedded in chatbots would affect the relationship between system and user characteristics of CA. For the study, we developed two mock-up chatbots to understand the effect of anthropomorphic vs. non-anthropomorphic chatbots on the system and user characteristics of CA.

The analysis of the data involved a sequential application of two methodologies, namely partial least squares structural equation modeling (PLS-SEM) and fuzzy sets qualitative comparative analysis (fsQCA), depicted in Fig. 2. PLS-SEM is appropriate for our study as the key objective is to determine the critical structure (i.e., finding factors that influence CA on chatbot users) [58]. Further, it is relevant for complex research models [59]. Furthermore, formative and reflective constructs are also measured well by PLS-SEM [59] as CA [60] in our study.

As PLS-SEM is based on regression, it includes shortcomings such as causal symmetry and dependency on the global tets of model fit the data

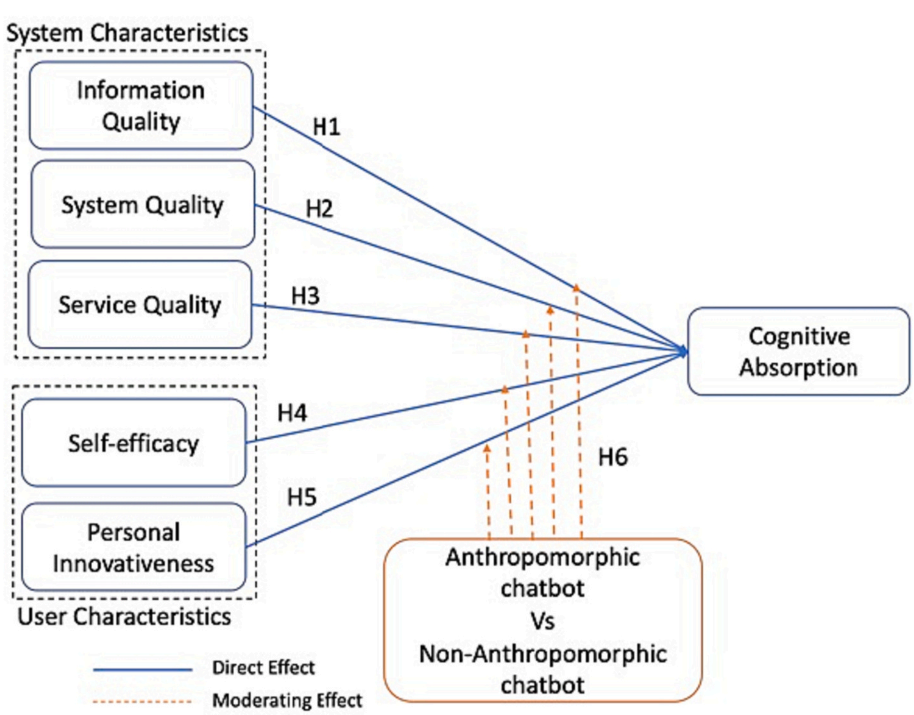


Fig. 1. Conceptual Model of SUCCAST

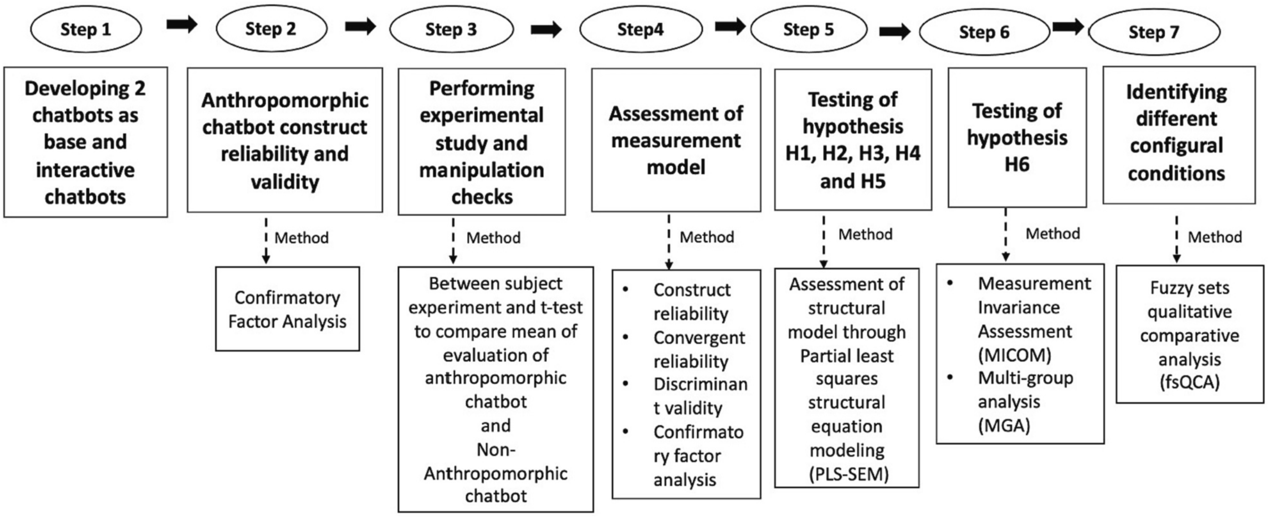
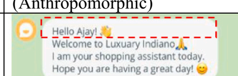
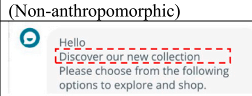
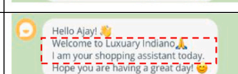
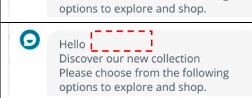
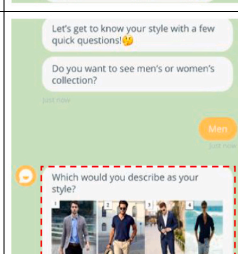
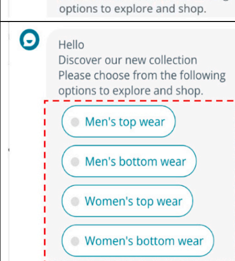
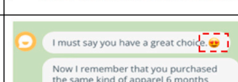
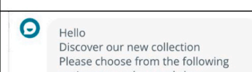
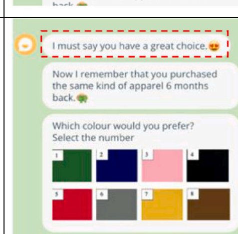
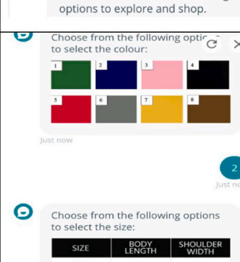
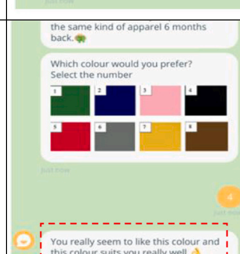
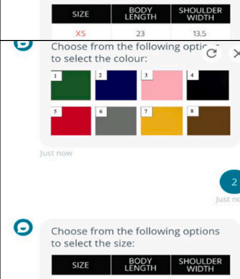


