Journal of Retailing and Consumer Services 66 (2022) 102900

Contents lists available at ScienceDirect

Journal of Retailing and Consumer Services

journal homepage: www.elsevier.com/locate/jretconser

Will artificial intelligence replace human customer service? The impact of communication quality and privacy risks on adoption intention

Mengmeng Song [a], Xinyu Xing [a], Yucong Duan [b], Jason Cohen [c], Jian Mou [d,*]

[a] Department of Tourism Management, Hainan University, China
[b] Department of Computer Science and Cyberspace Security, Hainan University, China
[c] School of Business Sciences, University of the Witwatersrand, Johannesburg, South Africa
[d] School of Business, Pusan National University, South Korea

ARTICLE INFO

Keywords:
Human–computer interaction
Chatbots
Computers as social actors
Communication quality
Privacy risks

ABSTRACT

In the digital environment, chatbots as customer service agents assist consumers in decision making. Based on the computers-are-social-actors paradigm, this study examines the perceived differences in communication quality and privacy risks between different service agents and their impact on consumers' adoption intention, and investigates whether these perceived differences might depend on differences in the user's human interaction need. A series of five scenario-based experiments were carried out to collect data and test hypotheses. It was discovered that: different types of service agents directly affect consumers' adoption intention; perceived communication quality and privacy risk mediate the effect of service agent type on adoption intention; the effects of service agent type on perceived accuracy, communicative competence, and privacy risk are moderated by the need for human interaction. The findings of this study provide important insights into the rational use of human–computer interacation in e-commerce.

1. Introduction

Retail and consumer services continue to be significantly influenced by the rapid advance of digital technologies such as artificial intelligence (AI) (Kai et al., 2020). One area of growing interest in the application of AI for online retail is the area of AI-based chatbots. These chatbots have been introduced as digital assistants into online retail environments to enhance customer experience and fulfill expectations through real-time interactions (Cheng et al., 2021). According to Business insider (2020), the chatbot market is predicted to grow at a rate of 29.7% per year and is expected to reach $125 million by 2025. The compound annual growth rate is expected to be 24.3% (Pantano and Pizzi, 2020). However, despite the proliferation of chatbots, research suggests that they often fall short of consumer expectations owing to their inability to fully understand users' need (Sheehan et al., 2020), and consumer willingness to accept chatbots has been lower than industry expectations. A study of facebook users suggests more than 70% perceive their interactions with chatbots as failures and there is thus still a strong demand for human interaction (Ashfaq et al., 2020). Given these results, it may be difficult for chatbots to completely replace humans with some suggesting that human and AI-based agents will need to work together to provide better services (Xiao and Kumar, 2021). Delegating service tasks and finding a service balance between the efficiency of chatbots and the empathic ability of humans is therefore an important problem. In particular, we believe this requires important clarifications regarding how differences in the type of service agent (chatbots vs. human beings) affects communication quality and consequently consumer perceptions of the interaction process. Miscommunication is a frequent condition in human–computer interaction (Sheehan et al., 2020). Although the user's language skills can be easily transferred in human–computer communication, the perception and quality of the interaction could still differ significantly from human interaction (Adam et al., 2021). For example, users may not fully trust the advice provided by chatbots (Følstad et al., 2018), and may not believe that chatbots have the communication ability to solve actual tasks and service problems (Følstad and Skjuve, 2019). Hence, it becomes important to clarify the impact of communication quality in human–computer interaction to improve the value of chatbot usage (Sheehan et al., 2020).

In addition, the development of AI has enabled the collection, storage, and processing of information on an unprecedented scale (Mazurek and Małagocka, 2019), thereby becoming extremely easy to identify, analyze, and use personal data at low cost without the consent of others

* Corresponding author. School of Business, Pusan National University, 2, Busandaehak-ro 63beon-gil, Geumjeong-gu, Busan, 46241, South Korea.
E-mail address: jian.mou@pusan.ac.kr (J. Mou).

https://doi.org/10.1016/j.jretconser.2021.102900
Received 29 August 2021; Received in revised form 25 November 2021; Accepted 23 December 2021
Available online 5 January 2022
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(Mazurek and Małagocka, 2019). Thus privacy leakage from interaction with AI technologies has become another topic of consumer concern. Unlike offline transactions, most consumers have to input personal information when using online platforms. However, consumers have a strong need to protect personal data and are often concerned about chatbots sharing the collected and stored data to a distant cloud (Milne and Culnan, 2004). Thus, the use of chatbots in service interactions may raise greater consumer concerns regarding privacy risk issues.

Previous studies have focused on how humans and computers interact. However, little research focused on service agent type and how consumer perceptions of communication and privacy in human−human interaction differs from human−computer (chatbot) interaction. In terms of consumer attitudes, studies have focused on consumer satisfaction (Chung et al., 2020), loyalty (Følstad et al., 2018), and intention to continue using chatbots (Ashfaq et al., 2020); however, in order to advance the new technology of chatbots, it is also necessary to understand why customers choose to accept or resist this new channel for service provision. Some studies have addressed this question by extending Davis' (1989) technology acceptance model (TAM) to consider consumers' acceptance of chatbots from the perspective of perceived usefulness and perceived ease of use along with factors from the IS success model (Ashfaq et al., 2020) and uses and gratification theory (Rese et al., 2020). These studies, suggest that chatbot acceptance is partly explained by factors such as perceived enjoyment and chatbot ease of use. However, there is a lack of research exploring consumers' willingness to accept chatbots from the perspective of communication quality and privacy risks. Given that chatbots are designed to replace human service agents and simulate communication with human users over the open communication medium of the Internet, understanding adoption from the perspective of communication quality and privacy risks is necessary. To fill this research gap, this study adopts an experimental research design and draws on the computer as a social actor (CASA) paradigm to explore differences among the types of service agents in perceived communication quality and privacy risk and how this impacts on consumer adoption in the context of online retailing. Previous studies have focused on the effects of user need for human interaction on robot anthropomorphism and adoption intention or satisfaction (Sheehan et al., 2020; Ashfaq et al., 2020; Hu et al., 2021). These studies suggest that need for human interaction can negatively influence user satisfaction with using chatbots but that more anthropomorphic chatbots might be able to satisfy the social desires of consumers high in need for human interaction. For example, the effect of chatbot anthropomorphism on adoption has been shown to increase as the need for human interaction increases (Sheehan et al., 2020). This suggests consumers with higher need for human interaction may require chatbots that are more humanlike. Consequently, this study introduces the need for human interaction as a moderating variable in the study of service agent type on adoption intention and considers whether differences between chatbots and humans in perceived communication quality and privacy risk might depend on differences in the user's human interaction need.

Therefore, the objective of this study is to explore how customers react to different types of service agents in e-commerce and thus help online service providers to find the service balance between robot and human agents. More specifically, this study examines the mediating roles of perceived communication quality and perceived privacy risk in service agent acceptance; and the moderating role of human interaction need in the perceived communication quality and privacy risks associated with service agent types. The conclusions of this study can enrich understanding of the influence mechanisms in human-computer interaction and the boundary conditions of human−computer interaction theory. Results also have important implications for e-commerce platforms by aiding them to make appropriate use of human−computer cooperation in service delivery, and to help them better understand factors influencing consumer acceptance of chatbots.

The rest of this article is structured as follows. Section 2 reviews the relevant literature on comparision of AI-based agents vs. human beings, perceived communication quality and perceived privacy risk. The hypotheses are developed in section 3. Section 4 describes how the study was conducted, followed by the results presented in Section 5. Summary of findings, implications, and limitations and future research are discussed in Section 6.

2. Literature review

2.1. Chatbots vs. human beings

Service agents are key to solving customers' problems (Chakrabarty et al., 2014) and determining users' purchasing behavior (Godes et al., 2005). E-commerce platforms use service agents for many reasons, mainly to strengthen the relationship between the customer and the brand (Fionda and Moore, 2009), to provide services and give a pleasant experience to the customer (Serban et al., 2018), to meet customer expectations and create value for the company (Choi et al., 2016). The development of new technologies has paved the way for platforms to introduce chatbots to assist human beings. Chatbot is an important form of robotic agent that purports to enhance customer experience and fulfil expectations through real-time interactions. Studies have investigated users' interactions with and perceptions of chatbots (see Table 1), and some have shown they may be equally trustworthy and capable communication objects (Edwards et al., 2014; Pillai et al., 2020) for enhancement of the customer experience. Hill et al. (2015) compared human−human interaction online with human−computer interaction and observed the latter interaction lasting longer because chatbots can provide uninterrupted service and reduce response time, which is an important factor in enhancing customer experience (Radziwill and Benton, 2017). A study by Chung et al. (2020) examined the relationship between marketing efforts, communication quality, and customer satisfaction of chatbots. They found that the use of chatbots can increase customer satisfaction with a brand because they can engage and provide interactive services to customers. Cheng and Jiang (2020) investigated how AI-driven chatbots affect user's experience and showed that perceived entertainment, attraction, and social presence associated with the use of chatbots would enhance such.

