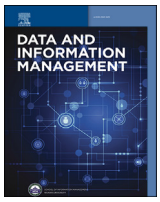
Data and Information Management 7 (2023) 100047

Contents lists available at ScienceDirect

Data and Information Management

journal homepage: www.journals.elsevier.com/data-and-information-management



Understanding the joint effects of internal and external anthropomorphic cues of intelligent customer service bot on user satisfaction

Yuxin Hu [a], Yongqiang Sun [b,*]

[a] Antai College of Economics & Management, Shanghai Jiao Tong University, Shanghai, China
[b] School of Information Management, Wuhan University, Wuhan, Hubei, China

ARTICLE INFO

Keywords:
Intelligent customer service bot
Anthropomorphism
Virtual appearance
Empathy
Customer satisfaction

ABSTRACT

As one specific type of chatbot, Intelligent Customer Service Bot (ICSB) satisfies users by providing uninterrupted customer service and reducing response time. However, users still prefer to interact with humans rather than robots. In previous studies, scholars have focused more on enhancing the anthropomorphic characteristics of chatbot by treating anthropomorphic characteristics as a general concept. Few literatures have studied the influence of both external and internal features on user satisfaction and the possible interactive effects between the two dimensions of chatbot anthropomorphic cues. Therefore, this paper studies the main effects of internal anthropomorphic constructs (cognitive empathy and emotional empathy) and external anthropomorphic constructs (virtual appearance) of ICSB on user satisfaction, as well as the two-way and three-way interaction effects among them. With a scenario-based survey of 331 respondents, the results confirm the hypotheses about the main effects, the two-way and three-way interaction effects in the model.

1. Introduction

With the development of information technology, chatbots, as one outcome of artificial intelligence, have been widely used in people's daily life. Chatbots are able to provide information to users, interact with users as personal assistants, and even satisfy a variety of user needs during the conversation (M. Chung, Ko, Joung, & Kim, 2020; Holzwarth, Janiszewski, & Neumann, 2006). Intelligent customer service bot (ICSB), as one specific type of chatbot, not only provides corresponding information for users, but also interacts with users in a human-like way, which are important factors to improve customer satisfaction (Radziwill & Benton, 2017).

Customer satisfaction with ICSB is a primary determinant of user acceptance and continuous intention of ICSB, however, the user acceptance and continuous intention to use is still relatively low (Ashfaq, Yun, Yu, & Loureiro, 2020). A survey conducted by Forbes in 2019 reveals that 87% of customers prefer communicate with real-human service instead of chatbot[1] because they believe human can understand and satisfy them better. Therefore, it's of great significance to investigate the influencing factors of user satisfaction with ICSB. The anthropomorphism of ICSB plays an important role in user satisfaction with ICSB, for the reason that more users still prefer to interact with humans rather than robots (Ashfaq et al., 2020). Therefore, researchers try to facilitate chatbots to be more human-like. With the development of cutting edge of technologies, the intelligence of chatbot has been updated and iterated with breakthroughs, achieving a qualitative leap for the improvement of the service of ICSB. For example, a chatbot named Ralph in Christmas sales had a distinct personality and provided an enjoyable experience for users. Thus, Ralph played a significant role in generating 25% of sales from social media and reduced the cost per conversion by over 70%.[2] Moreover, ChatGPT, developed by OpenAI, is a deep learning-based language model that has quickly gained popularity in the field of intelligent customer service. Within two months of its launch, ChatGPT has accumulated over 30 million users, with a daily visit volume of approximately 5 million times, which makes it one of the fastest-growing software products.[3] ChatGPT's ability to generate high-quality, human-like responses to user inquiries has been a key factor in its success, as it has significantly improved the conversational interaction performance of intelligent customer service and increased user satisfaction and loyalty (Peres, Schreier, Schweidel, & Sorescu, 2023).

* Corresponding author.
E-mail addresses: jojo_magic_adventure@sjtu.edu.cn (Y. Hu), sunyq@whu.edu.cn (Y. Sun).

[1] https://www.forbes.com/sites/gilpress/2019/11/25/ai-stats-news-chatbots-increase-sales-by-67-but-87-of-consumers-prefer-humans/.
[2] https://gettalkative.com/info/ecommerce-chatbot.
[3] https://www.demandsage.com/chatgpt-statistics/.

https://doi.org/10.1016/j.dim.2023.100047
Received 17 February 2023; Received in revised form 27 July 2023; Accepted 30 July 2023

Based on the existing literature review, on the one hand, scholars' research is more focused on how to use technology to enhance the anthropomorphic features and the corresponding performance and evaluation of chatbots. The pervasiveness of machine learning and deep learning techniques results in significant advancements in the development and deployment of ICSB with human-like characteristics. Whereas they fail to consider the influence of those anthropomorphic characteristics on user satisfaction in an empirical research dimension. For example, McTear, Callejas, and Griol (2016) constructed the overall architecture of chatbots. Zhao et al. (2019), Tran and Luong (2020), Aleedy, Shaiba, and Bezbradica (2019) and other scholars applied NLP (Natural Language Processing), NLU (Natural Language Understanding), NLG (Natural Language Generation) and other technologies for word segmentation and semantic analysis. In addition, the application of sequence-to-sequence (Seq2Seq) technology and deep learning methods (Suhaili, Salim, & Jambli, 2021) enables chatbots to generate responses based on user information more accurately and intelligently. The application of these technologies can greatly improve the intelligence of chatbots. However, the mechanism about the influence of some anthropomorphic characteristics (such as the characteristics facilitating cognitive empathy) of ICSBs on user satisfaction has not been well studied so far. Therefore, this paper tries to investigate the determinants of user satisfaction from the perspective of chatbot algorithm (e.g., retrieval-based mode versus generative mode).

On the other hand, the existing literature has studied the influence of some of the chatbot's anthropomorphic features on user experience from empirical dimensions, such as the perception of users' emotions or the visual expression, can increase user experience. However, they rarely connect the relationship between specific technologies of ICSB application and user behavior, exploring the impact of specific technologies of application on user satisfaction and user experience. To be specific, Rhim, Kwak, Gong, and Gweon (2022) designed a more humanized chatbot based on the study of the interactive experience between chatbots and users and chatbot's perception of users' emotions. Go and Sundar (2019) found that chatbots with information interaction and visual cues can improve user expectations and interactivity based on the research of human-computer interaction. Compared with the intelligent improvement by technology, these anthropomorphic cues to ICSBs pay more attention to the enhancement of user experience, such as emotional empathy of chatbots, helping the user to obtain a more satisfying service experience.

Therefore, empathy is a key factor in determining the success of information systems in terms of performance improvement brought by technology (Gao, Waechter, & Bai, 2015; Teo, Srivastava, & Jiang, 2008; Veeramootoo, Nunkoo, & Dwivedi, 2018). Besides, in terms of user experience, empathy is a key factor to improve customer satisfaction and continuous innovation, especially in the context of technology (Choi, Wang, & Sparks, 2019; Hong, Thong, & Tam, 2006; Thong, Hong, & Tam, 2006). The easier and more pleasant a service is to use, the more positive customers' attitude towards it. Therefore, empathy serves as an important internal cue to determine the performance conditions of ICSB and effect on user behavior. Hence, this study introduces the cognitive empathy and the emotional empathy together, which constitutes the anthropomorphic internal cues of ICSB. The existing literature studied little about the possible relationship of each specific anthropomorphic internal cues of ICSB on the user satisfaction. According to the dual-process theory (Heuristic-Systematic Model, HSM), cognitive empathy follows the central route, while emotional empathy follows the peripheral route and there may exist a substitution effect between the two empathies, with both meeting users' needs for empathy (Chaiken, 1989; Zhang & Watts, 2008). ICSB's high cognitive empathy satisfies users' demands for service quality, reducing the need for emotional empathy (Cheung, Lee, & Rabjohn, 2008; Cyr, Head, Lim, & Stibe, 2018). As a result, cognitive empathy compensates for the impact of emotional empathy on user satisfaction, resulting in a negative synergistic effect between the two. (Chen & Chaiken, 1999; Petty & Cacioppo, 1986; Sun, Wang, Shen, & Zhang, 2019). Hence, this paper studies the possible interaction effects of cognitive empathy and emotional empathy on user satisfaction.

On the one hand, external anthropomorphic features, such as virtual appearance, are directly associated and displayed with ICSBs through visual cues (such as real person avatars) and unique identity names, which can enhance users' perception of human identity of ICSBs. On the other hand, internal anthropomorphic features, such as cognitive empathy and emotional empathy, enable ICSBs to better understand the conversation, perceive users' emotions more accurately, and respond to them based on previous information, improving users' satisfaction with services.

Additionally, the potential interactive effects between these dimensions of chatbot anthropomorphic cues on user experience remain unexplored in the existing research. Anthropomorphic cues can evoke human schemas when they involve visual cues (e.g., virtual appearance) and linguistic cues (e.g., cognitive empathy, emotional empathy) (Epley, Waytz, & Cacioppo, 2007; Guthrie, 1995; X. Zhou, Kim, & Wang, 2019), which can influence user behavior patterns and attitudes. ICSB with a real person appearance is more likely to trigger the heuristic path and suppress systematic path, requiring high levels of emotional empathy and cognitive empathy to meet user expectations. Therefore, the effect between cognitive empathy and emotional empathy is more significant. In contrast, a robot appearance ICSB has lower user expectations, resulting in an insignificant effect between cognitive empathy and emotional empathy, leading to a negative interaction effect. Based on this, it can lead us to explore a three-way interaction role about the influence of virtual appearance, emotional empathy and cognitive empathy on user satisfaction. Hence, this paper investigates the joint impacts of the external and internal anthropomorphic dimension of ICSB on user satisfaction.