Fig. 2. Sequential approach for validation of the model.

Table 3
Humanization techniques applied to the chatbots.

Humanisation techniques	Interactive chatbot (Anthropomorphic)	Baseline chatbot (Non-anthropomorphic)
A. Addressing users by name		
B. Self-Introduction		
C. Personalised Recommendation		
D. Using Emoticons		
E. Display of Appreciation		
F. Varied Response		

[61]. Subsequently, fsQCA was used in the study to provide deeper insights into PLS-SEM results. As per the set-theoretic approach, fsQCA investigates the overall effect of exogenous variables on the outcome and highlights the causal linkages between the variables [62]. It examines the model in equifinality, causal asymmetry, and conjectural causation [63].

The complementarity between PLS-SEM and fsQCA arises from their ability to address different aspects of research questions and data characteristics. PLS-SEM is well-suited for hypothesis testing and exploring linear relationships between latent constructs, while FSQCA excels in capturing complex causal configurations and non-linear relationships amongst conditions. Further, integrating PLS-SEM and FSQCA encourages a more holistic research approach. Researchers can gain deeper insights into complex research problems by combining qualitative and quantitative perspectives. Integrating PLS-SEM and FSQCA in research fosters a synergetic relationship that enriches understanding of complex phenomena. These two methodologies combine the advantages of variable and case analysis [64], investigating the net effect of system and user characteristics and identifying the configurations that lead to higher CA. This multi-method study helps to provide practical insights.

5.1. Anthropomorphic chatbot vs non-anthropomorphic chatbot

In this study, we developed and deployed two distinct iterations of a chatbot to understand the influence of anthropomorphism on users' CA within an online shopping context. We built the chatbots by using an online platform, Collect.Chat to help users shop for apparel. The chatbots were hosted in Collect.Chat in an experimental setting for an fictitious e-commerce platform called "Luxury Indiano". The two types of chatbot designs were an anthropomorphic, i.e., interactive chatbot, and a non-anthropomorphic, i.e., baseline chatbot. The interactive design included six specific humanization strategies.

In this context, anthropomorphism refers to chatbots' underlying expectation of human-like behaviors. There were no observable human-like social cues, personality traits, or empathetic responses from the baseline chatbot that acted as the control. The six techniques used for humanization are as follows: 1) chatbot self-introduction, 2) engaging with the users by their name, 3) use of emoticons, 4) varied responses, 5) display of appreciation, and 6) personalized recommendation. These humanization strategies are integrated from current studies to accomplish the CA impression [19,65]–[69].

Table 3 provides examples of sample conversations obtained from the baseline and interactive chatbot versions to illustrate the effectiveness of various humanization tactics. This comparative example explains the various effects of these strategies on user-chatbot interactions and how those effects affect users' CA.

Table 3 (a) demonstrates that the chatbot anthropomorphically addressed the participant by name (e.g., "Ajay"). In contrast, the non-anthropomorphic chatbot used broad phrases (for example, "You"). Table 3 (b) illustrates that the anthropomorphic chatbot introduced itself as a shopping assistant at the start of the interaction. In contrast, the non-anthropomorphic chatbot delivered a short introduction focused on assisting. Third, in Table 3 (c), the anthropomorphic chatbot tried to provide personalized recommendations where the chatbot presented a few pictures to understand the user's style preference. A predefined list containing different style options is created for the anthropomorphic chatbot. However, the non-anthropomorphic chatbot offered generalized suggestions that did not include personal information shared by the user earlier.

Table 3 (d) Fourth, the anthropomorphic chatbot used appropriate emoticons in its messages, while the non-anthropomorphic chatbot employs a text-based communication devoid of emoticons. Fifth, in Table 3 (e), the anthropomorphic chatbot appreciates the users, such as "I must say, you have great taste; this would look great". In contrast, the non-anthropomorphic chatbot follows a transactional and non-emotive communication pattern. Finally, Table 3 (f) shows that anthropomorphic chatbots used varied responses, such as offering users save or purchase options. The save option would help the user save the product in their wish list, and in case of purchases, the user can purchase the product. However, the non-anthropomorphic chatbot provides more standardized and restricted alternatives in the responses.