Although these scholars have concluded that the use of chatbots enhances customer experience, other scholars argue that many chatbots currently on the market fail to meet users' need due to the relatively high frequency of meaningless responses, unclear purpose or lack of usability, and thus users still have a strong desire to interact with human beings. For example, a study by Luo et al. (2019) confirmed that customers get annoyed and purchase less when they know that the conversation partner is not human. Similarly, Spence et al. (2014) and Edwards et al. (2016) found that consumers face greater uncertainty and expect a less favorable experience and lower social presence when they are told that they will interact with a chatbot rather than a human. Users who conduct online transactions perceive that text-based virtual agents fail in more than 70% of all interactions and require the intervention of people (Ashfaq et al., 2020). Therefore, these scholars argue that human beings typically provide a better experience for customers. Additionally, human beings are better able to respond to and solve problems in complex situations (Ashfaq et al., 2020).

In summary, chatbots and human beings are two different types of service agents which can cause differences in people's perception of the service process. Therefore, it is important to understand the advantages and disadvantages of different agent identities (chatbots vs. human beings) (Shank, 2013). This study tests consumers' perception of chatbots and human beings on communication quality as well as on their privacy risks, discussed next.

Table 1
Previous studies on service agents.

Study	Study focus	Theory	Key findings
Holzwarth et al. (2006)	The effect of virtual agents on consumer satisfaction with the retailer, product attitude, and purchase intention in e-commerce.	Social response theory.	A virtual agent leads to more satisfaction with the retailer, more attitude toward the product, and more intention to purchase.
Edwards et al. (2014)	A comparison between a bot and a human agent regarding communication quality on Twitter.	The CASA (computers-are-social-actors) paradigm.	Drawing on the CASA paradigm, the authors found there is no difference between a bot and a human agent regarding source credibility, intentions of interaction, or communication competence. In addition, bot is perceived as attractive, credible, and competent both in communication and interactional intentions; finally, the human agent was perceived as more attractional both in social and task than the bot.
Hill et al. (2015)	Comparison between human-chatbot and human-human conversations.	Systematic literature review.	Users are more likely to communicate with the chatbot for longer time with shorter messages lengths than with human.
Mou & Xu (2017)	Whether users' communicative attributes and personality traits are different when they initially interact with human-artificial intelligence (i.e., chatbot) and human-human interaction.	The CASA paradigm.	Users confirmed different communicative attributes and personality traits when they interact with human-human and human-artificial intelligence, especially when they are interacting with a human, they are "more open, more conscientious, more extroverted, more agreeable, and self-disclosing than AI.
Chung et al. (2020)	The effect of chatbot e-service on customer satisfaction in luxury contexts.	Social media marketing activities model.	E-service through chatbot assistances in engaging the customer and delivers interactive customer service. Moreover, using chatbot e-service leads to customer satisfaction with the brand.
Ashfaq et al. (2020)	I, Chatbot: Modeling the determinants of users' satisfaction and continuance intention of AI-powered service agents.	Expectation-confirmation model, information system success model, technology acceptance model.	Chatbots should enhance their information and service quality to increase users' satisfaction. The findings imply that digital technologies services, such as chatbots, could be combined with human service employees to satisfy digital users.
Sheehan et al. (2020)	Customer service chatbots: Anthropomorphism and adoption.	Systematic literature review.	Unresolved errors are sufficient to reduce anthropomorphism and adoption intent. However, there is no perceptual difference between an error-free chatbot and one which seeks clarification. The ability to resolve miscommunication (clarification) appears as effective as avoiding it (error-free).
Rese et al. (2020)	Consumer acceptance of a chatbot in Germany	TAM and Uses and Gratification theory	Authenticity of conversation, perceived usefulness and perceived enjoyment positively influence acceptance but privacy concerns and immaturity of the technology had negative effects.
Cheng et al. (2021)	This study aims to explore consumers' trust and response to a text-based chatbot in e-commerce, involving the moderating effects of task complexity and chatbot identity disclosure.	Stimulus–organism–response model.	The findings showed (a) the consumers' perception of both the empathy and friendliness of the chatbot positively impacts trust; (b) task complexity negatively moderates the relationship between friendliness and consumers' trust; and (c) disclosure of the text-based chatbot negatively moderates the relationship between empathy and consumers' trust, while it positively moderates the relationship between friendliness and consumers' trust.

2.2. Social response theory, CASA paradigm and perceived communication quality

Social response theory, proposed by Nass et al. (1996) clarifies the similarities between social and human−technology interactions. Social response theory suggests that when a technology possesses a set of characteristics that are similar to people, a person's reaction to the technology will reflect as a social behavior and will respond to it with social rules (Nass et al., 1996). Previous studies have confirmed that trust (Gaudiello et al., 2016) and interactive experience (McLean and Wilson, 2016) can thus also occur in human−computer interaction. Moreover, as an important means of interaction, language has been shown to stimulate social responses to some extent (Johnson and Valente, 2009). Such social reactions are inevitable during human−computer interactions (Nass et al., 1996). Thus, individuals will unconsciously perceive a computer as a social actor (CASA), even though people know that the machine has no feelings nor intentions.

CASA has therefore become a useful conceptual paradigm for the study of human's social cognition of computers (Nass et al., 1996). CASA is often used to explain human understanding of machines and attitudes held towards them in interactive contexts. Individuals expect computers to act like social actors in compliance with the existing rules of society (Nass et al., 1996). Therefore, the same expectation is likely to apply to other devices e.g AI related devices (Wang, 2017). With the rapid development of AI, the application of CASA is no longer limited to traditional computers and has been extended to the study of human−computer interaction in different contexts. According to this, people do not only communicate through machines, but also interact with them as partners (Fortunati and Edwards, 2020). Ho et al. (2018) found that the positive effects of interpersonal emotional expressions also apply to the perception of emotions in the interaction with chatbots. This paradigm has also demonstrated the effectiveness of human avoidance (Lee and Liang, 2019) and robots' politeness strategies for asking for help from humans in human−computer communication (Srinivasan and Takayama, 2016). Based on the CASA paradigm, consumers expect AI to be empathetic and have good communication skill (like human beings), but the inability to deal with complex situations makes humans reluctant to use AI devices in certain situations (Pelau et al., 2021). The CASA research paradigm thus underpins how we understand communication processes in human−computer interaction.

The quality of communication is an important factor that affects the service quality (Sheehan et al., 2020). This is because it can create value for customers through providing high interaction quality, enhancing the functionality (i.e., improve decision making efficiency) (Ben Mimoun et al., 2017; Yoon et al., 2013), and socializing of interactions (i.e., derive pleasure from interactions) (Holzwarth et al., 2006). Empirically, Giulia et al. (2019) explored the impact of different communication styles on customer service quality and attitudes. A communication process must meet the requirements of multiple dimensions of communication quality in order for the client to perceive an overall experience of high quality communication and respond positively during the process (Maltz, 2000; Mohr and Sohi, 1995). For example, customers perceive an experience in quality communication when they feel responses are fluent, timely, effective, and accurate during the communication process (Emmers-Sommer, 2004; Mohr and Sohi, 1995; Vos, 2009). It has been suggested that customers focus on the accuracy of information during communication (Mohr and Sohi, 1995) and believe that accurate and credible information is what they require (Ubisend, 2017). Brands or platforms are constantly refining their communication methods in the quest to build positive customer relationships (Kim et al., 2012), and when customers build good relationships with service agents, they perceive the information in the communication as credible and persuasive. Thus, quality communication must make customers feel that the service agents will understand their concerns, accurately diagnose their problems, and provide the required information during the communication (Clokie and Fourie, 2016). Chung et al. (2020) studied the impact of communication quality on customer satisfaction in a luxury retailing environment and discussed accuracy, credibility, and communication capability as dimensions of communication quality. Lowry et al. (2010) also identified openness as an important factor influencing communication quality, defined as the willingness of parties to be receptive to the communication experience. Spence et al. (2014) suggested that credibility, attraction, and communicative competence are the key variables on which to focus in communication quality research; thus, these variables have an impact on interaction (Edwards et al., 2016; Lundy and Drouin, 2016; McCroskey and McCain, 1974).