Therefore, based on the existing research of the mechanism of chatbots on user satisfaction, this study carries out the research of three specific variables of the cognitive empathy and emotional empathy, as the internal anthropomorphic cues, and the virtual appearance, as external anthropomorphic cues of ICSB and studies the mechanism and possible interaction effect of the three variables on user satisfaction. By constructing an empirical research based on scenario experiment, this paper verifies the existence of the two-way and three-way interaction effects between the three variables on user satisfaction.

2. Literature review and theoretical background

2.1. Anthropomorphic cues of intelligent customer service bot

Chatbot is a human-machine conversation system, applying natural conversational language to interact with human users (Shawar & Atwell, 2005), which is also defined as "an artificial device that uses natural language as input and output to communicate with people" (Brennan, 2006). ICSB, as one type of the chatbot, is one of the outcomes of the development of artificial intelligence, big data, information communication and other technologies, as well as the update and iteration between different robot entities and intelligent systems.

Anthropomorphism refers to some anthropomorphic attributes, emotions, and characteristics (such as personality, verbal and non-verbal behavior, politeness, etc.) endowing to non-human entities (such as computers) (Nass & Moon, 2000). These characteristics enable ICSB look more like human service agents which may affect the efficiency of user interaction. The anthropomorphic design of ICSB can help it serve users better and enable users' Q&A experience more humanized (Bridges & Florsheim, 2008; Gefen & Straub, 2004; Kohler, Fueller, Stieger, & Matzler, 2011). Based on the literature review in the fields of human-computer interaction, service marketing, etc., this research divides the anthropomorphism of ICSB into two dimensions: external and internal anthropomorphic cues. Among them, internal cues include **emotional empathy** (Go & Sundar, 2019; Rhim et al., 2022) and **cognitive empathy** (Suhaili et al., 2021), while external cues refer to **virtual appearance** (Go & Sundar, 2019).

2.2. Cognitive empathy

Cognitive empathy means that ICSBs are able to make an accurate and clear cognition of user's semantic environment information. Then they can provide users' expected responses or actions based on the correct understanding of the user's intentions (Corvello, Pantano, & Tavernise, 2011; Suhaili et al., 2021). The realization of cognitive empathy requires the algorithm technology of chatbots. The core concept of design is that the chatbot can provide accurate responses according to user requests. A successful chatbot has the ability to understand and follow the information provided by the user, and then retrieve the necessary information and respond accurately. Therefore the user perceives the conversation as a conversation with almost any other human being (Suhaili et al., 2021). Researchers keep improving chatbot development technology, trying to find the most suitable solution for satisfying both users and service providers (Suhaili et al., 2021). From the technical perspective, ICSB can be divided into **retrieval-based mode** and **generative mode** according to different response mode (Chou & Hsueh, 2019; Khurana, Agarwal, Shroff, & Vig, 2018; Wu, Li, Wu, & Zhou, 2018; L. Yang et al., 2019; M. Yang et al., 2017).

Retrieval-based chatbots typically respond based on the retrieval technologies. Firstly, they retrieve in a pre-built database of conversation storage in order to select the response that best matches the user's request (Bartl & Spanakis, 2017; Wang et al., 2019). Since the response is pre-set, there will not contain syntax errors in the database (Yan et al., 2018). This is the most basic intelligence a chatbot possesses which means it is simple in design. Whereas, this type of chatbot is limited by its capabilities and cannot be used in scenarios involving advanced queries because it is difficult to collect sufficient response data in the database in practical scenarios, especially in some intersecting or multiple domains (Suhaili et al., 2021). In addition, since the retrieval is simply performed according to the user's request, the retrieval-based chatbot will ask and answer with the user in a one round question-and-answer (Q&A) way, without the ability to contact the context to comprehensively give a more "humanized" response. Thus, it is an answering program based on the pattern matching technology.

The generative model is based on machine translation technology that applies a sequence-to-sequence (Seq2Seq) model. The operation mode of generative chatbots is to convert the input into an output response and autonomously generates the response verbatim after training a large amount of data (Serban, Sordoni, Bengio, Courville, & Pineau, 2016). Such chatbots are also known as AI chatbots because of their human-like capabilities and their flexible properties. Thus, they are able to work in a variety of domains because it can learn from a large amount of interaction data. Accordingly, the generative ICSB possesses a more complex architecture and more expensive cost. Instead of searching for the best match between requests and responses as the retrieval-based chatbot operates, the generative ICSB will generate the correct response based on the correct understanding of the request semantics which usually goes through multiple rounds of interaction and belongs to a task-oriented pattern.

Based on the research on cognitive empathy of retrieval-based mode and generative mode, this paper sorts out the differences between these two cognitive empathy levels in Table 1.

Table 1
Differences between high and low cognitive empathy of ICSB.

	RETRIEVAL-BASED MODE	GENERATIVE MODE
RESPONSE MODE	Getting available responses from predefined datasets	Generating a new response verbatim from a specific request
APPLIED TECHNOLOGY	Pattern matching	Machine learning and deep learning
DEGREE OF RESPONSE STRUCTURE	Highly structured	Non-structured
INTERACTION ROUND	Single round	Multiple round
INTERACTION	Inability to contextualize	Being able to contextualize
TASK TYPE	Q&A	Task-oriented
LEVEL OF INTELLIGENCE	Low	High

2.3. Emotional empathy

Emotional empathy, as the second internal anthropomorphic cue, refers to the degree to which the ICSB can perceive users emotion and respond accordingly in the service perceived the user (Corvello et al., 2011). An important dimension of emotional empathy is the degree to which the ICSB can perceive and respond to users' real-time emotions. Humans are inherently social, and people achieve satisfaction in social connection, whereas non-human subjects can also satisfy people's need for social connection by exhibiting human-like characteristics (Epley et al., 2007). ICSB can identify and judge users' emotions through the information or instructions input by them. Then it will give corresponding feedback accordingly, thus the response achieves empathic results. The other dimension is interactivity, which refers to the responsiveness and ability of continuous dialogue demonstrated by ICSB in the process of communicating with users (Corvello et al., 2011). When two people are talking, if one of them not only acknowledges the other's information, but also responds to the message based on the previous content, the dialogue will follow an extended run-through pattern and can be considered as fully interactive. This interaction will enable the online chat agent seem like human, as it mimics the contingency in message exchanges between human interactors (Go & Sundar, 2019).

The two dimensions of emotional empathy take users' emotion as the core. The chatbot is intended to perceive the user's emotion and respond and interact during the service. On the one hand, if the ICSB perceives dissatisfaction of the user and negative emotions such as anger and anger are expressed in the service, it will appease and adjust response strategy, trying to return users' emotion to the positive range. On the other hand, when users' emotions are perceived as positive emotions such as happiness, affirmation, approval, etc., then the ICSB will go along with them to keep their emotion positive. Thus, emotional empathy can be achieved, thereby providing a better user service experience.

2.4. Virtual appearance

Virtual appearance of ICSB is regarded as the external anthropomorphic cue, including two dimensions. The first dimension is anthropomorphic visual cues. In nature, people classify each other according to different aspects, such as their physical characteristics (Argyle, 1988). Thus, the visual image of the chatbot's appearance is an important feature to consider when designing an interface (Appel, von der Pütten, Krämer, & Gratch, 2012). Appel et al. (2012) emphasizes the importance of the proper design of chatbots as their appearance will affect user interaction and perception. Therefore, by creating embodiments of chatbots, it is possible to make up for the lack of social presence in virtual environments (Raunio, 2021). Real human images give the chatbot a human-like virtual appearance. Such visual cue can play a strong suggestive role, in addition to shaping the user's social cognition. Thus, the ICSB can be inspired towards a more "human" aspect (Sundar, 2008), which in turn causes users to regard chat agents as human beings and socialize with them (Baylor & Kim, 2003; Gong & Nass, 2007; Y. Kim & Sundar, 2012; Kristine L. Nowak, 2017). The reason is attributed to mindlessness, priming and over-attribution, etc. (J. Kim, 2010; Lee & Oh, 2015).

The second dimension of virtual appearance refers to the assignment of identity to ICSB, because people tend to perceive things through labels. Users tend to use the main attributes on labels when making judgments or forming impressions of others in order to minimize cognitive effort (Ashforth & Humphrey, 1997; Gelman & Heyman, 1999). Tversky and Kahneman (1974) also explained that individual users tend to estimate

from initial values. According to the Modality-Agency-Interactivity-Navigability (MAIN) model, if a user is informed whether the chat agent with whom he is talking is a real person or a robot, it may cause the user's heuristic thinking on the comparison of machines and humans related to the anthropomorphic perception. This theory argues that interface cues shape user perceptions by triggering cognitive heuristics about the nature and substance of interactions (Sundar, 2008). If a chat agent is considered as a chatbot, users are more likely to evaluate the quality of its performance based on their previous perceptions of the chatbot (Go & Sundar, 2019).

2.5. Dual-process theories

Dual process theory refers to the individual's process of processing, evaluating, and reaching decision-making outcomes in response to information. ELM (elaboration likelihood mode) and HSM (heuristic-systematic model) are the most classic models in the dual process theory and both explain individuals' information processing strategies with similar mechanisms. Among them, the theory of HSM can explain a wider range of information processing activities (Zhang & Watts, 2008). Additionally, HSM has more theoretical expansions (Chaiken, 1989). Thus, this study references the article of Zhang and Watts (2008) and adopts HSM as the main model.

According to the HSM, systematic processing refers to an individual using high level of cognitive effort to evaluate information and form a decision, while heuristic processing refers to an individual using heuristics and simple decision rules to form a quick judgment of the information, corresponding to the central route and peripheral route in ELM respectively. Therefore, systematic processing takes priority over heuristic processing. Based on the sufficiency principle, when individuals possess sufficient motivation and ability, they will make decisions through systematic processing, otherwise, the peripheral route will be activated (Chen & Chaiken, 1999; Petty & Cacioppo, 1986; Sun et al., 2019).