5.2. Participants and stimulus

In study 1, we conducted an experimental investigation to examine the influence of human-like features of chatbots on system characteristics and user characteristics on CA. In this study, 285 practitioners from 87 organizations participated in a twelve-month program conducted at the Indian Institute of Technology, Delhi, about digital transformation and digital marketing represented the sample. Working professionals involved in designing and implementing marketing automation in their organizations participated in the experiment. The program participants were chosen from over 1300 candidates based on the relevance of their work experience, academic background, and online interviews conducted by a different faculty team. We collected data in December 2021.

The chatbots were assigned to participants at random, namely (1) anthropomorphic chatbot ($n = 145$) and (2) non-anthropomorphic chatbot ($n = 140$). We told the participants to "use the assigned chatbot to place an order for apparel for yourself." Specifically, we mentioned to the participants that the two chatbots are different based on six parameters, i.e., 1) chatbot self-introduction, 2) engaging with the users by their name, 3) use of emoticons, 4) varied responses, 5) display of appreciation, and 6) personalized recommendation. After completing the shopping session, subjects answered an online questionnaire about their experience with the chatbot. We controlled the total time spent to reduce time bias and did not allow interaction between participants to reduce social desirability bias. The participants had 10 min to complete the experiment and 30 min to respond to a questionnaire. Data analysis was performed through this sample, including descriptive statistics, confirmatory analysis, manipulation check, PLS-SEM, and fsQCA.

5.3. Measurement

Online questionnaires were used for data collection. Each item was evaluated using a five-point Likert scale. Items for IQ, SYQ, and SEQ are adapted from [70]. Three items measured SE adapted from [71]. PIIT is evaluated by the items obtained from [15]. Items for CA are adapted from [14].

The anthropomorphic chatbot was assigned the value of 1, whereas, for non-anthropomorphic chatbots, 0 was assigned. Details of the questionnaire instrument and associated measurement items are outlined in detail in the appendix (A1).

6. Data analysis

6.1. Participants profile and descriptive statistical analysis

There were a total of 285 participants across 87 organizations in our sample. A detailed demographic characteristic has been discussed in Table 4.

Table 4
Sample's demographic characteristics.

Variables	Characteristics	Count	Percentage
Gender	Male	201	73.68
	Female	84	26.11
Age Group	23–30	195	68.42
	31–55	90	31.58
Education Qualification	Graduation	109	38.25
	Post-graduation	137	48.07
	PhD	39	13.68

6.2. Confirmatory factor analysis (CFA) for anthropomorphism

The CFA was performed using SPSS 19 to check the reliability and validity of all the items of anthropomorphism for further data analysis, i.e., manipulation check. As per the results, the factor loadings were above 0.06, commonality was >0.5, KMO was >0.5, cumulative explained >60%, and the eigenvalue was >1. Also, Cronbach's alpha was >0.6, and the item-to-item correlation was >0.5. The results are in table appendix (A2).

6.3. Manipulation checks

We performed manipulation checks to ensure the scenario was realistic; it was a between-subject experiment with 74 subjects randomly assigned to the chatbot to complete the assigned task (37 subjects were assigned anthropomorphic chatbot, and 37 others were assigned non-anthropomorphic chatbot). We then measured anthropomorphism through human-like social cues [22], human-like personality [13], and human-like empathy [23]. The *t*-test revealed a statistically significant difference in human-like social cues between anthropomorphic chatbots (mean = 2.7) and non-anthropomorphic chatbots (mean = 5.87), $p < 0.05$. Secondly, in the case of human-like personality between anthropomorphic chatbot (mean = 2.69) and non-anthropomorphic chatbot (mean = 5.77), $p < 0.05$. Lastly, in the case of human-like empathy between anthropomorphic chatbot (mean = 3.97) and non-anthropomorphic chatbot (mean = 6.05), $p < 0.05$. Thus, it highlights that there is a significant difference between the participants. As a result, it can be concluded that there is an influence of anthropomorphism on the perception of chatbots.

6.4. PLS-SEM

6.4.1. Measurement model analysis

All reliability and validity measurements met the threshold values. Items loadings were >0.5. Cronbach's alpha and composite reliability are >0.50. AVE readings are also over 0.50. As a result, the item and construct reliability and validity metrics are validated, appendix (A1).

According to the Fornell-Larcker criterion, the square root of each construct's AVE is greater than its highest correlation with other constructs, showing that the variables have discriminant validity (Appendix A3). Moreover, discriminant validity is demonstrated because all Heterotrait-monotrait (HTMT) latent variable pairs are smaller than 1.00 [72] (Appendix A4).

We accessed the chances of common method bias between the latent variables; the partial least square method was used for the multi-collinearity analysis, and the values of the variables ranged between 1.218 and 2.416, i.e., below 5 thresholds [73]. The test attested to the absence of common method bias. Hence, we moved to the structural model.

6.4.2. Structural model analysis

PLS-SEM structural model analysis uses significance levels and path coefficients for model testing. To verify the reliability of the results, the pathways' relevance is assessed using *p*-values generated from a bootstrap study of 5000 subsamples. The predictability of our model was determined using the R-square (R2) value. R2 values of 0.75, 0.50, or 0.25 are considered significant, moderate, or weak in IS and marketing studies, respectively [74].