According to the CASA paradigm, consumers expect robots to have the same communication skills as humans in online interactions. The choice of these five dimensions is not only based on previous studies (Table 2), but more importantly, accuracy, credibility, attractiveness, openness and communication capability are five attributes that consumers are likely to pay great attention to when interacting with chatbots. Accuracy is considered to be the main indicator of consumer evaluation of chatbot services (Vos, 2009). Different from human agents, chatbots can quickly access datastores to promptly give highly accurate answers to users' questions, and thus delivering better user experience. Credibility is also considered a major factor affecting the user experience in an online environment (Ubisend, 2017). The humanoid nature of chatbots such as their natural language interaction with consumers can be important to building trust. Additionally, openness is an important attribute to help users be more relaxed when interacting with chatbots. The higher the openness perceptions, the higher the comfort level in communication (Mou and Xu, 2017). Attraction becomes another attribute of chatbots to give users a better experience (Edwards et al., 2016). Robots with "fun souls" can interact with consumers in a more humorous and friendly way. Communication capability refers to the robot agent's ability to effectively deal with complex problems. This dimension of communication quality of chatbots has emerged as a major indicator to judge the usage value of chatbots (Mou and Xu, 2017; Ramadan, 2021). Therefore, this current study conceptualizes the perceived quality of communication along these five dimensions as summarized in Table 2: accuracy, credibility, openness, attraction, and communication capability.

Table 2
Five dimensions of communication quality.

Dimensions	Description	Sources
Accuracy	prompt and correct communication	Mohr and Sohi (1995); Vos (2009); Ubisend (2017); Chung et al. (2020).
Credibility	trusting and sincere communication	Spence et al. (2014); Ubisend (2017); Chung et al. (2020).
Openness	receptive communication	Lowry et al. (2010); Mou and Xu (2017).
Attraction	friendly communication	Spence et al. (2014); Edwards et al. (2016).
Capability	effective communication to solve complex problems	Spence et al. (2014); Mou and Xu (2017); Chung et al. (2020).

2.3. *Perceived privacy risk*

The use of online platforms has led to the disclosure of hundreds of millions of users' personal information online, therefore, privacy has become a major concern for users (Chen et al., 2010). The term "privacy risk" refers to the concern about the possible loss of privacy due to self-revelation and disclosure of personal information on online platforms (Dinev and Hart, 2006; Xu et al., 2008). It relates to a variety of issues such as unauthorized disclosure of personal information of consumers to third parties, unsolicited contact by online marketers via email, and tracking of consumers' online behavior (Milne and Culnan, 2004). AI, as a common new technology in life, has increased consumers' concerns about personal privacy risks due inter-alia to its unpredictability, low transparency of algorithms, lack of humanity, and lack of ethical clarity (Zarifis et al., 2021). Privacy risks in the use of AI has thus gained attention of scholars. For instance, Ho (2006) found that users have concerns about the amount of personal information collected when accessing personalized services on websites; Sundar and Marathe (2010) also noted that AI personalized services increase convenience while increasing users' privacy concerns. Research on the issue of privacy risks in the use of AI has emerged in different fields. In the healthcare domain, Zarifis et al. (2021) finds that health insurance intelligence increases consumers' risk perceptions. In the service domain, previous studies have shown that consumers have some degree of privacy risk concerns about new technologies such as mobile payments (Gao and Waechter, 2017), mobile banking (Farah et al., 2018) and smart watches (Dehghani, 2018). Concerns are also being further exacerbated with the popularity of real-name systems and precisely tailored marketing of products targeting consumers (Milne and Culnan, 2004). A survey of 8000 respondents in the 2019 China Economic Life Survey, jointly conducted by China Central Television and Tencent Research Center, revealed that nearly 77% believed that AI posed a threat to their privacy during use (China economic life survey, 2019). With chatbot as a new form of AI, consumers may be concerned that personal information sent to chatbots may be used for inappropriate business purposes (Sundar and Kim, 2019). Similarly, in the retail industry, brands or platforms deploying chatbots to serve customers may face the same challenges (Eeuwen, 2017). Therefore, on the basis of these studies, this study also considers the perceived privacy risks associated with chatbot communication in service.

2.4. *Need for human interaction*

The need for human interaction can be defined as the consumer's desire for human contact during the service experience (Dabholkar, 1996). It reflects a consumer's preference for human social interaction, and is considered a consumer trait that has implications for interactions with technology in service encounters (Dabholkar and Bagozzi, 2002). Many consumers prefer to interact with human service agents (Sheehan et al., 2020), and are thus considered to have a high need for interpersonal interaction. Others however may have a preference for avoidance of people (Meuter et al., 2000). Dabholkar and Bagozzi (2002) suggest that consumers with high need for interaction are more likely to look forward to interactions with human service agents and are less likely to look favorably on computer-interactions, viewing those as incompatible with their desires. Mou and Xu (2017) suggested that consumers can display different personality traits when interacting with people and with machines, and that many show more openness, extroversion, and preference for self-disclosure when interacting with other people. Customers can believe they will obtain better experience when interacting with a human compared to a computer, especially for their better ability to deal with various problems in complex situations (Ashfaq et al., 2020). In addition, several disadvantages of chabot interactions, such as uncertainty of chatbot performance (Ashfaq et al., 2020) and feelings of discomfort (Luo et al., 2019), can be heightened for consumers with greater need for human interaction. This may be especially where chatbots lack empathy for consumers and are unable to understand a consumer's situation and alleviate their negative emotions (Ashfaq et al., 2020). At the same time, robots can only provide homogeneous emotional services and cannot provide personalized services according to the emotions of each consumer (Osawa et al., 2017). Consumers tend to think that robot services are not sincere enough (Shin and Jeong, 2020). These negative beliefs about chatbots are exacerbated where consumers have a need for human interaction. Ashfaq et al. (2020) confirmed that users with high human interaction need prefer human interactions to human–computer interactions, and would value more the service approach of human beings (Ben Mimoun et al., 2017), especially for more personalized services (Dabholkar and Bagozzi, 2002). In contrast, users with a low human interaction need prefer more comfortable, reliable and fun ways of service (Dabholkar and Bagozzi, 2002). In addition, users with a high need for human interaction have lower expectations of service delivery from chatbots compared to those with weaker human interaction needs (Ashfaq et al., 2020). This difference in expectations for chatbots will affect consumers' requirements for chatbot service quality. Consequently, in this study, we examine the boundary conditions of human–computer interaction to investigate whether differences in perceptions about chatbots versus human agents can be explained by the differences in a consumer's need for human interaction. More specifically, the need for human interaction is considered a moderating variable influencing the effect of service agent type on perceived communication quality and perceived privacy risk.

3. Research model and hypotheses

Our research model is depicted in Fig. 1. The model illustrates that consumers' willingness to adopt service agent types (chatbots and humans) will differ. Moreover, consumers' adoption of a service agent is considered a function of communication quality and privacy risk perceptions. A consumer's need for interaction influences the relationship between service agent type and perceptions of communication quality and privacy risks. The arrows in the model reflect the underlying hypotheses developed next.

3.1. Type of service agent and adoption intention

Service agents are the key to solving user problems (Chakrabarty et al., 2014). As service agents, chatbots act as virtual assistants that provide automated customer support and business guidance in a conversational manner. Chatbots have advantages such as being highly available and offering more timely responses and longer opportunities for interaction (Hill et al., 2015). However, some studies have shown that users have higher expectations of humanoid chatbots (Diederich et al., 2020), and a lower tolerance for errors (Lee and Lyu., 2016). Moreover, owing to the lack of empathic perception, users usually demonstrate negative attitude towards humanoid chatbots even chatbots services as a whole, compared to human beings (Touré-Tillery and McGill, 2015). Chatbots may also create negative user emotions due to excessive anthropomorphism (Mori et al., 2012). Consequently, in the use of service agents, users are generally expected to have a weaker willingness to accept chatbots compared to human beings. Based on above, the following hypothesis is proposed:

H1. There is a significant difference between service agent types in consumers' willingness to adopt.

H1a. Consumers have lower adoption intention of chatbots compared to human service agents.