In this study, cognitive empathy serves as the systematic route because cognitive empathy of ICSB performs the quality of information through accurate understanding of semantics and generative responses provided by ICSB (Cheung et al., 2008). Whereas, the peripheral cue differs from cognitive empathy which is not related to the information or questions inputted by the user, but rather to the emotional issues experienced by users in the current context (Cyr et al., 2018). Therefore, this study adopts emotional empathy as the peripheral route. Besides, virtual appearance can serve as a cue to trigger two paths (Cheung et al., 2008), the real person appearance ICSB is more likely to trigger the peripheral path and suppress the central path.

3. Research model and hypotheses

3.1. Research model

Based on the literature review, this research constructs the following research model (see Fig. 1). Firstly, the model considers cognitive empathy, emotional empathy and virtual appearance as independent variables, user satisfaction as dependent variable. Then, this model introduces interaction effect between cognitive empathy and virtual appearance, emotional empathy and virtual appearance and cognitive empathy and emotional empathy respectively. Finally, this model proposes the tripartite interaction of the three independent variables. As a consequence, this paper constructs the research model of the influence of anthropomorphic cues of ICSB on user satisfaction.

3.2. The effect of cognitive empathy on user satisfaction

The generative mode and the retrieval-based mode are corresponding to the high versus low levels of cognitive empathy. Specifically, the generative ICSB is able to learn and utilize the current interaction

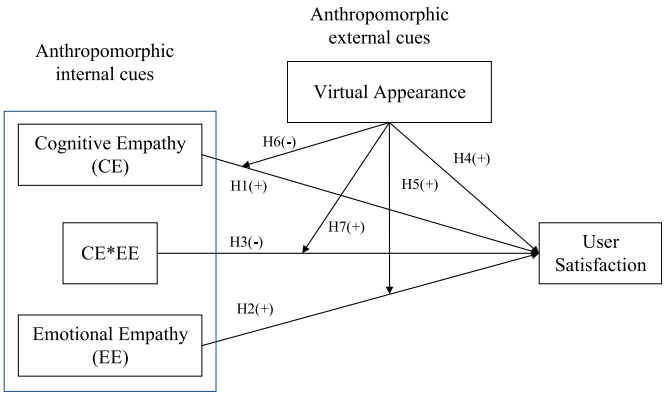


Fig. 1. Research model.

information. Then, it will match the correct response according to the correct understanding of the request semantics which usually will experience multiple rounds of interaction. Therefore, the generative ICSB is more likely to provide more accurate, relevant and sufficient information, that is, to provide higher information quality (Gao et al., 2015), the ICSB can grasp and satisfy cognitive empathy more accurately for the reason that obtaining sufficiently accurate and reliable information is decisive for user satisfaction (Teo et al., 2008; Veeramootoo et al., 2018).

In contrast, the retrieval-based ICCB searches according to the keywords and returns a fixed content template, thus it has a smaller probability of providing the requested information to users and its flexibility and usability will be limited (Suhaili et al., 2021), resulting in poor service information quality. Users may need to look for other sources to find information, which will require them to spend more time and effort (Gao et al., 2015). Thus, users may think it is difficult for the ICSB to truly understand their intentions, thereby reducing their satisfaction. Therefore, we propose that:

H1. Cognitive empathy can positively affect user satisfaction such that user satisfaction will be higher for the generative mode than for the retrieval-based mode.

3.3. The effect of emotional empathy on user satisfaction

When the ICSB possesses high level of emotional empathy, on the one hand, it is equipped with higher empathy for that they can perceive and respond to user emotions. Users may consider the ICSB “more open, more serious, more outgoing, more agreeable, and more self-disclosed” (Mou & Xu, 2017), thus they will perceive the conversation as more natural (Appel et al., 2012; Klopfenstein, Delpriori, Malatini, & Bogliolo, 2017). On the other hand, the ICSB with high emotional empathy has higher interactivity. The pattern of message interaction enables the ICSB like a human because it can respond to messages in a back-and-forth way based on the previous content. Thus, the quality of this service is more likely to satisfy the user, exerting a positive impact on the user's satisfaction (N. Chung & Kwon, 2009; Roca, Chiu, & Martínez, 2006; Veeramootoo et al., 2018).

Besides, ICSB with low level of emotional empathy is unable to sense users' emotion and respond to them timely and correctly. Therefore, users’ satisfaction with this service will be seriously reduced. Based on this, this paper proposes the second hypothesis.

H2. Emotional empathy can positively affect user satisfaction.

According to the dual-process theory (HSM), cognitive empathy performs the central route or the systematic route and emotional empathy performs the peripheral route or the heuristic route. When the user forms a high expectation of the ICSB's service quality as a human customer service, the individual will adopt the central route cognitive empathy, while the peripheral route emotional empathy will be used

when the expectation is at low level. The two empathies constitute a relation of substitution effect (Sun et al., 2019). Specifically, both cognitive empathy and emotional empathy can meet the user's needs for empathy. ICSB with high level of cognitive empathy can understand users' intention and provide corresponding responses accurately and clearly. Thus, their high level of users' empathy cognition, interactive and intelligent analysis capability are able to satisfy users' demand for service quality. At this time, the demand for emotional empathy dimension has decreased, thus cognitive empathy alleviates the effect of emotional empathy on user satisfaction. Therefore, there is a substitution effect, or negative synergistic effects, between cognitive empathy and emotional empathy. Thus, we propose:

H3. The effect of emotional empathy of ICSB on user satisfaction is stronger for the retrieval-based mode compared to the generative mode.

3.4. The effect of virtual appearance on user satisfaction

When ICSB possesses high anthropomorphic virtual appearance (such as a real person image), users have a stronger feeling of interacting with a real person (Y. Kim & Sundar, 2012), because the added real human image can make users feel like they are in touch with people (Cyr, Head, Larios, & Pan, 2009). In addition, users' perceived homophily is also enhanced (Rocca & McCroskey, 1999). Therefore, compared with a low anthropomorphic virtual appearance (such as an image composed of lines), the presence of a "human" image attached to the ICSB can imply the user's perception of another person's presence during the interaction process (Go & Sundar, 2019). Secondly, ICSB given an identity, such as a human name or an identity label, enables users to form more perceptions of them for the reason that users tend to use the primary attributes on labels when making judgments or forming impressions of others to minimize cognitive effort (Ashforth & Humphrey, 1997; Gelman & Heyman, 1999).

Therefore, considering the two dimensions of virtual appearance, it can be suggested that ICSB with high anthropomorphic level of virtual appearance can lead users to perceive and psychologically suggest their identity as human beings. Moreover, users will trust them and be more willing to interact with them. Thus, virtual appearance of ICSB can positively affect user satisfaction.

H4. User satisfaction of ICSB with human appearance is higher than that of robot appearance.

According to the HSM, VA (Virtual Appearance) can serve as a cue to trigger both the systematic route CE (Cognitive Empathy) and the heuristic route EE (Emotional Empathy) (Cheung et al., 2008). Specifically, when VA is human, Users are more inclined to consider that the person they are talking with is a real person with identity, corresponding their identity to their virtual appearance image and name labels. Thus, users naturally assume that the customer service agent they are communicating with is equipped with the ability of emotional empathy. At this time, when ICSB also has high emotional empathy, they possess high level of interactivity and empathy, which helps them better understand and respond to users. On the contrary, ICSB with low level of emotional empathy cannot provide users with emotional value feedback and interaction, which is contrary to the user's expectations for the ICSB, enabling users' dissatisfaction increase.

When the ICSB bears robot appearance, users have almost no expectation to the ICSB for the reason that they know they are not communicating with a real person. They do not need to interact empathically with chatbots. Thus, the impact of emotional empathy of ICSB on users' satisfaction has been alleviated with robot appearance. Therefore, we propose:

H5. The effect of emotional empathy of ICSB on user satisfaction is stronger for the real person appearance compared to the robot appearance.

The interaction effect between virtual appearance and cognitive empathy can be inferred from the perspective of central route. When ICSB has high cognitive empathy, it can understand users' intentions more accurately and generate new response in order to meet or solve users' needs, meeting users' expectations of real human customer service. While, the retrieval-based ICSB is unable to meet the expectation of users from a real customer service, intensifying users' dissatisfaction.

On the contrary, if the virtual appearance of ICSB is at a low anthropomorphic level, users have almost no expectation of human communication with the ICSB. Thus, there is no need for accurate understanding and personalized interaction manifested by the chatbot. However, if ICSB demonstrates excellent accuracy in capturing users' intentions and generating a response based on the user's needs, the resulting satisfactory answer or solution completes the service perfectly and exceeds the user's original expectations, providing the user with a level of satisfaction beyond their expectations. As a result, when it comes to the robot appearance of ICSB, the effect of cognitive empathy on user satisfaction gets enhanced in fact. Thus, ICSB with robot appearance is referred to trigger the central route, and the effect of negative synergy is greater than that of positive synergy according to the HSM. This leads to Hypothesis 6.

H6. The effect of cognitive empathy on user satisfaction is stronger for the robot appearance compared to the real person appearance.

Anthropomorphic cues can evoke human schemas when they involve visual cues (e.g., virtual appearance) and linguistic cues (e.g., cognitive empathy, emotional empathy) (Epley et al., 2007; Guthrie, 1995; X. Zhou et al., 2019), which can influence user behavior patterns and attitudes. Based on this, it can lead us to introduce a three-way interaction role about the influence of virtual appearance, emotional empathy and cognitive empathy on user satisfaction.

Based on the assumptions, it can be inferred that the ICSB with real person appearance is more likely to trigger heuristic path and suppress systematic path. When ICSB bears real person appearance, users' perception of real human services reaches high level. In this scenario, more personalized and accurate answers from generative ICSB and a high level of emotional empathy are expected from users. Thus, the requirement of high anthropomorphic level of cognitive empathy and emotional empathy is essential to ICSB in order to satisfy users and perception. Therefore, the effect between CE and EE is more significant, which leads to a more significant two-way interaction effect between CE and EE.