Table 4 summarizes our findings of the structural model, including path coefficients and t-values. R^2 highlights the explained variance in the model for the dependent variable. Our complete model accounts for 50.9% of the variation in CA using the full sample. In the case of the non-anthropomorphic chatbot model, R^2 accounts for 53.8%, and in the case of the anthropomorphic chatbot, R^2 accounts for 52.8% (Fig. 3) of the variation in CA. To test the model fit the acceptable SRMR (Standardized Root Mean Squared Residual) cutoff value for PLS path models is 0.08 [72] to test the model fit. As a result, this investigation's SRMR value of 0.067 indicates that the model fit condition has been met. Using the entire sample, the Q2 values computed by the blind-folding process explain the predictive relevance of the structural model. The amount of the q2 effect assesses an exogenous construct's contribution to the Q2 values of an endogenous latent variable. We used PLS predict-based analysis, and the results showed that Q2 was >0 (Q2 predict >0).

We accepted H1, thus indicating that IQ is positively associated with user CA during chatbot usage ($p < 0.005$). Further, we rejected H2, indicating SYQ is not positively associated with CA ($p > 0.005$). Furthermore, accepted H3 suggests a positive association between SEQ and CA ($p < 0.05$). H4 was accepted, suggesting that SE is positively associated with CA ($p < 0.05$). Finally, H5 was rejected; there was no positive association between PIIT and CA ($p > 0.05$) (Table 5). H6 was

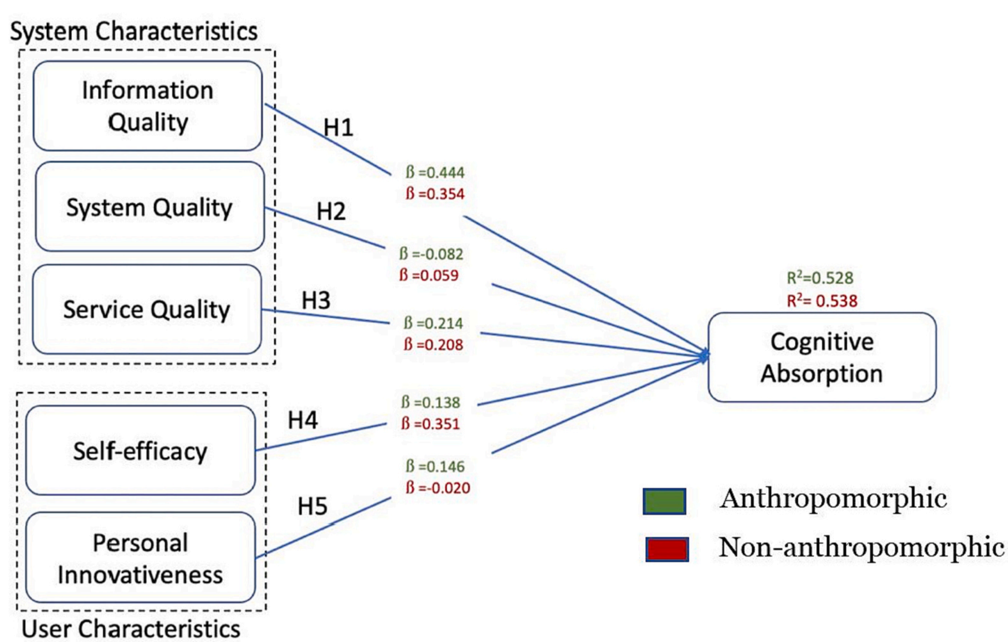


Fig. 3. Anthropomorphic and Non-anthropomorphic chatbot structural model.

Table 5
Hypotheses testing.

Hypothesis	Path Coefficient	t-values	Results
H1: IQ➔CA	0.417	9.285	Supported
H2:SYQ➔ CA	−0.022	0.410	Not Supported
H3:SEQ➔CA	0.204	3.560	Supported
H4: SE➔CA	0.232	5.153	Supported
H5:PIIT➔CA	0.071	1.188	Not Supported

tested using multigroup analysis.

6.4.3. Multigroup analysis (MGA)

MGA was conducted, as described by [75], with two groups: non-anthropomorphic chatbot users and anthropomorphic chatbot users. It is divided into two stages: a) calculation of invariances using the MICOM (Measurement Invariance Assessment) procedure, which ensures that potential variations are due to the moderating variable rather than the potential differences in each group's measurement model, and b) PLS-MGA analysis, the multigroup analysis for considering the moderating effect of anthropomorphic vs non-anthropomorphic chatbots between system and user characteristics.

The MICOM procedure to access the invariance of the measurement model. It consists of three steps: (1) configurational invariance assessment; (2) correlation values assessment; as C (correlation values) values did not differ significantly from 1, we proceeded with step 3; (3) confidence intervals based on mean value and variance permutations, determining if the mean value is composite and differentiating between group variance. The MICOM results are presented in Table 6. These results are essential to reveal partial or full measurement invariance. The results established full invariance, supporting group-specific comparisons [76].

Table 5 illustrates MGA results using Henseler's bootstrap-based MGA [76]. One out of five paths was significantly different between anthropomorphic and non-anthropomorphic chatbots. There was a significant difference between anthropomorphic and non-anthropomorphic chatbots for SYQ on CA (Hanseler's p value = 0.020). Hence, accepting H6b. However, no significant structural path difference exists between non-anthropomorphic and anthropomorphic chatbots on IQ, SEQ, SYQ, and PIIT on CA ($p > 0.005$). Therefore, hypothesis H6a, H6c, H6d, and H6e were rejected.