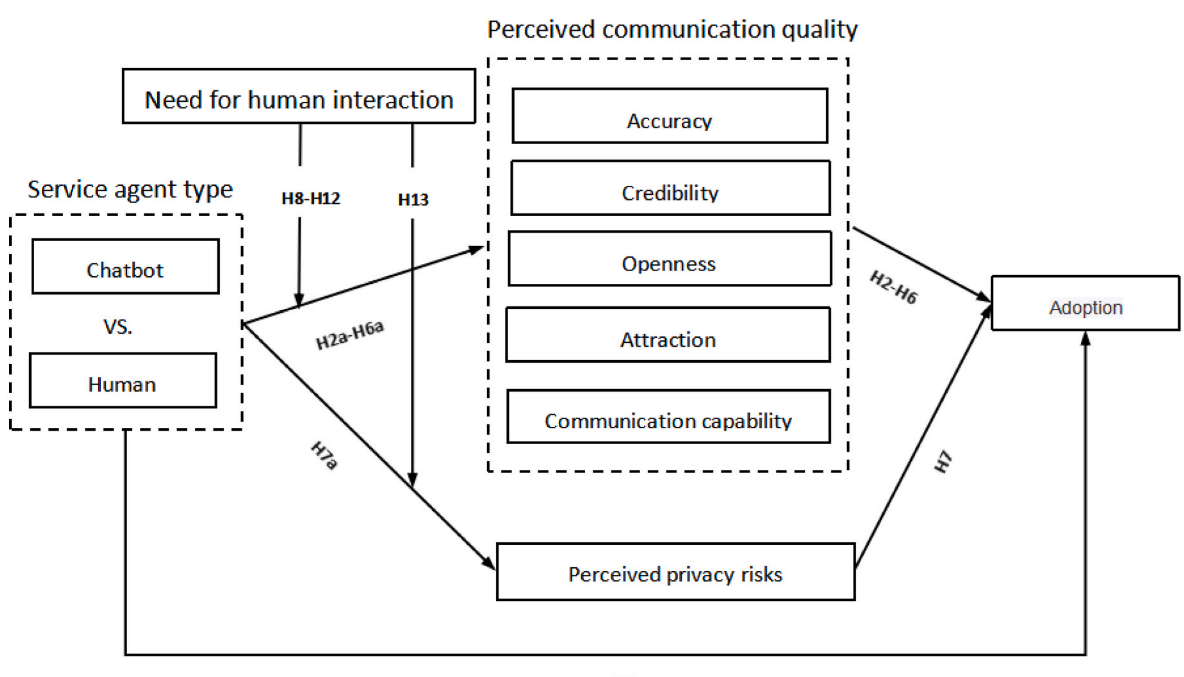

Fig. 1. Research model.

3.2. The mediating role of perceived communication quality in service agent type and adoption intention

Perceived communication quality is a major indicator of service effectiveness (Sheehan et al., 2020) and an important factor influencing consumer attitudes (Chung et al., 2020). Consumers are likely to have different perceptions of communication quality when interacting with chatbots versus human beings, as two types of service agents (Shank, 2013). Based on the CASA paradigm, consumers expect AI to communicate as well as humans (Pelau et al., 2021). Therefore, perceived communication quality was classified into five dimensions of accuracy, credibility, openness, attraction, and communication capability, which our literature review shows are five qualities of communication that matter to consumers and are likely to be important in their chatbot interactions. We develop five hypotheses suggesting that users may have higher accuracy and openness perceptions of chatbots as compared to human agents, but lower perceptions of their credibility, attraction and communication capability.

Accuracy is defined as the ability to respond to users with the most current and relevant information (Huang and Chueh, 2021). Accurate communication content is more likely to match users' need (Park et al., 2009). Chatbots are equipped with advanced language processing systems and can objectively communicate and respond to users without getting frustrated nor tired like humans (Luo et al., 2019) and providing uninterrupted continuous service (Hill et al., 2015). In addition, chatbots are able to respond to users' need accurately using minimal text and symbols compared to linguistically cumbersome human beings. Similarly, Ubisend (2017) argued that chatbot is more efficient at capturing the keywords of the user's problem and responding to the point of the problem. It has been demonstrated that if communication with service agents meets customers' need with high quality, it motivates users to use it and they are more likely to be accept the service (Pillai and Sivathanu, 2020). Therefore, in the use of service agents, communication with chatbots provides customers with higher accuracy perceptions and greater likelihood of receiving those responses in a short period of time, which enhances the adoption intention. Based on above, the following hypotheses are proposed:

H2. Perceived communication accuracy explains (mediates) the effect of service agent type on consumer adoption.

H2a. Consumers have higher perceptions of communication accuracy of chatbots compared to human service agents.

Credibility defines the user's perception on the reliability of the communication process (Edwards et al., 2014) and has further been shown to be an important factor in user adoption of new technologies (Corritore et al., 2005). The information or recommended products provided by the chatbots are controllable by the e-merchant and users often perceive that the information provided by the chatbots is related to the merchant's interests. In addition, the information provided by chatbots is one-sided and less comprehensive in responding to users' questions than human beings (Ashraf et al., 2019), which can gradually weaken users' trust in chatbots. It has been noted that users generally perceive robots as lacking knowledge and empathy compared to human beings and have less trust in the information provided by the former (Dietvorst et al., 2018). Therefore, in the use of service agents, communicating with human beings provide customers with higher credibility perceptions; hence are better able to generate a stronger empathic knowledge and obtain comprehensive information. In view of this, the following hypotheses are proposed:

H3. Perceived communication credibility explains (mediates) the effect of service agent type on consumer adoption.

H3a. Consumers have lower perceptions of communication credibility of chatbots compared to human service agents.

Openness is defined as the user's willingness to be receptive to the communication experience (Lowry et al., 2010). Hill et al. (2015) found that computer interactions can be timelier and the anonymity of the human−computer interaction can lead to a less bounded user communication compared to human interaction. Therefore, in the use of service agents, communication with chatbots allow for higher openness perceptions; hence customers are better able to express their need without scruples, thus being more receptive to the communication experience and enhancing adoption intention. Based on the above, the following hypotheses are proposed:

H4. Perceived communication openness explains (mediates) the effect of service agent type on consumer adoption.

H4a. Consumers have higher perceptions of communication oppeness with chatbots compared to human service agents.

Attraction is another major factor affecting the quality of communication. Attraction can be divided into social and task attraction (McCroskey and McCain, 1974), This study will focus mainly on social attraction that can be defined as the perception of the friendliness of the service agents. In contrast to human beings, chatbots communicate in an overly rigid manner, and the lack of tone words and emoticons increases the psychological distance of users. Similarly, Kim et al. (2019) found that users felt more warmth in interaction with other people. Therefore, human beings as service agents, give customers a higher attraction perceptions and customers are more likely to feel humor and warmth, which enhances the adoption intention. Thus, the following hypotheses are proposed.

H5. Perceived communication attractiveness explains (mediates) the effect of service agent type on consumer adoption.

H5a. Consumers have lower perceptions of communication attractiveness of chatbots compared to human service agents.

Perceived communication capability refers to the perception of the ability to solve complex problems effectively (Clokie and Fourie, 2016). It has been noted that most users believe that the robot with which they have interacted can only handle simple requests and do not expect it to have the same capabilities as human beings (Følstad and Skjuve, 2019). Specifically, human beings are better able to respond and solve problems in complex situations, which can result in a better service experience. For example, in complex service situations, such as queries on fraud, infringement, and theft, human beings can better understand the users' need and respond to the problem, thus enhancing the adoption intention. Therefore, human beings as service agents, provide customers a higher communication capability perception. Based on aforementioned, the following hypotheses are proposed:

H6. Perceived communication capability explains (mediates) the effect of service agent type on consumer adoption.

H6a. Consumers have lower perceptions of communication capability of chatbots compared to human service agents.

3.3. The mediating role of perceived privacy risk in the effect of service agents type on adoption intention

Privacy concerns are one of the reasons why consumers are reluctant to communicate important personal information online (Milne and Culnan, 2004). Shankar et al. (2003) demonstrated that privacy risk and security concerns reduced user satisfaction with the online environment, and privacy risk is considered a major barrier to technology adoption (Featherman and Pavlou, 2003; Pillai and Sivathanu, 2020). It has been demonstrated that different types of service agents have different perceptions of privacy risk (Zarifis et al., 2021).

The perceived privacy risk during service agent use refers to the user's perceived uncertainty about the service agent, which mostly arises from concerns about potential negative outcomes from the service agent's disclosure of their personal information (Wang and Lin, 2017).

Although it is difficult for human beings to remember all the information about the user and analyze it successively, the superb analytical and memory properties of computer agents such as chatbots can acquire and process large amounts of data from conversations and can affect privacy in many forms (Mazurek and Małagocka, 2019). Moreover, because AI can infer or predict users' personal information using advanced algorithms, this increases users' concerns about privacy risks when using AI technologies (Mazurek and Małagocka, 2019). Consequently, the following hypotheses are proposed:

H7. Perceived privacy risk explains (mediates) the effect of service agent type on consumer adoption.

H7a. Consumers have higher perceptions of privacy risk when interacting with chatbots compared to human service agents.

3.4. Moderating role of need for human interaction

The need for human interaction is understood as the consumer's desire for human contact during the service experience (Dabholkar, 1996). Users with strong need for interaction prefer human interaction to human−computer interaction. They feel more comfortable and convenient in communicating with human beings. In addition, they have lower expectations of chatbots, while users with weak human interaction need have higher expectations of chatbots (Ashfaq et al., 2020). When interacting with a robot, users with strong human interaction need will perceive the lower communication quality and high privacy risks as consistent with their low expectations of the robot, contrary to expectations of users with weak human interaction need. Conversely, users with strong human interaction need have high expectations of human beings, while users with weak human interaction need have low expectations of a human beings (Ashfaq et al., 2020). When interacting with human agents, users with strong human interaction need perceive lower communication quality and higher privacy risks contrary to their high expectations of human beings, but consistent with the expectations of users with weak human interaction need. Therefore, it is reasonable to assume that strong/weak human interaction need will enhance/reduce the requirements for perceived communication quality and privacy risk in humans, but reduce/enhance these requirements in the use of chatbots. In view of this, the following hypotheses are proposed:

H8. The effect of service agent type on perceived accuracy is moderated by the need for human interaction. Specifically, strong/weak human interaction need will increase/decrease the requirement for perceived accuracy in the use of human beings.