Conversely, for a robot appearance ICSB, users have lower expectations for a human-like service. As a result, due to the comparatively lower expectations and demands for the service quality, the effect between CE and EE is insignificant which leads to a negative interaction effect between CE and EE. Thus, we propose:

H7. There is a three-way interaction effect between virtual appearance, emotional empathy and cognitive empathy on user satisfaction such that the interaction effect between emotional empathy and cognitive empathy is stronger for the real person appearance compared to the robot appearance.

4. Research method

4.1. Scenario design

This study conducts a scenario-based experiment and designs a questionnaire to collect data. In the scenario design part, this research focuses the ICSB on a specific field of after-sales service, which is specifically set in the routers after-sales field. The scenario assumes that there is a problem with the WIFI when the customer uses the router at home after purchasing this router. Therefore, the user enters the router brand App, searching for after-sales consultation. Then he or she has a conversation with the online after-sales ICSB of the router about solving the problem of WIFI router.

Based on the previous literature, eight (i.e., 2*2*2) sets of scenarios simulating the dialogue between a ICSB and a user are set up based on the high and low levels of the three independent variables "virtual appearance", "emotional empathy" and "cognitive empathy". The two categories of virtual appearance are set as the robot avatar and real person avatar; the two levels of emotional empathy are set as high emotional empathy and low emotional empathy; the two categories of cognitive empathy are set as the retrieval-based and generative ICSB, which corresponds to low and high level of cognitive empathy. The specific settings of different independent variables are described with the following details.

4.1.1. Manipulation of virtual appearance

This study followed the method of manipulating anthropomorphic visual cues used in previous studies, such as Cyr et al. (2009); Y. Kim and Sundar (2012) and so on. To be specific, this study sets the virtual appearance of ICSB with a high anthropomorphic visual cue as a picture of an actual person, while the virtual appearance of online ICSB with a low anthropomorphic visual cue as an avatar composed of lines, where the graphic is set as a robot silhouette graphic. The user is constantly exposed to its visual cues while conversing with the ICSB. Thus, the virtual appearance of the ICSB is always displayed.

In addition, in the dimension of identity, the ICSB with high anthropomorphic visual cue is attached to a human name to increase the identity label. The specific operation is to give the ICSB a human name and the name will be displayed next to the avatar all the time when the user interacts with the ICSB. Besides, the ICSB will introduce itself to the user upon entering the interface to increase the user's perception of its anthropomorphic nature (Rhim et al., 2022).

4.1.2. Manipulation of emotional empathy

Based on previous literature, emotional empathy as the anthropomorphic cues for ICSB covers two dimensions, which are designed in terms of interactivity and empathy.

The purpose of the design in the interactivity dimension is to reflect the responsiveness and the ability to sustain a conversation demonstrated by the ICSB during communication with the user (Corvello et al., 2011), in other words, the ability of the ICSB to respond to the content of the user's conversation so that the user perceives that the ICSB can understand their thoughts and responds to them. The methods used are: (1) addressing the user by name when talking to them; (2) responding in conjunction with the content of the previous conversation, as measured by partially repeating the user's response (Go & Sundar, 2019; Sannon, Stoll, DiFranzo, Jung, & Bazarova, 2020).

In terms of the empathy dimension, ICSB with high empathy is able to perceive and judge the consumer's emotions and respond accordingly. This approach can establish rapport with the conversation partner. The specific manipulation is the ICSB perceiving and responding to the user's emotions.

4.1.3. Manipulation of cognitive empathy

ICSB can be classified into retrieval-based and generative models according to the cognitive method (Chou & Hsueh, 2019; Khurana et al., 2018; Wu et al., 2018; L. Yang et al., 2019; M. Yang et al., 2017).

Firstly, the responses of retrieval-based ICSB (1) have highly structured response templates without grammatical errors, (2) return responses based on keyword retrieval, and the response content is not changed, and (3) the response content completes the task within one round.

Secondly, the responses of generative ICSB (1) uses unstructured response content which can be varied instead of being fixed; (2) generates responses based on the word sequence relationship in sentences, and the response content is changed according to the utterance; (3) the response content is carried out in multiple rounds to complete the task.

The specific scenario manipulation setting for different levels of three anthropomorphic cues are detailed in Table 2.

4.2. Measurement of variables

Based on the previous literature review, this paper carried out the measurement questions. The scale reference of questionnaire design is shown in Table 3.

4.3. Data collection

This research organizes the measurement scale and the scenario design into a questionnaire for data collection. The questionnaire items are measured on a 7-point Likert scale. Respondents could score the items according to their own understanding of the scale, where 1–7 are divided into seven levels from completely negative to completely positive, and the fourth level is neutral.

The content of the questionnaire consists of the following three parts: introduction of situational information, basic information of the respondents and the main scale. The first part is the introduction of the scenario. The second part is the basic user information, consisting of the age, gender, professional knowledge background, education received and other aspects of respondents. The third part is the main scale of the questionnaire. The scale sets a random scenario from 1 to 8 at first. The user is supposed to brows the random scenario article and then responded to measurement scale of each variable separately.

A total of 391 questionnaires were collected from several universities. To ensure the validity of the research data, all questions in the questionnaire were selected as compulsory. Besides, the questionnaire could be submitted only after the user had answered all questions, thus avoiding the existence of missing data. After a manual data cleansing, 331 valid questionnaires were finally screened, with a recovery efficiency of 85%.

Firstly, the result of descriptive statistics in terms of respondents' gender, age, educational background and profession is shown in Table 4. In terms of gender, female respondents outnumbered male respondents; Users aged 18–25 account for the highest proportion, reaching 89.4%. In terms of educational background, the sample data are mainly gathered at the stage of higher education, with undergraduates accounting for the highest proportion of 63.7%, and graduates and above accounting for 28.1%.

5. Data analysis

This paper mainly uses SPSS25 and SmartPLS3.0 software to carry out the data analysis including the variance test, reliability and validity analysis, main effect and interaction effect analysis.

5.1. Reliability and validity analysis

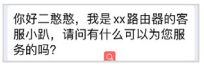
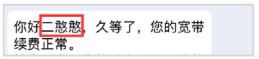
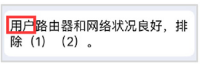
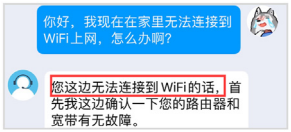
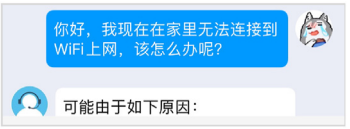
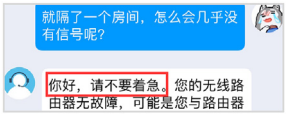
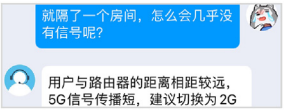
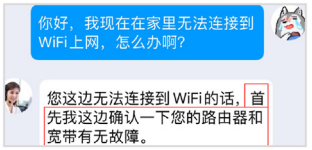
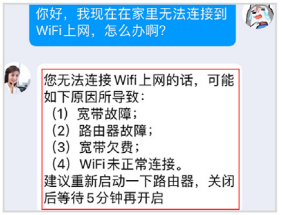
The result of the analysis is shown in Table 5. The values of Cronbach's α coefficient for each variable are basically within the range of 0.8–0.9 thus they meet the reference standard. In addition, the CR values are all greater than 0.8, which also meet the requirements. In summary, it indicates that the questionnaire in this paper has high reliability.

Using SmartPLS3.0 software, this paper analyzes the sample data for convergent validity. The results are shown in Table 6. The factor loadings of all variables are higher than 0.83, the CR values are higher than 0.85, and the AVE values are all above 0.88. Thus, the results indicate that the data has a good convergent validity.

By verifying the square root of AVE value and correlation coefficient between variables, this paper conducts the discriminant validity analysis on the sample data. The results are shown in Table 7.

Firstly, the first two columns show the mean value and standard deviation. In the subsequent matrix table, the diagonal data represents the square root of AVE, and the rest are the correlation coefficient between variables. It can be seen from the data that the square root of AVE of all variables is greater than the correlation coefficient between variables. Thus, it can be considered that the research model has a good discriminant validity.

Table 2
Scenario-design of anthropomorphic cues.

Variable	Anthropomorphic cues setting	High anthropomorphic group	Low anthropomorphic group
Virtual Appearance	Visual avatar		
	Identity label of human name		
		Router after-sales service ***'Papi'***	Router after-sales service
	Self-introduction at beginning		
		ICSB: ***Hello Chloe, I am the customer service of xx router 'Papi', how can I help you?***	Blank
Emotional Empathy	Addressing the user by name		
		ICSB: Hello ***Chloe***, sorry to have kept you waiting, your broadband renewal is normal.	**ICSB**： ***User***'s router and network condition is good, exclude (1) (2)
	Partially repeating user responses		
		User Chloe: Hello, I can't connect to WIFI at home now, what should I do? **ICSB:** ***If you are unable to connect to WIFI,*** it may be due to the following reasons:	**User Chloe:** Hello, I can't connect to WIFI at home now, what should I do? **ICSB:** It may be due to the following reasons:
	Perceiving and responding to user emotions		
		User Chloe: I'm just one room away from the router. How can there be almost no signal? **ICSB:** ***Please don't worry.*** 5G signals travel a short distance.	**User Chloe:** I'm just one room away from the router. How can there be almost no signal? **ICSB:** 5G signals travel a short distance.
Cognitive Empathy	Whether fixed template of response content or not		
		User Chloe: Hello, I can't connect to WIFI at home now, what should I do? **ICSB:** If you can't connect to WIFI, ***I'll check if your router and broadband are faulted at first.***	**User Chloe:** Hello, I can't connect to WIFI at home now, what should I do? **ICSB:** If you can't connect to Wifi, **it may be caused by the following reasons:** ***(1) Broadband failure;*** ***(2) Router failure;*** ***(3) Broadband unpaid bill;*** ***(4) WIFI is not properly connected.*** ***It is recommended to restart the router, turn it off and wait for 5 min before turning it on again.***