Although some structural model path differences between non-anthropomorphic and anthropomorphic chatbots were identified (Table 7), statistical models for both chatbots are similar. As a result, PLS-SEM provides limited insights into the factors of chatbot users' CA.

6.5. FsQCA

PLS-SEM results highlighted that the CA of a chatbot user is not dependent on a single factor; instead, it depends on the interactive relationship between IQ, SYQ, SEQ, SE, and PIIT. FSQCA offers detailed and richer insights into different configurations that can contribute to higher CA. Hence, we employed fsQCA to access the necessary and sufficient conditions for the outcome (CA) for non-anthropomorphic and anthropomorphic chatbots. For fsQCA, we calibrated fuzzy set memberships based on 95th, 50th' and 5th percentiles for full-set membership, cross-over, and full-set non-membership, respectively [77].

We tested the following model:

$$CA_{non-anthropomorphic\ chatbot} = f\ (IQ, SYQ, SEQ, SE, PIIT) \tag{1}$$

$$CA_{anthropomorphic\ chatbot} = f\ (IQ, SYQ, SEQ, SE, PIIT) \tag{2}$$

6.5.1. Necessary conditions

We then conducted the necessary condition analysis for CA of non-anthropomorphic and anthropomorphic chatbots, as shown in Table 8.

6.5.2. Sufficient condition

Sufficient conditions were identified for the CA of anthropomorphic and non-anthropomorphic chatbots. Our first step towards obtaining sufficient conditions was generating a truth table. All five conditions, i.e., IQ, SEQ, SYQ, SE, and PIIT, were listed in the truth table and their possible combinations for obtaining the output. The truth table had 285 possible combinations listed in the rows. We sorted the column 'number' in decreasing order and selected a threshold of 1; we deleted all combinations lesser than the threshold [78]. Next, we sorted the column 'raw consistency' in decreasing order and considered a threshold of 0.8; we attempted to identify the solution sets [63]. In both the outcome columns (CAcv) for anthropomorphic and non-anthropomorphic chatbots, firstly, we assigned '0' to the combinations below our raw consistency threshold of 0.8. Next, we considered qualitative breakpoints in the raw consistency column and considered values depicting qualitative breakpoints as statistically insignificant [79]. We also assigned a value of 0 to these combinations. We marked the rest of the combinations of the conditions with 1. These combinations represented the presence of the solution, whereas combinations marked with 0 represented the absence of the solution. Then, we proceeded with the command' standard analyses' to generate the complex, parsimonious, and intermediate solution sets. For fsQCA results interpretation, we used the intermediate solution set [77], Table 9.

6.5.3. Results

The preceding study highlighted the limitations of PLS-SEM, with QCA discovering numerous anthropomorphism and non-anthropomorphism-specific combinations that promote higher CA. Analyzing the results of PLS-SEM and fsQCA enables us to make several interpretations, illustrating the role of fsQCA in providing deeper insights. Table 10 represents a comparison of PLS-SEM and FSQCA.

The analysis highlighted the shortcomings of PLS-SEM, with QCA discovering various anthropomorphism and non-anthropomorphism combinations that facilitate effective CA (Table 10). The results highlighted three solutions for non-anthropomorphic chatbots and two for anthropomorphic chatbots. The solution coverage for CA of non-anthropomorphic chatbots is 0.9087 (0.8415 for anthropomorphic chatbots). FsQCA allows researchers to explore the possible attribute (e.g., IQ, SYQ, SEQ, SE, PIIT) combinations leading to the same outcome (high CA) [62]. The approach to equifinality enables the researchers to

Table 6
Results of MICOM.

Construct	Step 1	Step 2		Step 3		Full measurement invariance
	Configurational variance	C = 1	Partial Invariance	Mean value Difference	variances Difference	
CA	Yes	0.999	Yes	−0.088	0.298	Yes
IQ	Yes	0.999	Yes	0.015	0.217	Yes
SYQ	Yes	0.993	Yes	0.025	0.158	Yes
SEQ	Yes	0.999	Yes	0.035	0.425	Yes
SE	Yes	0.994	Yes	−0.138	0.219	Yes
PIIT	Yes	0.991	Yes	−0.083	0.252	Yes

Table 7
Moderating effect of anthropomorphism (non-anthropomorphism chatbot).

Hypothesis	anthropomorphic chatbot (140)		Non-anthropomorphic chatbot (145)		Multigroup Analysis		
	Path test ß	t	Path test β	t	Difference of ß	p	Result
H6a: IQ➔CA	0.444	7.250	0.354	5.035	0.090	0.336	Not Supported
H6b:SYQ➔ CA	−0.082	1.046	0.059	1.010	−0.141	0.147	Not Supported
H6c:SEQ➔CA	0.214	2.439	0.208	2.732	0.006	0.957	Not Supported
H6d: SE➔CA	0.138	2.570	0.351	4.768	−0.213	0.020	Supported
H6e:PIIT➔CA	0.146	1.603	−0.020	0.276	0.166	0.154	Not Supported

(Based on t(5000), two tail test) $p < 0.05$,

Table 8
Necessary conditions.