H9. The effect of service agent type on perceived credibility is moderated by the need for human interaction. Specifically, strong/weak human interaction need will reduce/increase the requirement for perceived credibility in the use of chatbots.

H10. The effect of service agent type on perceived openness is moderated by the need for human interaction. Specifically, strong/weak human interaction need will increase/decrease the requirement for perceived openness in the use of human beings.

H11. The effect of service agent type on perceived attraction is moderated by the need for human interaction. Specifically, strong/weak human interaction need will reduce/increase the requirement for perceived attraction in the use of chatbots.

H12. The effect of service agent type on perceived communication capability is moderated by the need for human interaction. Specifically, strong/weak human interaction need will reduce/increase the requirement for perceived communication capability in the use of chatbots.

H13. The effect of service agent type on perceived privacy risk is moderated by the need for human interaction. Specifically, strong/weak human interaction need will reduce/increase the requirement for perceived privacy risk in the use of chatbots.

4. Design of experiments

The experimental design was used to collect data to test the hypotheses. Experiment 1 examined the effect of service agent type (chatbots vs. human beings) on consumer adoption intention to verify H1. Experiment 2 investigated the mediating role of perceived communication quality in the effect of service agent type on consumer adoption intention to verify H2, H3, H4, H5 and H6. Experiment 3 investigated the mediating role of perceived privacy risk in the influence of service agent type on consumer adoption intention to verify H7. Experiment 4 studied the effect of need for human interaction (strong vs. weak) moderating service agent type on perceived communication quality to verify H8, H9, H10, H11 and H12. Experiment 5 investigated the effect of need for human interaction (strong vs. weak) moderating service agent type on perceived privacy risk to verify H13.

4.1. Experiment 1: effect of service agent type on adoption

4.1.1. Pre-experiment

The purpose of the pre-experiment was to select the experimental stimulus and avoid the influence of gender factors. The pre-experiment was conducted in the form of an online situational experiment. According to the annual data of Taobao app in 2020, the apparel category steadily ranked first in the sales, indicating that consumers were generally familiar with apparel products when shopping online (Zhao, 2010). Therefore, this category was chosen as the focus of the experimental stimulus for this study.

In further determination of the experimental stimulus, subjects ($N = 60$, female = 50%) were recruited from the Wenjuanxing platform to participate in an online questionnaire. The platform is equivalent to the Amazon MTurk portal and is used for online recruitment of willing research study participants. The participants were recruited using an invitation to participate in the study posted onto the portal. The majority of participants are between 18 and 40 years old (71.7%). Apparel products were classified into "casual wear", "sportswear", "professional wear", "home wear ", and "performance wear" in the pre-experiment. Subjects were asked to answer two measures of product familiarity in turn for the common types of clothing: "I have had many experiences buying this type of products online (1 = strongly disagree, 7 = strongly agree)", "I know a lot of brand information about this type of products (1 = strongly disagree, 7 = strongly agree). The results showed that, casual wear ($M_{female} = 4.68$, $M_{male} = 5.02$, $p = 0.21 > 0.05$), sportswear ($M_{female} = 4.22$, $M_{male} = 4.57$, $p = 0.36 > 0.05$) and home wear ($M_{female} = 4.10$, $M_{male} = 4.10$, $p = 0.92 > 0.05$) were not significantly influenced by gender but professional wear ($M_{female} = 2.97$, $M_{male} = 3.93$, $p = 0.01 < 0.05$) and performance clothes ($M_{female} = 1.93$, $M_{male} = 2.88$, $p = 0.02 < 0.05$) were significantly affected by gender; hence, in order to exclude the interference of gender on the experiment results, "home clothes" was selected as the experimental stimulus.

4.1.2. Design of experiment

Experiment 1 used a single factor (service agent type: chatbots vs. human beings) within-subject group experimental design. The manipulated material for the service agent type in this experiment consisted of two parts: The first part was textual material asking participants, "Imagine you want to purchase a piece of home wear through an online platform, and the following is the interface between you and the merchant's customer service". The second part is the picture material used to give the subject stimulus by depicting a conversation occurring between the consumer on Taobao app and the merchant's customer service chatbot agent (as in Fig. 2a) and human agent (as in Fig. 2b). In the human beings' scenario, the picture showed that when the subject asked the customer service three questions: "How to choose the size", "When to ship" and "Pick the color", the subject received humanized reply, such as: "We suggest you choose a medium size; however if you want to be loose, you can also wear large size.", "We will arrange delivery for you as

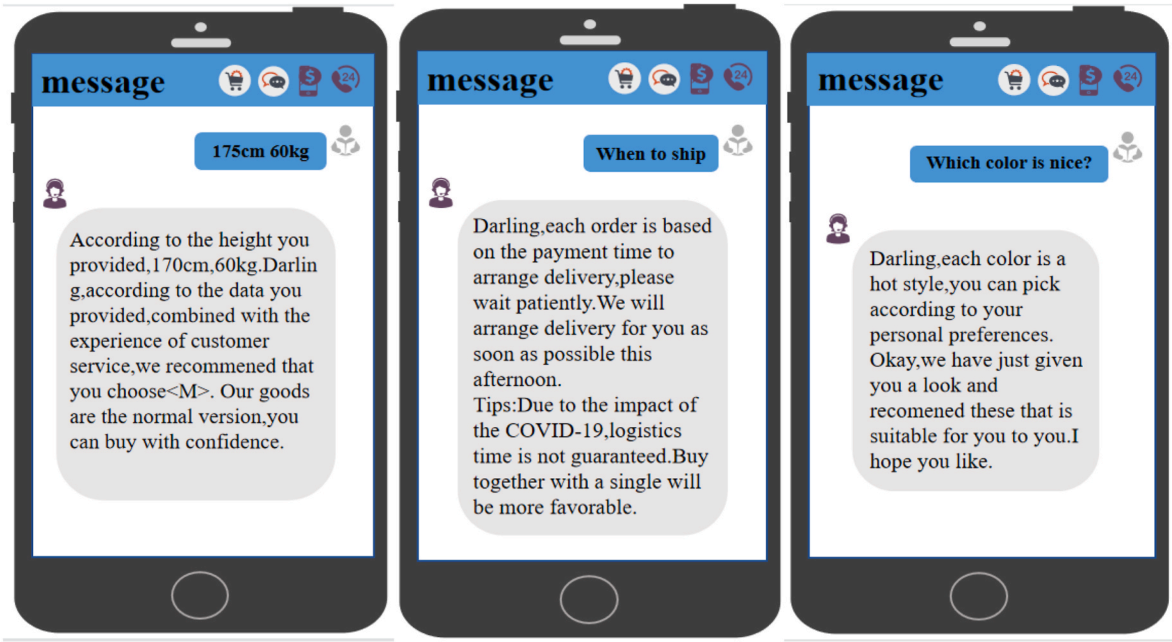

Fig. 2a. chatbots scenario.

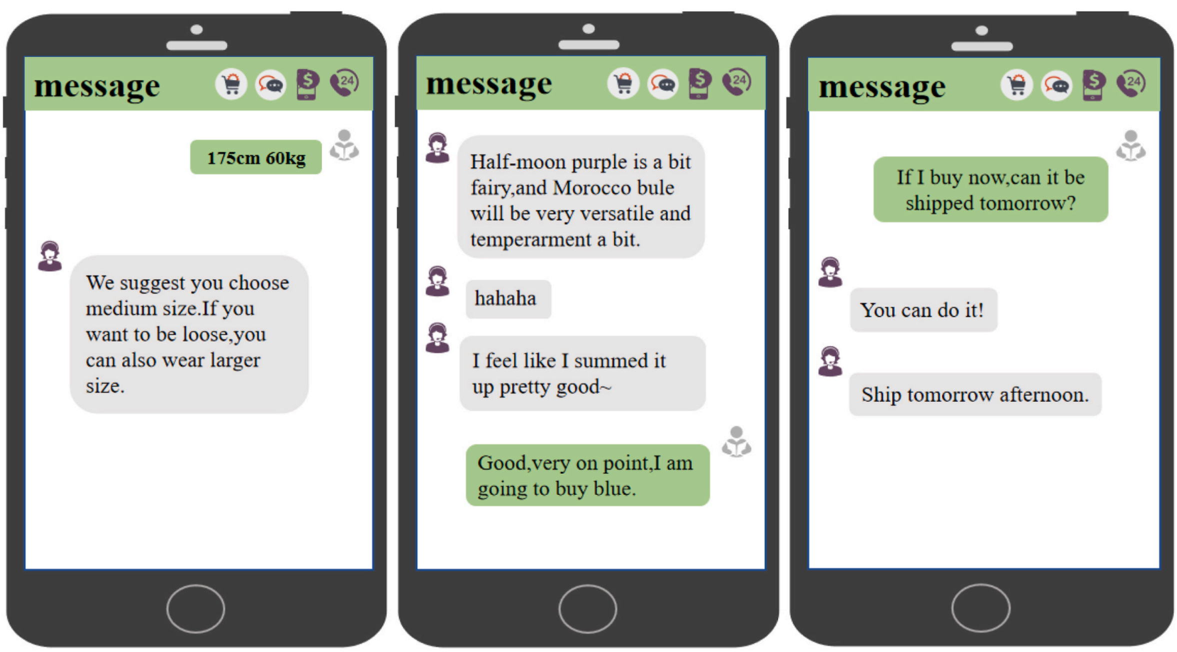

Fig. 2b. human beings scenario.