(*continued on next page*)

Table 2 (*continued*)

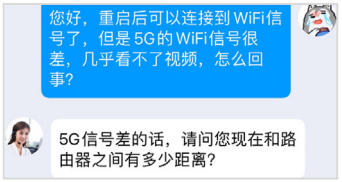
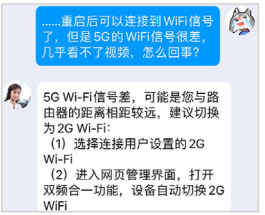
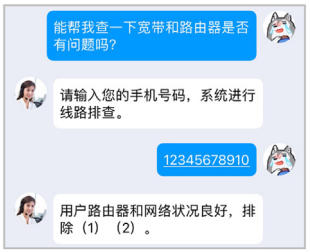
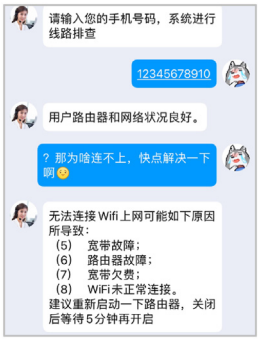
Variable	Anthropomorphic cues setting	High anthropomorphic group	Low anthropomorphic group
	The ability to distinguish user intentions based on the context	 **User:** Hello, after rebooting I can connect to the WIFI signal, but the 5G WIFI signal is very poor, I can hardly watch the video, what happened? **ICSB:** If the 5G signal is poor, ***how much distance do you have between you and the router now***?	 **User:** Hello, after rebooting I can connect to the WIFI signal, but the 5G WIFI signal is very poor, I can hardly watch the video, what happened? **ICSB:** Poor 5G Wi-Fi signal ***may be due to the distance between you and the router***, it is recommended to switch to 2G Wi-Fi with the following methods: … …
	Task-oriented or Q&A type (whether completing the Q&A in a round or not)	 **User:** Could you check if there is a problem with the broadband and router? **ICSB:** Please enter your mobile phone number, the system will check the line. **User:** (Phone number) **ICSB:** The router and network are in good condition. ***Cause (1) and (2) are excluded.Then please check … …***	 **User:** Could you check if there is a problem with the broadband and router? **ICSB:** Please enter your mobile phone number, the system will check the line. **User:** (Phone number) **ICSB:** The router and network are in good condition. **User:** Then why isn't it connected? Just fix it! **ICSB:** If you can't connect to Wifi, **it may be caused by the following reasons: *(1) Broadband failure;*** ***(2) Router failure;*** ***(3) Broadband unpaid bill;*** ***(4) WIFI is not properly connected.*** ***It is recommended to restart the router, turn it off and wait for 5 min before turning it on again.***

Table 3
Constructs and measures.

Variables	Measures	References
Virtual appearance	The avatar of the customer service chat looks like a real person. The avatar of the customer service chat doesn't look like a robot.	Kristine L Nowak and Rauh (2005)
Emotional empathy	The customer service provides me with personalized recommendations. The customer service responds to my emotions. My communication with the customer service is pleasant. The customer service will try to understand my interactions and interact with my emotions.	Parasuraman, Zeithaml, and Berry (1988), T. Zhou and Lu (2007), Shen, Zhang, and Xie (2007)
Cognitive empathy	The customer service replies to me automatically based on the preset corpus. The responses of the customer service are newly generated based on the communication. The customer service is able to understand my opinions and propositions based on situational information.	Suhaili et al. (2021)
User satisfaction	This service solves my initial problem very well. I am quite satisfied with the service this time. I think the customer service has done a good job. I am willing to use the customer service in my daily life. I would recommend others to do the same.	Nguyen, Sidorova, and Torres (2022); Oghuma, Libaque-Saenz, Wong, and Chang (2016)

Table 4
Demographical statistics.

Demographics		Frequency	Percentage
Gender	Male	121	36.6
	Female	210	63.4
Age	<18 years old	3	0.9
	18–25 years old	296	89.4
	26–30 years old	12	3.6
	31–40 years old	8	2.4
	41–50 years old	7	2.1
	51–60 years old	3	0.9
	>60 years old	2	0.6
Education	< Junior high school	1	0.3
	Senior high school	11	3.3
	Technical secondary school	2	0.6
	Junior college	13	3.9
	Undergraduate	211	63.7
	> Undergraduate	93	28.1
Major	Humanities	104	31.4
	Social Science	25	7.6
	Mathematics	63	19.0
	Business	91	27.5
	Medical Science	2	0.6
	Politics and Law	4	1.2
	Agriculture & Forestry	3	0.9
	Arts	7	2.1
	Engineering	3	0.9
	Education	29	8.8
	Others	29	8.8

Table 5
Reliability.

	AVE	Composite Reliability	Cronbach's Alpha
VA	0.761	0.864	0.703
CE	0.785	0.879	0.734
EE	0.835	0.938	0.901
SA	0.898	0.963	0.943

Notes: VA = Virtual appearance, EE = Emotional empathy, CE = Cognitive empathy, SA = Satisfaction.

5.2. Manipulation check

Manipulation tests are used to test whether the differences between the high and low anthropomorphic groups of virtual appearance, emotional empathy, and cognitive empathy are significant (see Table 8).

First of all, the variance test can be continued only if the premise of the homogeneity of variance is satisfied. It can be seen that the different groups obey the variance homogeneity. From the variance test results, it can be seen that the P (sig) of three groups is all less than 0.01, indicating significant differences among different groups.

Table 6
Cross loadings.

	VA	EE	SA	CE
VA1	0.913	0.395	0.335	0.318
VA2	0.830	0.254	0.209	0.191
EE1	0.342	0.901	0.672	0.616
EE2	0.339	0.916	0.609	0.570
EE3	0.367	0.924	0.718	0.574
SA1	0.298	0.607	0.928	0.599
SA2	0.307	0.732	0.954	0.609
SA3	0.306	0.728	0.960	0.631
CE1	0.185	0.452	0.452	0.844
CE2	0.328	0.657	0.665	0.926

Notes: VA = Virtual appearance, EE = Emotional empathy, CE = Cognitive empathy, SA = Satisfaction.

Table 7
Correlations and discriminant validity.

	Mean	Standard deviation	VA	EE	CE	SA
VA	3.009	1.713	0.872			
EE	3.907	1.661	0.382	0.914		
CE	3.697	1.142	0.301	0.642	0.886	
SA	4.590	1.492	0.321	0.729	0.647	0.948

Notes: VA = Virtual appearance, EE = Emotional empathy, CE = Cognitive empathy, SA = Satisfaction.

5.3. Hypothetical test

5.3.1. Main effects

This paper uses the generalized linear model method in SPSS to perform hypothesis test analysis of main effects, the results are shown in Table 9. The result shows that the significance P values between the mean of the dependent variable between the two groups of three variables are all significant, indicating that the hypothesis proposed in this study about the impact of anthropomorphic internal and external cues on user satisfaction is true.

5.3.2. Interaction effects

Then, the specific tests of the two-way interaction effect and the three-way interaction effect are carried out. This paper analyzes the data

Table 8
Manipulation test.

Variable	Level	Mean	Test of variance homogeneity	F	Significance
Virtual appearance	High (Person)	3.276	0.473	7.124	0.008
	Low (Robot)	2.777			
Emotional empathy	High	4.775	0.634	102.856	0.000
	Low	3.153			
Cognitive empathy	High (Generative)	4.511	0.750	9.100	0.003
	Low (Retrieval-based)	4.029			

Table 9
Main effects.

Variable	Group	Mean	Standard error	Mean value difference	p-value
Virtual appearance	Robot	4.442	0.113	−.334[a]	0.033
	Person	4.776	0.109		
Emotional Empathy	High level	5.078	0.115	.938[a]	0.000
	Low level	4.140	0.106		
Cognitive Empathy	Generative	4.775	0.105	.333[a]	0.033
	Retrieval-based	4.442	0.116		

using the generalized linear model method in SPSS25 software. In general, generalized linear models are extensions of linear models which use link functions to establish relationships between response variables.

The result presents that the likelihood ratio chi-square is 912.717, the degree of freedom is 275, and P = .000 <0 .05. The result of generalized linear models is shown in Table 10, indicating that the significance of both two-way interaction effect and three-way interaction effect is significant. Thus, we prove the significant existence of interaction effect, which verifies that the model as a whole has a significant interaction effect.

Table 11 shows the mean and standard error between different groups of VA, EE and CE. With the specific values, the interaction effects can be visualized in graphs.

This paper visualizes the interaction effect of emotional empathy and cognitive empathy, as shown in Fig. 2. Retrieval-based ICSB exerts a more significant effect of emotional empathy on user satisfaction than generative ICSB which supports the previous hypothesis.

The interaction effect between virtual appearance and emotional empathy is visualized in Fig. 3. When emotional empathy of ICSB is high, user satisfaction is significantly higher for real person appearance than for robot appearance. While, when emotional empathy is low, the difference between real person versus robot appearance on user satisfaction is not so significant. This result is consistent with H5.

The interaction effect between virtual appearance and cognitive empathy is visualized in Fig. 4, from which there is a certain interaction effect between these two variables. For real person appearance, the positive effect of cognitive empathy on user satisfaction is not as strong as that of robot appearance, which supports H6.

Following the suggestion of Dawson and Richter (2006) to test the existence of three-way interactions, this paper visualizes the effect of three-way interactions in Fig. 5. The statistical slope difference test shows that the slope difference between the high emotional empathy & high cognitive empathy group and the high emotional empathy & low cognitive empathy group is significant (p < .01); the slope difference between the high emotional empathy-low cognitive empathy group and the low emotional empathy-high cognitive empathy group is significant

Table 10
Test of model interaction effect.