Conditions tested	Non-anthropomorphic chatbot		Anthropomorphic chatbot	
	Consistency	Coverage	Consistency	Coverage
IQ	0.992	0.895	0.990	0.887
~IQ	0.061	0.848	0.055	0.668
SE	0.955	0.896	0.947	0.877
~SE	0.099	0.873	0.108	0.906
SYQ	0.941	0.922	0.890	0.883
~SYQ	0.140	0.875	0.180	0.937
PIIT	0.919	0.903	0.892	0.806
~PIIT	0.140	0.862	0.176	0.805
SEQ	0.919	0.919	0.920	0.920
~SEQ	0.151	0.855	0.149	0.749

capture real-life phenomena and their complexities for a deeper understanding of the variables of interest [80]. Table 9 highlights sufficient conditions for the CA of non-anthropomorphic and anthropomorphic chatbots.

For non-anthropomorphic chatbots, solution 1a highlighted that users can experience higher CA when non-anthropomorphic chatbots have higher IQ, SEQ, SE, and PIIT; however, they exhibit insignificant SYQ. 2a solution highlights that users experience higher CA when non-anthropomorphic chatbots have higher IQ, SYQ, SEQ, and SE. Under these conditions, PIIT was not significant. Lastly, in solution 3a, the user experiences higher CA when a non-anthropomorphic chatbot exhibits higher IQ, SYQ, SE, and PIIT; however, non-significant SEQ.

The following two solutions emerged in the case of an anthropomorphic chatbot. Solution 1b informed us that users can experience higher CA when anthropomorphic chatbots have high IQ, SYQ, SEQ, and SE. Under these conditions, PIIT was not significant. Solution 2b shows that users experience higher CA when anthropomorphic chatbots have higher IQ, SYQ, SE, and PIIT. SEQ is not significant under these conditions.

7. Discussion

In this digital era, organizations consider chatbots a critical element of customer service. [81] highlighted that chatbots offer individual attention to the users and enable brand and user interaction in case of customer support. Users have also been using chatbots not only as an information source but as a tool to be asked to complete a task, like ChatGPT.

Fewer studies prove that system and user characteristics are essential to improve user CA; however, our research contributes to the literature by conducting a configurational study of causal conditions that lead to the same. This contribution fills the gap of reflecting one particular pattern of causes. It brings into the picture all combinations of causes that can lead to the outcome, in our case, achieving higher CA for anthropomorphic and non-anthropomorphic chatbots.

PLS-SEM findings outlined that both anthropomorphic and non-anthropomorphic outlined IQ SEQ and SE have a significant relationship with CA. However, SYQ and PIIT have a non-significant relationship with CA. However, our QCA outcomes offer rich evidence of anthropomorphic and non-anthropomorphic chatbots, concluding that no single recipe exists for effective CA. As per the solution of causal

Table 10
Comparison of PLS-SEM and fsQCA findings.

Method		Non Anthropomorphism		Anthropomorphism	
		PLS-SEM	fsQCA	PLS-SEM	fsQCA
Solutions Model Strength		1 solution Moderate r^2 (0.538)	3 solutions Substantial Coverage (0.90)	1 solution Moderate r^2 (0.528)	2 solution Substantial Coverage (0.84)
CA Antecedents	IQ	Significant	3 solutions	Significant	2 solution
	SYQ	Non-Significant	2 solutions	Non-Significant	2 solution
	SEQ	Significant	2 solutions	Significant	1 solution
	SE	Significant	3 solutions	Significant	2 solution
	PIIT	Non-Significant	2 solutions	Non-Significant	1 solution

Table 9
Configurations for cognitive absorption (CA).

		Cognitive Absorption: Non-Anthropomorphic Chatbot			Cognitive Absorption: Anthropomorphic chatbot	
		1a	2a	3a	1b	2b
System Characteristics	Information quality (IQ)	•	•	•	•	•
	Service quality (SEQ)	•	•		•	
	System quality (SYQ)		•	•	•	•
User Characteristics	Self-efficacy (SE)	•	•	•	•	•
	Personal innovativeness in the domain of information technology (PIIT)	•		•		•
	Consistency	0.9385	0.9478	0.9455	0.9371	0.9511
	Raw Coverage	0.8565	0.8596	0.8608	0.8220	0.7911
	Unique Coverage	0.0223	0.0254	0.0267	0.0503	0.0194
	Solution Coverage	0.9087			0.8415	
	Solution Consistency	0.9299			0.9325	

Note: Black circles suggest the presence of a condition; empty circles suggest the absence. Frequency cutoff: 1.

conditions, the presence of IQ, SEQ, and SE can be observed in most of the solutions to obtain non-anthropomorphism and anthropomorphism, respectively, supporting the results yielded through the SEM analysis. However, the partial presence of SYQ for non-anthropomorphism chatbots and PIIT for both anthropomorphism and non-anthropomorphism chatbots in the solution configurations further complements the fact that the relations of SYQ and PIIT to attain the outcomes were rendered non-significant in the PLS-SEM findings. A literature review was conducted to explore the theoretical reasoning using existing theories to understand service-based chatbots enabled by anthropomorphism.

7.1. Theoretical contribution

Chatbot design literature is still growing within information systems [13]. With many industrial innovations in technologies like Generative AI, the behavioral dimensions of chatbots are poised to gain significance in the coming decade [82]. Past studies have validated that well-designed, integrated technologies [83] are vital in strengthening the relationship with the users. However, reviews indicate that the design of chatbots is under-explored in existing literature [84].