soon as possible." and "Half-moon purple is a bit fairy, and Morocco blue will be very versatile and temperamental a bit." In the chatbot scenario, the picture showed that when the subject also asked the customer service these three questions, the subject received official replies, such as: "According to your height and weight, we recommend that you choose a medium size", "Each order is based on the payment time to arrange delivery, please wait patiently" and "Each color is a hot model, and we recommend that you choose according to personal preferences".

4.1.3. Procedure of experiment and variable measurement

Experiment 1 was conducted as a situational experiment with a questionnaire. Data were collected through the online survey platform namely Wenjuanxing, 157 subjects consisting of 56 males were recruited and the data was collected through an online questionnaire. The participants were recruited using an invitation to participate in the study posted onto the portal. Our experiment conforms to the experimental requirements and the real situation of online shopping using an experimental scenario from a realistic customer service encounter. To ensure participants could relate to the overall experimental scenario, we only recruited participants who understood the scenario of online shopping, had social experience and were able to answer the study questions. We ensured the participants found the study relatable by requiring them to indicate that they were familiar with online purchasing and that the scenario had relevance to them. Subjects were randomly assigned to receive one of the two experimental contexts (human agent material or chatbot agent material). After reading the experimental design materials, the success of the independent variable manipulation was first examined by asking subjects about the type of service agent they perceived being depicted in the scenario, followed by questions on attention measures, measures of adoption intention, and measures of demographic characteristics. Attention measures are used to measure participants' familiarity and immersion in the situation. Two attention measures asked: "Do you feel familiar with this experience?" and "Can you imagine yourself as the main character in the above scenario?". Adoption intention as the dependent variable was measured using three questions (Sawang et al., 2014), as shown in Appendix A, for example, "I'm willing to accept this kind of customer service in the future". A 5-point Likert scale was used for all measures, with "1" representing strong disagreement and "5" representing strong agreement. A total of 157 questionnaires were collected in Experiment 1, of which 32 were deleted for failing the attention measures, leaving 125 valid questionnaires. The demographic results showed that female subjects accounted for 70.4% of the total number of subjects with male subjects accounting for 29.6% of the total number. The average age of subjects was mainly between 18 and 24 (60.8%). In addition, 63.2% of subjects shopped online more than 5 times monthly on average, 73.6% used customer service more than 3 times when shopping online, and 67.8% encountered chatbots more than 3 times when shopping online, indicating that subjects were highly familiar with online shopping and could better integrate into the shopping environment, which made the experimental data more realistic.

4.1.4. Results of experiment 1 and discussion

With reference to a manipulation test, the experiment was conducted by asking subjects such as "Which type of customer service do you think the above image is?" (1 = chatbots, 5 = human beings) to test for manipulation of the independent variables. A 5-point Likert scale was used for this measures, with "1" representing strongly believe that this picture refers to interacting with chatbot, and "5" representing strongly believe that this picture refers to interacting with human agent. As shown in Table 3, for material 1 (human beings), $M_{\text{human beings}} = 3.95$ ($SD = 1.419$, $t = 5.373$, $p < 0.001$), with a lower limit of 95% confidence interval of 0.60 and an upper limit of 1.31, indicating that subjects perceived a higher degree of human beings in material 1 (above the median of 3). For material 2, $M_{\text{chatbots}} = 1.36$ ($SD = 0.684$, $t = -18.721$, $p < 0.001$) indicates that subjects perceived a high level of chatbots in material 2. The two independent samples *t*-test showed that $M_{\text{human beings}} = 3.95 > M_{\text{chatbots}} = 1.36$ ($t_{(123)} = 12.9$, $p < 0.001$), indicating the success of the service agent type manipulation.

Satisfied with the manipulation test, we could proceed to test hypothesis 1. The dependent adoption intention question items exhibited high reliability ($\alpha = 0.964$) with the Cronbach's α coefficient greater than 0.8 and a composite adoption score was then calculated.

The study used independent sample *t*-test to test hypothesis 1, and the results showed a significant difference in the effect of service agent type on adoption with adoption willingness being highest in the group exposed to the human agent scenario ($M_{\text{human beings}} = 4.22 > M_{\text{chatbots}} = 2.61$, $t = 9.524$, $p < 0.001$). Thus consumers' willingness to adopt chatbots is weaker compared to human beings; hence, hypothesis 1 was verified.

Experiment 1 demonstrated a significant difference in the effect of service agent type on consumers' adoption intention. Consumers were more willing to accept a scenario considered a human interaction scenario than a scenario considered a chatbot interaction. This verifies hypothesis 1. In addition to the direct effect, what exactly is the mechanism regarding the intrinsic effect of service agent type on adoption intention? How can we make chatbots (vs. human beings) more advantageous and enhance the quality of communication? To this end, Experiment 2 focuses on these questions, as hypothesized in H2-H6, by analyzing differences in consumers' willingness to accept service agent types based on the five dimensions of perceived communication quality.

4.2. Experiment 2 Mediating effects of perceived communication quality

4.2.1. Design of experiment

Experiment 2 used a single factor (type of service agent: chatbots vs. human beings) within-subject group experimental design. The experimental material was the same as in Experiment 1, and subjects in both groups answered the questions separately after reading the scenario. In order to distinguish Experiment 2 from Experiment 1 and to increase the generalizability of our findings, we recruited different subjects in Experiment 2. At the same time, it tested the mediating roles of the five dimensions of perceived communication quality by adding relevant question items to the survey for measuring variables needed to verify H2- H6.

4.2.2. Procedure of experiment and variable measurement

Experiment 2 was conducted as a situational experiment with a questionnaire. Subjects ($N = 156$, female = 75%) were recruited from the Wenjuanxing platform. The participants were recruited using an invitation to participate in the study posted onto the portal. Subjects were randomly assigned to the two experimental contexts as described under Experiment 1. After reading the experimental design materials, the success of the independent variable manipulation was first tested by asking subjects about the type of service agent perceived. Second, the subjects were required to answer a survey about the five dimensions of perceived communication quality, adoption intention, and demographic characteristics at the end of the attention measure. A total of 156 questionnaires were collected in Experiment 2. The demographic results showed that female and male subjects accounted for 75% and 25% of the total number of subjects respectively with ages mainly ranging from 18 to 24 (52.6%). In addition, 59.6% of subjects shopped online more than 5 times monthly on average, 64.1% used customer service more than 3 times when shopping online, and 50.6% encountered chatbots more than 3 times when shopping online, indicating that subjects were more familiar with online shopping and could better integrate into the shopping environment.

Along with the same adoption intention measures as Experiment 1 (Sawang et al., 2014), the questionnaire included 15 question items, as shown in Appendix A, to measure the five dimensions of perceived communication quality. Among them, perceived accuracy included three items (e.g., "I feel that customer service replies me timely") (Chung et al., 2020). Perceived credibility included two items (e.g., "I feel the customer service replies me sincerely") (Chung et al., 2020), and perceived attraction used McCroskey's scale (1974), which was appropriately modified in the experiment and included four items (e.g., "I feel the customer service attitude is very friendly"). The perceived openness included three items (e.g., "I can easily have a free communication with customer service") (Lowry et al., 2009). Perceived communication capability included three items (e.g., "I feel this kind of customer service

Table 3
Manipulation test (one-sample *t*-test).

Materials	Contexts	Mean (M)	SD	t	Sig. (Bilateral)	95% Confidence interval	
						Minimum	Maximum
Material 1	human beings	3.95	1.419	5.373	0.000	0.60	1.31
Material 2	chatbots	1.36	0.684	−18.721	0.000	−1.81	−1.46

can deal with complex problems more efficiently than offline stores") (Chung et al., 2020). All measures were administered on a 5-point Likert scale, with "1" representing strong disagreement and "5" representing strong agreement. The same manipulation test question was used as in Experiment 1.