	Wald	Degree of Freedom	p-value
(intercept)	3471.843	1	0.000
VA	4.552	1	0.033
EE	35.968	1	0.000
CE	4.543	1	0.033
VA * EE	41.958	3	0.000
EE * CE	44.721	3	0.000
VA * CE	9.158	3	0.027
VA * EE * CE	52.196	7	0.000

Notes: VA = Virtual appearance, EE = Emotional empathy, CE = Cognitive empathy, DV: Satisfaction.

Table 11
Mean values between groups of VA, EE and CE.

VA	EE	CE	Mean	Standard error
Robot-avatar	High level (1)	Generative (1)	5.009	0.225
		Retrieval-based (2)	4.635	0.245
	Low level (2)	Generative (1)	4.312	0.202
		Retrieval-based (2)	3.811	0.228
Real person-avatar	High level (1)	Generative (1)	5.357	0.185
		Retrieval-based (2)	5.310	0.262
	Low level (2)	Generative (1)	4.423	0.228
		Retrieval-based (2)	4.012	0.185

Notes: VA = Virtual appearance, EE = Emotional empathy, CE = Cognitive empathy.

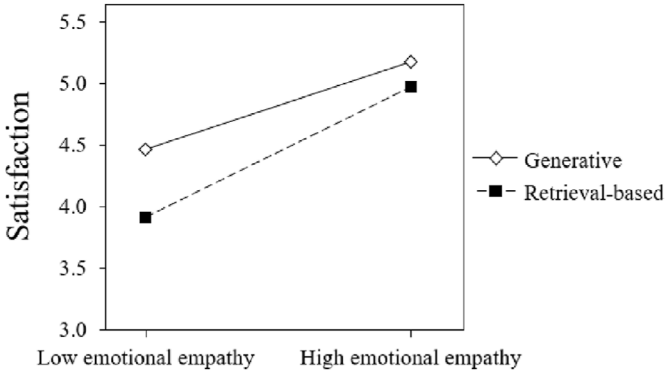


Fig. 2. Interaction effect between emotional empathy and cognitive empathy.

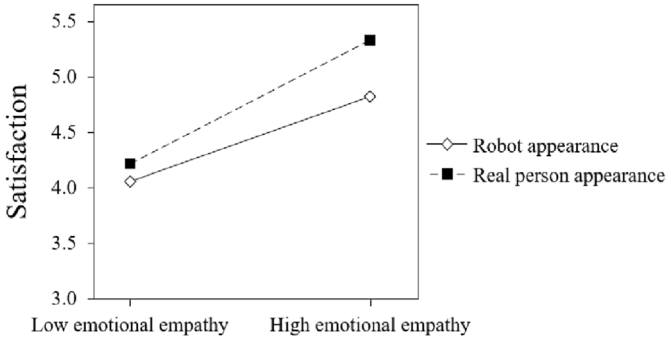


Fig. 3. Interaction effect between emotional empathy and virtual appearance.

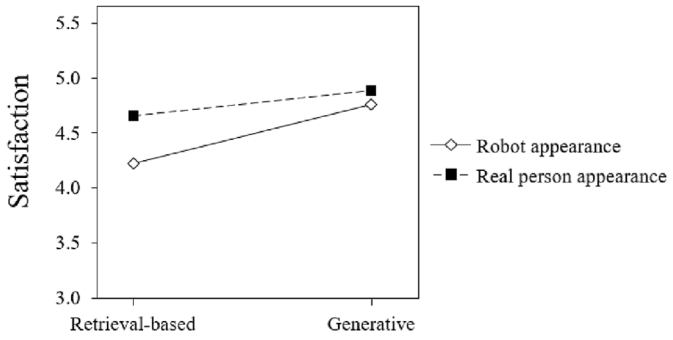


Fig. 4. Interaction effect between virtual appearance and cognitive empathy.

($p < .01$); and the slope difference between the low emotional empathy-high cognitive empathy group and the low emotional empathy-low cognitive empathy group is significant ($p < .05$). These results further support H7.

Consistent with the two-way interaction effects analysis conducted previously, the positive effect on user satisfaction is the most significant in the three-way interaction when all three independent variables are at high anthropomorphic levels.

A summary list of research hypothesis testing results is shown in Table 12:

Table 12
Testing results of hypothesis.

	Hypothesis	Results
H1	Cognitive empathy can positively affect user satisfaction.	Supported
H2	Emotional empathy can positively affect user satisfaction.	Supported
H3	The effect of emotional empathy of ICSB on user satisfaction is stronger for the retrieval-based mode compared to the generative mode.	Supported
H4	The user satisfaction of ICSB with human appearance is higher than that of robot appearance.	Supported
H5	The effect of emotional empathy of ICSB on user satisfaction is stronger in the real person appearance compared to the robot appearance.	Supported
H6	The effect of cognitive empathy on user satisfaction is stronger for the robot appearance compared to the real person appearance.	Supported
H7	There is a three-way interaction effect between virtual appearance, emotional empathy and cognitive empathy on user satisfaction.	Supported

6. Discussion and implication

6.1. Discussion

This paper investigates the effects of cognitive empathy, emotional empathy, and virtual appearance, as the three anthropomorphic cues of ICSB on user satisfaction and reveals the following key findings.

First, cognitive empathy, emotional empathy and virtual appearance have significant impacts on user satisfaction. Specifically, as to cognitive empathy, compared to the retrieval-based ICSB, the generative ICSB has a higher probability of providing more accurate, relevant, and adequate information, i.e., providing higher information quality (Gao et al., 2015), thus they can accurately grasp and satisfy the cognitive empathy of users. As to emotional empathy, ICSB with high emotional empathy has high interactivity and can respond to messages in a back-and-forth manner based on the previous content, making the service quality more satisfying (N. Chung & Kwon, 2009; Roca et al., 2006; Veeramootoo et al., 2018). As to virtual appearance, compared to ICSB with robot appearance, ICSB with real person appearance can guide users' perceptions and psychological cues about their identities as human beings, and make users be more likely to trust the ICSB.

Second, the three two-way interaction effects among cognitive empathy, emotional empathy, and virtual appearance are significant. Specifically, the high level of cognitive empathy is able to satisfy users' demand for service quality, which decreases the demand for emotional empathy dimension, thus reducing the effect of emotional empathy on user satisfaction (i.e., the substitution effect). Further, for ICSB with real person appearance, it can positively guide the users' perception and psychological implication of their identity as human beings, which makes users look forward to communicating with the ICSB (i.e., the heuristic or peripheral route). At this time, high emotional empathy can satisfy such expectations, so the relationship between emotional empathy and user satisfaction should be stronger. Moreover, the relationship between cognitive empathy and user satisfaction is stronger for ICSB with robot appearance than the ICSB with real person appearance, because the robot appearance will trigger the systematic or central route of decision making which is consistent with the function of cognitive empathy.

Third, the three-way interaction effect between cognitive empathy, emotional empathy, and virtual appearance has been proved. Specifically, the results suggest that the substitution effect between cognitive empathy and emotional empathy is stronger for the real person appearance than for the robot appearance. Specifically, the substitution effect occurs based on the assumption that the existence of one single dimension of empathy is adequate to trigger user satisfaction. Since real person appearance, compared to robot appearance, can lead to high user satisfaction, the user needs for high service quality will be relatively low for real person appearance than for robot appearance. In this situation, one single dimension of empathy may be enough, so the substitution effect should be stronger.

6.2. Theoretical implications

This study makes several theoretical contributions to the research on ICSB. First, this paper introduces the anthropomorphic cue of cognitive empathy of ICSB from the perspective of chatbot algorithmic technology application. The realization of cognitive empathy requires the use of chatbot algorithm technology. Cognitive empathy can be classified into two categories based on the level of applied technology, retrieval-based and generative modes (Chou & Hsueh, 2019; Khurana et al., 2018; Wu et al., 2018; L. Yang et al., 2019; M. Yang et al., 2017). Retrieval-based chatbots respond to users based on retrieval, which refers to that they

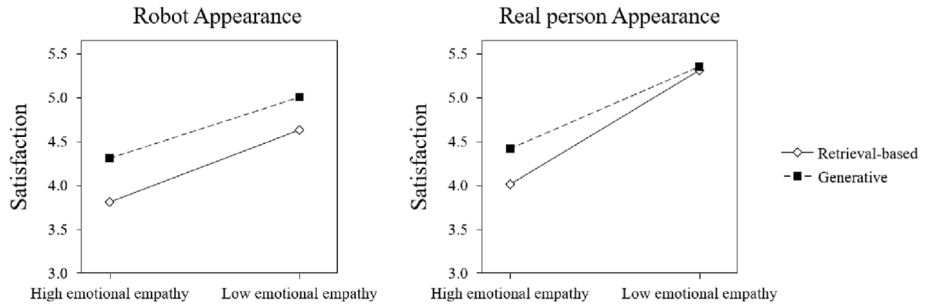


Fig. 5. Three-way interaction effect.

search and match questions in a pre-constructed database to select the response that best matches the user's request (Bartl & Spanakis, 2017; Wang et al., 2019). In contrast, the generative model have been trained and have achieved "self-learning" by trained with a large amount of data, which refers to that they can autonomously generate word-by-word responses to users' input (Serban et al., 2016) and can return a more accurate understanding of the context by obtaining the current interaction history. Therefore, the study of cognitive empathy of ICSB enriches the theory in the field of ICSB anthropomorphism and combines computer technology with empirical research to investigate the anthropomorphic cues of ICSB from an interdisciplinary perspective and confirms the hypothesis that cognitive empathy can positively affect user satisfaction.