In this context, the first contribution to this research comes from the complex configurations of conditions of user and system attributes that lead to CA. This study follows a deductive research approach and develops a conceptual model based on theoretical foundations [85]. Factors indicative of outcomes, such as user behavior or experiences in Information Systems (IS), are conceived of as interconnected structures rather than isolated entities in the context of configurational approaches [86]. FsQCA emerges as a versatile analytical method capable of accommodating inductive, deductive, and abductive types of theorizing [87]. Our methodology employs fsQCA, chosen for its capacity to unearth intricate causal conditions that may influence the CA of chatbot users [88]. FsQCA is a complementary analysis approach to the traditional variance-based approach, i.e., SEM, as it helps overcome the limitations of the variance-based approach. SEM is generally used to evaluate and model the association between variables in a hypothesis-driven way. FsQCA, on the other hand, is a qualitative method focused on identifying necessary and sufficient conditions to explain the outcome [89].

In detail, the findings reveal that to achieve CA in a chatbot with anthropomorphic characteristics, IQ, SYQ, SE, and PIIT form complex configurational conditions that lead to the outcome. On the other hand, to achieve the same for a non-anthropomorphic chatbot, the presence of IQ, SEQ, SYQ, and SE plays the most crucial role. The findings are in line with the configurational and complexity theories of fsqca, different configurations of causal conditions exist in achieving CA for anthropomorphic and non-anthropomorphic chatbots, and no single best combination of configurations exists. However, multiple combinations of causal conditions lead to yielding the same.

Second, this study makes a novel theoretical contribution by developing the SUCCAST model, a parsimonious model drawn from the information technology literature. SUCCAST has been developed by synthesizing two established frameworks, the IS success model [30] and CA theory [15], to elucidate the intricate dynamics underlying user engagement with technology. Our study amalgamates these two established theories, a path less trodden in existing literature. This innovative amalgamation extends the theoretical boundaries of both frameworks and offers a holistic lens for comprehending the interplay between human cognition, system attributes, and technology assimilation. Such pioneering insights offered by SUCCAST hold substantial implications for designing user-centric technological interfaces and optimizing user engagement in industries aiming for effective human-computer interaction.

Third, this study finds that respondents preferring anthropomorphic and non-anthropomorphic behavior from chatbots require different psychological and behavioral patterns for higher CA. Specifically, IQ and SE have a significantly stronger effect on respondents interacting with a non-anthropomorphic chatbot. In contrast, IQ, SYQ, and SE significantly influence respondents interacting with anthropomorphic chatbots. Hence, this study addresses the gap in the literature by supporting the argument [90] that non-anthropomorphism and anthropomorphism play a moderating role in the CA of working professionals involved in designing and implementing marketing automation in their organizations.

7.2. Managerial implications

Organizations can develop chatbots in three ways, i.e., (1) by developing chatbots by themselves, (2) by purchasing the chatbots from IT firms that specialize in them, and (3) by using social media chatbots for their platforms [18]. Hence, there are three stakeholders: (1) chatbot developers, (2) organizations that use chatbots, and (3) end users. By analyzing PLS-SEM and fsQCA, this study provides significant findings for all three stakeholders, highlighting different requirements or objectives that may exist at the stakeholders' end [91]. It focuses on an important design element, i.e., anthropomorphism for higher CA.

First, for chatbot designers, effective development surpasses algorithmic intricacies. Product development managers are essential in seamlessly merging system attributes with user-centric qualities, fostering enhanced CA. Here, the introduction of anthropomorphic AI chatbots, integrating human-like social cues, personality, and empathy, is a critical facet to be integrated. This managerial insight underscores the pressing need to harmonize technological advancements with a profound grasp of user behaviors, culminating in chatbot creations that transcend functional utility, enriching the user experience.

Second, in organizations deploying chatbots to replace human customer service, the functional managers must ensure that anthropomorphic chatbots can help achieve business goals, especially for less technologically innovative employees. This study focuses on the different levels of CA, measured by factors such as focused immersion, control, curiosity, temporal dissociation, and focused immersion. Based on our findings, the organization should choose the anthropomorphic chatbot, i.e., solution 2b (consistency = 0.9511), focusing on IQ, SYQ, SE, and PIIT. However, if the organization employs a non-anthropomorphic chatbot, they should instead opt for solution 2a (consistency = 0.9478), which focuses on IQ, SEQ, SYQ, and SE. The presence or absence of PIIT does not impact the CA of non-anthropomorphic chatbot users. In this case, a non-anthropomorphic chatbot with lower PIIT amongst users can help the organization with higher CA; however, higher PIIT amongst users would lead to higher CA in the case of the anthropomorphic chatbot, which is evident from our solution 2b. The findings highlighted that the level of CA is most strongly associated with chatbot interactions, including focused immersion, control, curiosity, and temporal dissociation. Leveraging users' elevated PIIT levels enhances platform interest and satisfaction, warranting personalized features. Adopting anthropomorphic chatbots ensures efficient, engaging services, fostering ease and emotional connection. Such design aligns with tech-savvy users' preferences, potentially driving profits through heightened engagement, satisfaction, and social presence.

Last, for users, anthropomorphic chatbots are designed to replicate human-like cues, personality, and empathy, offering end users heightened emotional connection, reliability, and positive system evaluations. They foster familiarity, streamline interactions, and drive holistic engagement, enriching user experiences and forging lasting relationships while aligning with organizational objectives.

7.3. Limitation and future research

As identified in this study, certain constraints will guide future research inquiries. First, the study has limited humanization techniques; future studies can use more humanization techniques to assess chatbot

CA. Second, research endeavors should investigate additional system and user characteristics in the domain of information technology that can impact CA. Lastly, the scenario considered for this study was limited to shopping; other scenarios can also be considered for understanding effective CA.