4.2.3. Results and discussion

The event familiarity test was designed as a question, "Would I be familiar with such an experience?". The data showed that M = 4.11 (SD = 0.99) [$t = 13.492$, $p < 0.001$], indicated that subjects were relatively familiar with the experimental situation, which subsequently laid the foundation for the experimental situation immersion. The immersion level was designed with the question "Would I imagine myself as the main character in the above scenario?", and the data showed that M = 4.01 (SD = 0.91) [$t = 13.798$, $p < 0.001$], indicating that subjects were able to integrate well into the pre-defined situation. The results of the one-sample *t*-test for the manipulation test question for service agent type showed that, $M_{\text{human beings}} = 3.84$, $M_{\text{chatbots}} = 1.70$, with significant one-sample *t*-test results. Two independent sample *t*-test results showed $M_{\text{human beings}} = 3.86 > M_{\text{chatbots}} = 1.70$ ($t_{(154)} = 10.7$, $p < 0.001$), indicating successful manipulation of service agent type.

Subsequently, the scales for the five perceived communication quality dimensions were each tested for reliability, where perceived accuracy ($\alpha = 0.857$), perceived credibility ($\alpha = 0.826$), perceived openness ($\alpha = 0.873$), and perceived communication capability ($\alpha = 0.825$) all exhibiting high reliability. For perceived attraction dimension, the corrected item total correlation between the fourth question item of perceived attraction, and the total item was severely less than 0.400, whiles the α coefficient (0.495) was below 0.6. Hence this question item was removed, improving the reliabilty of the perceived attraction scale ($\alpha = 0.873$) The Cronbach's α coefficients were thus all greater than 0.8, indicating good reliability for all scales.

For hypothesis testing, service agent type was designated as the antecedent variable, with five dimensions of perceived quality of communication used as mediating variables and adoption intention used as the outcome variable. SPSS26 and Model4 of SPSS PROCESS macro (version 3.3) were used to test the mediating effect. The results showed that the effect of service agent type on consumers' purchase intention was significant ($t = -11.445$, $p < 0.01$), and hypothesis 1 was again verified. As shown in Table 4, the effect of service agent type on adoption intention remained significant ($t = -6.516$, $p < 0.01$) after the mediating variable perceived communication accuracy was inserted. The effect of perceived accuracy on adoption intention was significant ($t = 10.589$, $p < 0.01$), with a positive relationship; hence the higher the accuracy perceptions, the stronger the adoption intention. The mediated path of "service agent type-perceived accuracy-adoption intention" was significant (Indirect Effect = −0.235, LLCI = −0.309, ULCI = −0.166, at 95% confidence interval, which did not include zero). Thus supporting H2. The effect of service agent type on perceived accuracy was significant ($t = -8.289$, $p < 0.01$). However, there is a negative relationship between service agent type and perceived accuracy, indicating consumers' higher accuracy perceptions of human beings than chatbots, which did not support H2a.

As shown in Table 5, the effect of service agent type on adoption intention was still significant when the mediating variable perceived credibility was included ($t = -4.992$, $p < 0.01$). The effect of service agent type on perceived credibility was significant ($t = -9.761$, $p < 0.01$); however, service agent type had a negative relationship with perceived credibility, indicating a higher consumers' perceived credibility of human beings than of chatbots, which supported H3a. The effect of perceived credibility on adoption intention was also significant ($t = 11.727$, $p < 0.01$), with both having a positive relationship on each other; hence the higher the credibility perceptions, the stronger the adoption intention. The mediated path of "service agent type-perceived credibility-adoption intention" was significant (Indirect Effect = −0.293, LLCI = −0.365, ULCI = −0.220, at 95% confidence interval does not include zero), which supported H3.

When the mediating variable perceived openness was inserted, the effect of service agent type on adoption intention was still significant ($t = -5.796$, $p < 0.01$). In addition, the effect of service agent type on perceived openness was significant ($t = -8.875$, $p < 0.01$), and there was a negative relationship between service agent type and perceived openness, indicating that consumers' perceived openness towards human beings is higher than that of chatbots, which disputed H4a. The effect of perceived openness on adoption intention was also significant ($t = 13.856$, $p < 0.01$), and there was a negative relationship between perceived openness and adoption intention. The perceived openness had a positive relationship with adoption intention, thus the higher the openness perceptions, the stronger the adoption intention. The mediated path of "service agent type-perceived openness-adoption intention" was significant (Indirect Effect = −0.288, LLCI = -0.363, ULCI = −0.216, at 95% Confidence interval does not include zero), which supported H4.

The effect of service agent type on adoption intention was still significant when the mediating variable perceived attraction was included ($t = -6.349$, $p < 0.01$). The effect of service agent type on perceived attraction was significant ($t = -8.432$, $p < 0.01$), and service agent type was negatively related to perceived attraction, indicating that consumers' perceived attraction to human beings was higher than chatbots, which supported H5a. The effect of perceived attraction on adoption intention was also significant ($t = 11.143$, $p < 0.01$), with both having a positive relationship; hence the higher the attraction perceptions, the stronger the adoption intention. The mediated path of "service agent type-perceived attraction-adoption intention" was significant (Indirect Effect = −0.246, LLCI = −0.299, ULCI = −0.195, at 95% Confidence interval does not include zero), which supported H5.

When the mediating variable perceived communication capability was included, the effect of service agent type on adoption intention was still significant ($t = -6.934$, $p < 0.01$). The effect of service agent type on perceived communication capability was significant ($t = -7.861$, $p < 0.01$), and service agent type had a negative relationship with perceived communication capability, indicating that consumers' perceived communication capability was higher for human beings than chatbots, which supported H6a. The effect of perceived communication capability on adoption intention was also significant ($t = 11.058$, $p < 0.01$), and perceived communication capability had a positive relationship with adoption intention, thus the higher the communication capability perceptions, the stronger the adoption intention. The mediated path of "service agent type-perceived communication capability-adoption intention" was significant (Indirect Effect = −0.229, LLCI = −0.308, ULCI = −0.158, at 95% confidence interval does not include zero), so H6 was supported.

Discussion. Experiment 2 verified the mediating effect of perceived communication quality (accuracy, credibility, openness, attraction and communication capability), which supported H2, H3, H4, H5 and H6. In contrast with chatbots, human beings had higher perceived communication quality, which supported H3a, H5a, H6a and disputed H2a and

Table 4
Decomposition of mediating effect of accuracy.

	Effect	BootSE	BootLLCI	BootULCI
Total effects	−0.490	0.043	−0.575	−0.405
Direct effects	−0.255	0.039	−0.332	−0.178
Mediating effects	−0.235	0.037	−0.309	−0.166

Table 5
Decomposition of mediating effect of credibility.

	Effect	BootSE	BootLLCI	BootULCI
Total effects	−0.490	0.043	−0.575	−0.405
Direct effects	−0.197	0.040	−0.276	−0.119
Mediating effects	−0.119	0.037	−0.365	−0.220

H4a. Although communication quality was found highest for human service agents across all dimensions, the question as to which agent type (chatbots vs. human beings) will give customers a higher perception of privacy risk needed to be resolved. Experiment 3 was used to analyze the differences between chatbots and human beings from the perspective of perceived privacy risk and construct an internal mechanism based on service agent type and adoption intention.

4.3. Experiment 3 Mediating effect test of perceived privacy risk

4.3.1. Design of experiment

Experiment 3 used a single factor (service agent type: chatbots vs. human beings) within-subject group experimental design. The experimental stimulus materials were the same as in Experiment 1. In order to distinguish Experiment 3 from Experiment 1 and Experiment 2 and to increase the generalizability of our findings, we recruited different subjects in Experiment 3. At the same time, it tested the mediating role of the perceived privacy risks. The question items of the privacy risk mediation variable were also added to the survey to verify H7.

4.3.2. Procedure of experiment and variable measurement

Experiment 3 was conducted as a situational experiment with a questionnaire. Data were collected through the online survey platform Wenjuanxing, 87 subjects consisting of 55 females were recruited. The participants were recruited using an invitation to participate in the study posted onto the portal. Subjects were randomly assigned to the two experimental contexts. After reading the experimental design materials, the success of the independent variable manipulation was first tested by asking subjects about the type of service agents perceived. Experiment 3 then included the completion of a three-item perceived privacy risk scale (Dinev and Hart, 2006), as shown in Appendix A (e.g., "I'm worried about personal information being leaked and sold to third parties"). In addition, the same adoption intention measures (Sawang et al., 2014) as Experiment 1 were used along with measures of adoption intention and demographic characteristics. All scale measures were administered on a 5-point Likert scale, with "1" representing strong disagreement and "5" representing strong agreement. A total of 87 questionnaires were obtained in Experiment 3. The demographic results showed that female and male subjects accounted for 63.2% and 36.8% respectively of the total number of subjects and ages were mainly concentrated between 18 and 24 (50.6%). In addition, 73.6% of subjects shopped online more than 5 times monthly on average, 74.7% used customer service more than 3 times when shopping online, and 66.7% encountered chatbots more than 3 times when shopping online, thus suggesting sufficient familiarity of subjects with online shopping.