Second, based on the dual process theory, this paper considers cognitive empathy and emotional empathy as the two internal anthropomorphic cues of ICSB together, and explores the interaction effect between the two types of empathy, thus introduces the concept of anthropomorphic internal cues of ICSB, which enriches the dimension of the researches on the anthropomorphism of ICSB. The essence of emotional empathy and cognitive empathy is whether the ICSB can correctly understand the user's utterance and respond accordingly. Cognitive empathy pays more attention to the accuracy brought by algorithm technology, which is the basis for a smooth dialogue and service quality which performs the systematic processing (Aleedy et al., 2019; McTear et al., 2016; Suhaili et al., 2021; Tran & Luong, 2020; Zhao et al., 2019), while emotional empathy focuses on the impact of ICSB on user experience in the service which performs the heuristic processing (Go & Sundar, 2019). Besides, both cognitive empathy and emotional empathy belong to the ability of ICSB to receive, understand, process, analyze, and respond users' input. The two variables constitute the internal anthropomorphic cues of ICSB together in a substitutional relation, exerting an important impact on customer service quality and service satisfaction.

Third, this paper introduces virtual appearance as the external anthropomorphic cues of ICSB and simultaneously considers both internal and external anthropomorphic cues. Previous literature has studied the anthropomorphic features of chatbots more from one aspect only, such as only from the virtual appearance aspect (Go & Sundar, 2019) or only from the internal perspective such as interactivity (Rhim et al., 2022). Few studies have combined two dimensions of external features (e.g., virtual appearance) and internal features (e.g., cognitive empathy, emotional empathy, etc.) of chatbot anthropomorphic cues to consider their impact on user satisfaction and the possible interaction effects between factors. Therefore, this paper selects these two dimensions as ICSB anthropomorphic cues to study their joint impact on user satisfaction, enriching the research content and theory in this research area.

Finally, this study empirically investigates the potential main effects, two-way interaction effects, and three-way interaction effect of the three anthropomorphic cues. On the one hand, internal anthropomorphic cues, such as cognitive empathy and emotional empathy, consist negative synergistic effect based on the HSM. On the other hand, external anthropomorphic cues such as virtual appearance, as a cue to trigger two paths, the real person appearance ICSB is more likely to trigger the peripheral path and suppress the central path. Therefore, the discovery of the interaction of ICSB anthropomorphic cues in this paper makes a theoretical contribution to the research field of ICSB anthropomorphism.

6.3. Practical implications

Some practical implications can be derived from the study. First, this study can help ICSB marketers and programmers to adjust the design of chatbot systems, and provide a basis for optimizing the service effectiveness and customer service experience of business-oriented chatbots and social chatbots. Nowadays, ICSB has been applied to various industries, taking over a vast majority of customer service jobs. It is a challenge for enterprise platforms to meet users' needs to the greatest extent within limited time and resources, provide effective services, and allow users to obtain, judge, and use effective information with maximum efficiency. This study takes the perspective of chatbot anthropomorphic cues to help ICSB companies better think about designing more humane and intelligent chatbots from two dimensions of anthropomorphism. In the anthropomorphic internal cue dimension, this paper provides some inspiration on how to better control the balance between the algorithmic technology applied in chatbots and the user experience in human-computer interaction. Studying the effects of factors of ICSB on user satisfaction can help enterprises optimize the service model and service content of ICSB thus they can improve user experience and information service level.

Second, the study of the interaction effects between anthropomorphic internal and external cues of ICSB can help enterprise managers better grasp the balance between human and chatbot services so that user satisfaction can reach the most appropriate threshold interval for better service results. By focusing on the internal anthropomorphic cues of ICSB, such as cognitive empathy and emotional empathy, the study highlights the importance of understanding user preferences and expectations when it comes to human-computer interactions. By examining the influence of anthropomorphic cues on user satisfaction, the study helps businesses and organizations to better understand what users value most in their interactions with chatbots. This can help them to design chatbots that are more user-friendly and meet the needs and expectations of their target audience.

6.4. Limitations and directions for future research

While the findings of this study have some reference value for the development of ICSB, there are some limitations in this study. First, the generalization of this study remains questionable in some aspects. For example, the selection of different business scenario applications of ICSB is not broad and comprehensive enough. Future studies can be carried out to consider other functions or scenarios, so as to confirm the research findings in this study or further extend our research model. Second, this study model only investigated the effects of three intelligent customer service bot anthropomorphic variables namely cognitive empathy, affective empathy, and virtual appearance on user satisfaction. There may be other important variables which are not considered in our model. Therefore, future studies can further investigate the effects of other possible intelligent customer service bot anthropomorphic dimensions.

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.

Acknowledgment

The work described in this paper was partially supported by the grants from the Major Projects of Ministry of Education Humanities and Social Sciences Key Research Base (Project No. 22JJD870002), and the National Natural Science Foundation of China (Project No. 71974148, 71904149, 71921002).

Appendix. Relevant literature review of the anthropomorphic dimensions of ICSB

	REFERENCE	Dimension		
		Cognitive empathy	Emotional empathy	Virtual appearance
1	Suhaili et al. (2021)	✓		
2	Gao et al. (2015)	✓		
3	TEO ET AL. (2008)	✓		
4	SCHUETZLER, GRIMES, AND SCOTT GIBONEY (2020)	✓		
5	ALEEDY ET AL. (2019)	✓		
6	KHURANA ET AL. (2018)	✓		
7	Agarwal and Karahanna (2000)	✓		
8	Wu et al. (2018)	✓		
9	M. Yang et al. (2017)	✓		
10	Chou and Hsueh (2019)	✓		
11	Rhim et al. (2022)		✓	
12	Corvello et al. (2011)		✓	
13	Selamat and Windasari (2021)	✓	✓	
14	VEERAMOOTOO ET AL. (2018)	✓	✓	
15	Mou and Xu (2017)	✓	✓	
16	ASHFAQ ET AL. (2020)	✓	✓	
17	Klopfenstein et al. (2017)	✓	✓	
18	M. Chung et al. (2020)	✓	✓	
19	Roca et al. (2006)	✓	✓	
20	Araujo (2018)			✓
21	Appel et al. (2012)		✓	✓
22	Go and Sundar (2019)		✓	✓
23	Raunio (2021)	✓	✓	✓

References

Agarwal, R., & Karahanna, E. (2000). Time flies when you're having fun: Cognitive absorption and beliefs about information technology usage. *MIS Quarterly, 24*(4), 665–694.

Aleedy, M., Shaiba, H., & Bezbradica, M. (2019). Generating and analyzing chatbot responses using natural language Processing. *International Journal of Advanced Computer Science and Applications, 10*(9), 65–68.

Appel, J., von der Pütten, A., Krämer, N. C., & Gratch, J. (2012). Does humanity matter? Analyzing the importance of social cues and perceived agency of a computer system for the emergence of social reactions during human-computer interaction. *Advances in Human-Computer Interaction*. , Article 324694. https://doi.org/10.1155/2012/324694, 2012.

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.

Argyle, M. (1988). *Bodily communication*. London: Methuen & Co. *Ltd*.

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.

Ashforth, B. E., & Humphrey, R. H. (1997). The ubiquity and potency of labeling in organizations. *Organization Science, 8*(1), 43–58.

Bartl, A., & Spanakis, G. (2017). *A retrieval-based dialogue system utilizing utterance and context embeddings*. Paper presented at the 2017 16th IEEE International Conference on Machine Learning and Applications (ICMLA).

Baylor, A., & Kim, Y. (2003). *The role of gender and ethnicity in pedagogical agent perception*. Paper presented at the E-Learn: World Conference on E-Learning in Corporate, Government, Healthcare, and Higher Education.

Brennan, K. (2006). The managed teacher: Emotional labour, education, and technology. *Educational Insights, 10*(2), 55–65.

Bridges, E., & Florsheim, R. (2008). Hedonic and utilitarian shopping goals: The online experience. *Journal of Business Research, 61*(4), 309–314.

Chaiken, S. (1989). Heuristic and systematic information processing within and beyond the persuasion context. *Unintended thought*, 212–252.

Chen, S., & Chaiken, S. (1999). The heuristic-systematic model in its broader context. *Dual-process theories in social psychology*, 73–96.

Cheung, C. M. K., Lee, M. K. O., & Rabjohn, N. (2008). The impact of electronic word-of-mouth: The adoption of online opinions in online customer communities. *Internet Research, 18*(3), 229–247.

Choi, K., Wang, Y., & Sparks, B. (2019). Travel app users' continued use intentions: it'sa matter of value and trust. *Journal of Travel & Tourism Marketing, 36*(1), 131–143.

Chou, T.-L., & Hsueh, Y.-L. (2019). *A task-oriented chatbot based on lstm and reinforcement learning*. Tokushima Japan: Paper presented at the Proceedings of the 2019 3rd International Conference on Natural Language Processing and Information Retrieval.

Chung, M., Ko, E., Joung, H., & Kim, S. J. (2020). Chatbot e-service and customer satisfaction regarding luxury brands. *Journal of Business Research, 117*, 587–595.

Chung, N., & Kwon, S. J. (2009). Effect of trust level on mobile banking satisfaction: A multi-group analysis of information system success instruments. *Behaviour & Information Technology, 28*(6), 549–562.

Corvello, V., Pantano, E., & Tavernise, A. (2011). The design of an advanced virtual shopping assistant for improving consumer experience. In , *IGI globalAdvanced technologies management for retailing: Frameworks and cases* (pp. 70–86).

Cyr, D., Head, M., Larios, H., & Pan, B. (2009). Exploring human images in website design: A multi-method approach. *MIS Quarterly, 33*(3), 539–566.

Cyr, D., Head, M., Lim, E., & Stibe, A. (2018). Using the elaboration likelihood model to examine online persuasion through website design. *Information & Management, 55*(7), 807–821.

Dawson, J. F., & Richter, A. W. (2006). Probing three-way interactions in moderated multiple regression: Development and application of a slope difference test. *Journal of Applied Psychology, 91*(4), 917.

Epley, N., Waytz, A., & Cacioppo, J. T. (2007). On seeing human: A three-factor theory of anthropomorphism. *Psychological Review, 114*(4), 864.