8. Conclusion

This research delved into the impact of integrating anthropomorphic methods into the design of a chatbot on users' CA. We employed an experimental study to explain the concept of CA through PLS-SEM and fsQCA. Each application of chatbots likely has its own goal, creating different considerations for design. Specifically, we outlined the optimal solutions based on the highest consistency. For non-anthropomorphic chatbots, information quality, service quality, system quality, and self-efficacy contribute to a high level of CA amongst chatbot users. In the case of an anthropomorphic chatbot, information quality, system quality, self-efficacy, and personal innovativeness in information technology contribute to a higher level of CA amongst chatbot users. These results showcase how minor enhancements in chatbot anthropomorphic abilities can enhance perceptions of chatbots, reshape human-computer interactions, and provide a foundation for future studies exploring gradual enhancements of supplementary features to enhance human likeness and engagement.

CRediT authorship contribution statement

Shagun Sarraf: Methodology, Validation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization. **Arpan Kumar Kar:** Conceptualization, Methodology, Validation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing. **Marijn Janssen:** Conceptualization, Writing – original draft, Writing – review & editing.

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.

The authors declare that generative AI was not used in the writing of the paper.

The authors declare that the work submitted has not been published previously or is under consideration for publication elsewhere.

Data availability

Data will be made available on request.

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- The author have no conflict of interests to declare.

Appendix

A1:

Table: Construct results of the measurement model.

Measures	Item Loading
Information Quality (α = 0.806, CR = 0.886, AVE = 0.723) [70]	
IQ1: The chatbot provides accurate information on the item that I want to purchase.	0.785
IQ2 This chatbot provides reliable information.	0.874
IQ3 This chatbot provides sufficient information when I try to make a transaction.	0.888
Service Quality (α = 0.845, CR = 0.890, AVE = 0.619) [70]	
SEQ1 This Chatbot provides dependable services	0.699
SEQ2 This Chatbot provides services at the times	0.758
SEQ3 This chatbot gives prompt service	0.877
SEQ4 This chatbot is responsive to user's request	0.781
SEQ5 This Chatbot is designed to satisfy the needs of the users	0.806
System Quality (α = 0.789, CR = 0.877, AVE = 0.705) [70]	
SYQ1: This chatbot is easy to use.	0.865
SYQ2: The chatbot is user friendly.	0.776
SYQ3: I find it easy to get this chatbot to do what I wanted to do.	0.875
Self-Efficacy) (α = 0.732, CR = 0.849, AVE = 0.653) [71]	
SE1: I feel comfortable using the chatbot on my own.	0.878
SE2: I can easily operate the chatbot on my own.	0.761
SE3: I feel comfortable using the chatbot even there is no one around me to tell me how to use it.	0.780
Personal innovativeness in the domain of information technology (α = 0.819, CR = 0.883, AVE = 0.658) [15]	
PIIT1: If I hear about new technology, I would look forward to experiment with it.	0.897
PIIT2: Generally, I am hesitant to try out new technologies. (reversed)	0.910
PIIT3: Amongst my peers, I am usually the first to try out new technology.	0.762
PIIT4: I like to experiment with new technologies.	0.648
Cognitive Absorption (α = 0.952, CR = 0.959, AVE = 0.663) [14]	0.508
Temporal Disassociation	
CA1: Time appears to go by very quickly during the chatbot interaction.	0.772
CA2: Sometimes I lose track of time when I interact during service queries.	0.873
Focused Immersion	
CA3: While involved in the chatbot, I am absorbed in what I am doing.	0.839
CA4: During the chatbot interaction, I am immersed in the task I am performing.	0.802
Heightened Enjoyment	
CA5: I have fun during the chatbot interaction.	0.879
CA6: The interaction provides me with a lot of enjoyment.	0.774
CA8: The chatbot interaction excites my curiosity.	0.884

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(*continued*)

Measures	Item Loading
CA9: The chatbot interaction makes me curious.	0.855
CA10: The chatbot interaction arouses my imagination.	0.869
Control	
CA11: I feel that I have no control during my chatbot interactions. (reversed)	0.903
CA12: The chatbot allow me to control my interaction.	0.7733

A2:

Table: CFA Results.

Constructs	Items	Factor Loading	Eigen Value	Cumulative explained	Item to total Correlation	Cronbach's Alpha	Reference
Human-like Social cue	SC2	0.940	2.751	91.68	0.966	0.983	[16]
	SC1	0.923			0.954		
	SC3	0.750			0. 847		
Human-like Personality	P4	0.946	3.605	90.116	0.942	0.963	
	P1	0.916			0.913		
	P2	0.887			0.899		
	P3	0.870			0.942		
Human-like empathy	E1	0.958	5.562	92.694	0.959	0.984	
	E2	0.939			0.949		
	E3	0.920			0.945		
	E4	0.882			0.928		
	E5	0.908			0.958		
	E6	0.891			0.937		

A3:

Table: Fornell-Larcker Criterion.

	CA	IQ	PIIT	SE	SEQ	SYQ
CA	0.814					
IQ	0.620	0.850				
PIIT	0.456	0.391	0.811			
SE	0.450	0.258	0.421	0.808		
SEQ	0.587	0.594	0.634	0.425	0.786	
SYQ	0.250	0.248	0.239	0.307	0.390	0.840

A4:

Table: HTMT ratio of correlations.

	CA	IQ	PIIT	SE	SEQ	SYQ
CA						
IQ	0.699					
PIIT	0.504	0.468				
SE	0.541	0.338	0.549			
SEQ	0.645	0.712	0.751	0.541		
SYQ	0.288	0.309	0.290	0.399	0.471	

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