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.

Gefen, D., & Straub, D. W. (2004). Consumer trust in B2C e-commerce and the importance of social presence: Experiments in e-products and e-services. *Omega, 32*(6), 407–424.

Gelman, S. A., & Heyman, G. D. (1999). Carrot-eaters and creature-believers: The effects of lexicalization on children's inferences about social categories. *Psychological Science, 10*(6), 489–493.

Gong, L., & Nass, C. (2007). When a talking-face computer agent is half-human and half-humanoid: Human identity and consistency preference. *Human Communication Research, 33*(2), 163–193.

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.

Guthrie, S. E. (1995). *Faces in the clouds: A new theory of religion*. Oxford University Press.

Holzwarth, M., Janiszewski, C., & Neumann, M. M. (2006). The influence of avatars on online consumer shopping behavior. *Journal of Marketing, 70*(4), 19–36.

Hong, S., Thong, J. Y., & Tam, K. Y. (2006). Understanding continued information technology usage behavior: A comparison of three models in the context of mobile internet. *Decision Support Systems, 42*(3), 1819–1834.

Khurana, P., Agarwal, P., Shroff, G., & Vig, L. (2018). *Resolving abstract anaphora implicitly in conversational assistants using a hierarchically stacked rnn*. London United Kingdom: Paper presented at the Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining.

Kim, J. (2010). Balancing uniqueness and assimilation in computer-mediated groups. *Computers in Human Behavior, 26*(4), 778–784.

Kim, Y., & Sundar, S. S. (2012). Anthropomorphism of computers: Is it mindful or mindless? *Computers in Human Behavior, 28*(1), 241–250.

Klopfenstein, L. C., Delpriori, S., Malatini, S., & Bogliolo, A. (2017). *The rise of bots: A survey of conversational interfaces, patterns, and paradigms*. Edinburgh United Kingdom: Paper presented at the Proceedings of the 2017 conference on designing interactive systems.

Kohler, T., Fueller, J., Stieger, D., & Matzler, K. (2011). Avatar-based innovation: Consequences of the virtual co-creation experience. *Computers in Human Behavior, 27*(1), 160–168.

Lee, E.-J., & Oh, S. Y. (2015). Effects of visual cues on social perceptions and self-categorization in computer-mediated communication. In *The handbook of the psychology of communication technology* (pp. 115–136).

McTear, M., Callejas, Z., & Griol, D. (2016). *The conversational interface: Talking to smart devices*. Springer international publishing. https://doi.org/10.1007/978-3-319-32967-3

Mou, Y., & Xu, K. (2017). The media inequality: Comparing the initial human-human and human-AI social interactions. *Computers in Human Behavior, 72*, 432–440.

Nass, C., & Moon, Y. (2000). Machines and mindlessness: Social responses to computers. *Journal of Social Issues, 56*(1), 81–103.

Nguyen, Q. N., Sidorova, A., & Torres, R. (2022). User interactions with chatbot interfaces vs. Menu-based interfaces: An empirical study. *Computers in Human Behavior, 128*, Article 107093.

Nowak, K. L. (2017). The influence of anthropomorphism and agency on social judgment in virtual environments. *Journal of Computer-Mediated Communication, 9*(2). https://doi.org/10.1111/j.1083-6101.2004.tb00284.x

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.

Oghuma, A. P., Libaque-Saenz, C. F., Wong, S. F., & Chang, Y. (2016). An expectation-confirmation model of continuance intention to use mobile instant messaging. *Telematics and Informatics, 33*(1), 34–47.

Parasuraman, A., Zeithaml, V. A., & Berry, L. (1988). *Servqual: A multiple-item scale for measuring consumer perceptions of service quality* (Vol. 64, pp. 12–40), 1.

Peres, R., Schreier, M., Schweidel, D., & Sorescu, A. (2023). On ChatGPT and beyond: How generative artificial intelligence may affect research, teaching, and practice. *International Journal of Research in Marketing, 40*(2), 269–275.

Petty, R. E., & Cacioppo, J. T. (1986). The elaboration likelihood model of persuasion. In *Communication and persuasion: Central and peripheral routes to attitude change* (pp. 1–24). New York, NY: Springer New York.

Radziwill, N. M., & Benton, M. C. (2017). *Evaluating quality of chatbots and intelligent conversational agents. arXiv preprint arXiv:1704.04579*.

Raunio, K. (2021). *Chatbot anthropomorphism: Adoption and acceptance in customer service*. University of Twente. Retrieved from http://essay.utwente.nl/86151/.

Rhim, J., Kwak, M., Gong, Y., & Gweon, G. (2022). Application of humanization to survey chatbots: Change in chatbot perception, interaction experience, and survey data quality. *Computers in Human Behavior, 126*, Article 107034.

Roca, J. C., Chiu, C.-M., & Martínez, F. J. (2006). Understanding e-learning continuance intention: An extension of the Technology Acceptance Model. *International Journal of Human-Computer Studies, 64*(8), 683–696.

Rocca, K. A., & McCroskey, J. C. (1999). The interrelationship of student ratings of instructors' immediacy, verbal aggressiveness, homophily, and interpersonal attraction. *Communication Education, 48*(4), 308–316.

Sannon, S., Stoll, B., DiFranzo, D., Jung, M. F., & Bazarova, N. N. (2020). "I just shared your responses": Extending communication privacy management theory to interactions with conversational agents. *Proc. ACM Hum.-Comput. Interact., 4*, Article 08. https://doi.org/10.1145/3375188. GROUP.

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.

Selamat, M. A., & Windasari, N. A. (2021). Chatbot for SMEs: Integrating customer and business owner perspectives. *Technology in Society, 66*, Article 101685.

Serban, I., Sordoni, A., Bengio, Y., Courville, A., & Pineau, J. (2016). Building end-to-end dialogue systems using generative hierarchical neural network models. *Proceedings of the AAAI Conference on Artificial Intelligence, 30*(1). https://doi.org/10.1609/aaai.v30i1.9883

Shawar, B. A., & Atwell, E. S. (2005). Using corpora in machine-learning chatbot systems. *International Journal of Corpus Linguistics, 10*(4), 489–516.

Shen, W., Zhang, X., & Xie, l. (2007). An empirical study on the measurement and influence of service quality in network enterprises. *Management Science, 20*(1), 38–45.

Suhaili, S. M., Salim, N., & Jambli, M. N. (2021). Service chatbots: A systematic review. *Expert Systems with Applications, 184*, Article 115461.

Sundar, S. S. (2008). *The main model: A heuristic approach to understanding technology effects on credibility*. Cambridge, MA: MacArthur Foundation Digital Media and Learning Initiative (The MIT Press).

Sun, Y., Wang, N., Shen, X. L., & Zhang, X. (2019). Bias effects, synergistic effects, and information contingency effects: Developing and testing an extended information adoption model in social Q&A. *Journal of the Association for Information Science and Technology, 70*(12), 1368–1382.

Teo, T. S., Srivastava, S. C., & Jiang, L. (2008). Trust and electronic government success: An empirical study. *Journal of Management Information Systems, 25*(3), 99–132.

Thong, J. Y., Hong, S.-J., & Tam, K. Y. (2006). The effects of post-adoption beliefs on the expectation-confirmation model for information technology continuance. *International Journal of Human-Computer Studies, 64*(9), 799–810.

Tran, O. T., & Luong, T. C. (2020). Understanding what the users say in chatbots: A case study for the Vietnamese language. *Engineering Applications of Artificial Intelligence, 87*, Article 103322.

Tversky, A., & Kahneman, D. (1974). Judgment under Uncertainty: Heuristics and Biases: Biases in judgments reveal some heuristics of thinking under uncertainty. *Science, 185*(4157), 1124–1131.

Veeramootoo, N., Nunkoo, R., & Dwivedi, Y. K. (2018). What determines success of an e-government service? Validation of an integrative model of e-filing continuance usage. *Government Information Quarterly, 35*(2), 161–174.

Wang, Z., Wang, Z., Long, Y., Wang, J., Xu, Z., & Wang, B. (2019). Enhancing generative conversational service agents with dialog history and external knowledge. *Computer Speech & Language, 54*, 71–85.

Wu, Y., Li, Z., Wu, W., & Zhou, M. (2018). Response selection with topic clues for retrieval-based chatbots. *Neurocomputing, 316*, 251–261.

Yan, Z., Duan, N., Bao, J., Chen, P., Zhou, M., & Li, Z. (2018). Response selection from unstructured documents for human-computer conversation systems. *Knowledge-Based Systems, 142*, 149–159.

Yang, L., Hu, J., Qiu, M., Qu, C., Gao, J., Croft, W. B., … Liu, J. (2019). *A hybrid retrieval-generation neural conversation model*. Beijing, China: Paper presented at the Proceedings of the 28th ACM International Conference on Information and Knowledge Management.

Yang, M., Zhao, Z., Zhao, W., Chen, X., Zhu, J., Zhou, L., et al. (2017). *Personalized response generation via domain adaptation*. Shinjuku Tokyo Japan: Paper presented at the Proceedings of the 40th International ACM SIGIR Conference on Research and Development in Information Retrieval.

Zhang, W., & Watts, S. A. (2008). Capitalizing on content: Information adoption in two online communities. *Journal of the Association for Information Systems, 9*(2), 73–94.

Zhao, G., Zhao, J., Li, Y., Alt, C., Schwarzenberg, R., Hennig, L., … Xu, F. (2019). Moli: Smart conversation agent for mobile customer service. *Information, 10*(2), 63.

Zhou, X., Kim, S., & Wang, L. (2019). Money helps when money feels: Money anthropomorphism increases charitable giving. *Journal of Consumer Research, 45*(5), 953–972.

Zhou, T., & Lu, Y. (2007). Research of consumers' online repeated shopping behavior based on SERVQUAL. *Management Science, 20*(3), 61–67.