4.3.3. Results and discussion

Manipulation test. The familiarity of the event was designed as a question " Would I be familiar with such an experience?", and the data showed that $M = 4.40$ ($SD = 0.74$) [$t = 27.746$, $p < 0.001$], indicating that subjects were relatively familiar with the experimental situation, which subsequently laid the foundation for the integration of the experimental situation. The immersion level was designed with the question "Would I imagine myself as the main character in the above scenario?", and the data showed that $M = 4.37$ ($SD = 0.79$) [$t = 25.684$, $p < 0.001$], indicating that subjects were able to integrate well into the pre-defined scenario. The independent variable manipulation test asked "Which type of customer service do you think the above pictures belong to?". The results of the one-sample *t*-test showed that $M_{\text{human beings}} = 4.40$ and $M_{\text{chatbots}} = 1.77$, with significant one-sample *t*-test results. The results of the two independent sample *t*-test showed that $M_{\text{human beings}} = 4.40 > M_{\text{chatbots}} = 1.77$ ($t_{(216)} = 15.2$, $p < 0.001$), indicating the success of the manipulation test. The perceived privacy risk scale was subsequently tested for reliability, and the Cronbach's α coefficient was greater than 0.8 ($\alpha = 0.926$), indicating good reliabilty of the perceived privacy risk measure.

Hypothesis test. Service agent, human beings and chatbots were designated as the antecedent dummy variable with perceived privacy risk as the mediating variable, and adoption intention as the outcome variable. The results showed that the effect of service agent type on consumers' purchase intention was significant ($t = 19.880$, $p < 0.01$), and hypothesis 1 was again verified on this additional sample. As shown in Table 6, after insertion of the mediating variable perceived privacy risk, the effect of service agent type on adoption intention remained significant ($t = 11.120$, $p < 0.01$). The effect of service agent type on perceived privacy risk was significant ($t = -10.853$, $p < 0.01$); however, there was a negative relationship between service agent type and perceived privacy risk, indicating that consumers' perceived privacy risk was higher for human beings than chatbots, disputing H7a. The effect of perceived privacy risk on adoption intention was also significant ($t = -3.177$, $p < 0.01$) and perceived privacy risk had a negative relationship with adoption intention, thus the higher the privacy risk perceptions, the lower the adoption intention. The mediated path of "service agent type - perceived privacy risk - adoption intention" was significant (Indirect Effect = 0.287, LLCI = 0.075, ULCI = 0.509, at 95% confidence interval, which does not include zero), supporting H7.

Discussion. Experiment 3 verified the mediating effect of perceived privacy risk in linking type of service agent with adoption intention, supporting H7. Moreover, there were differences in consumers' perceptions on privacy risk between human beings and chatbots as different types of service agents. Compared with chatbots, consumers perceive a higher risk of privacy disclosure by using human agents, which disputed H7a. Experiments 4 and 5 considered whether a consumer's need for human interaction acts as a moderating variable influencing the relationships between service agent type and perceptions of communication quality and risk. Results are presented next.

4.4. Experiment 4 Moderating role of need for human interaction in service agent type on perceived communication quality

4.4.1. Design of experiment

Experiment 4 used a single factor (service agent type: chatbots vs. human beings) within-subject group experimental design. The manipulation of service agent types was still used as in Experiment 1, and was achieved through textual materials and chat log pictures. Participants in Experiment 4 were divided into high and low need for interaction groups based on their mean values after measurement.

4.4.2. Procedure of experiment and variable measurement

As with all prior experiments, Experiment 4 was conducted as a situational experiment with a questionnaire. The participants were recruited using an invitation to participate in the study posted onto the portal. 149 subjects were recruited from the Wenjuanxing platform and were randomly assigned to one of the two experimental contexts. After reading the experimental design materials, the success of the independent variable manipulation was first tested by asking subjects about the type of service agency perceived. Second, after the attention measure, subjects completed a four-item scale for the variable of need for human interaction (Ashfaq et al., 2020), as shown in Appendix A (e.g., "I enjoy the process of communicating with human service agent"). All measures were administered on a 5-point Likert scale, with "1" representing strong disagreement and "5" representing strong agreement. This was followed by the completion of the 5-dimensional scale of perceived communication quality with 15 question items, and the demographic

Table 6
Decomposition of mediating effects of perceived privacy risk.

	Effect	BootSE	BootLLCI	BootULCI
Total effects	1.604	0.081	1.443	1.764
Direct effects	1.317	0.118	1.081	1.552
Mediating effects	0.287	0.108	0.075	0.509

characteristics. A total of 149 questionnaires were obtained in Experiment 4. The demographic results showed that female and male subjects accounted for 61.1% and 38.9% of the total number of subjects respectively. In addition, 63.1% of the subjects shopped online more than 5 times monthly on average, 67.1% used customer service more than 3 times when shopping online, and 57.7% encountered a chatbots more than 3 times, indicating familiarity of subjects to online shopping and could better experience the shopping environment, making the experimental data more realistic.

4.4.3. Results and discussion

Manipulation test. The familiarity with the event was designed as a question "Would I be familiar with such an experience?", and the data showed that $M = 4.34$ ($SD = 0.98$) [$t = 16.745$, $p < 0.001$], indicating familiarity of those subjects with the experimental situation, which consequently laid the foundation for the integration of the experimental situation. The immersion level of the question "Would I imagine myself as the main character in the above scenario?" showed that $M = 4.34$ ($SD = 1.03$) [$t = 15.982$, $p < 0.001$], indicating that subjects were able to integrate well into the pre-defined situation. One-sample *t*-test results for the independent variable manipulation test question showed that $M_{\text{human beings}} = 4.56$, $M_{\text{chatbots}} = 1.34$, which were significant. The results of the two independent samples *t*-test showed that $M_{\text{human beings}} = 4.56 > M_{\text{chatbots}} = 1.34$ ($t_{(147)} = 23.8$, $p < 0.001$), indicating a successful manipulation test. The reliability test was then conducted on the need for human interaction scale ($\alpha = 0.884$). As the Cronbach's α coefficient was greater than 0.8, good reliability was evidenced.

Hypothesis test. Chatbots and human beings were set as dummy variable 1 and dummy variable 2 respectively. The results of the 2 × 2 variance with each of the five dimensions of perceived communication quality as dependent variables showed a significant positive effect of service agent type on perceived accuracy ($F = 6.520$, $p < 0.05$); hence a significant main effect. There was also a significant interaction effect between service agent type and need for human interaction on perceived accuracy ($F = 39.271$, $p < 0.05$), indicating the moderation of the effect of service agent type on perceived accuracy by the need for human interaction. Specifically, when the service agent type was human, consumers with strong human interaction need had higher accuracy perceptions compared to ones with weak human interaction need ($M_{high} = 3.813 > M_{low} = 2.989$); when the service agent type was a chatbot, consumers with strong human interaction need had lower accuracy perceptions compared to those with low human interaction need ($M_{high} = 3.495 < M_{low} = 3.743$). Strong/weak human interaction need will increase/decrease the requirement for perceived accuracy in the use of human beings (see Fig. 3), which verified H8. There is no significant moderating effect of need for human interaction on service agent type and perceived credibility ($F = 0.633$, $p > 0.05$). This implied that the perceived credibility for subjects with low and strong human interaction need were not significantly different for either chatbots or human being, which disputed H9. Perceived openness was also not significantly moderated by the effect of need for human interaction ($F = 2.359$, $p > 0.05$), which disputed H10. There was also no significant difference in the effect of need for human interaction on service agent type and perceived attraction ($F = 0.070$, $p > 0.05$), implying that there was no significant difference in perceived attraction between weak and strong human interaction need subjects for either chatbots or human being, which disputed H11. There was a significant positive effect of service agent on perceived communicaiton capability ($F = 11.194$, $P < 0.05$). In addition, there was also a significant interaction effect between service agent type and need for human interaction on perceived communicaiton capability ($F = 10.997$, $P < 0.05$), indicating the moderation of the effect of service agent type on perceived communicaiton capability by the need for human interaction. Specifically, when the service agent type was human, consumers with strong human interaction need had higher communication capability perceptions compared to ones with weak human interaction need ($M_{high} = 3.826 < M_{low} = 3.194$); when the service agent type was a chatbot, consumers with strong human interaction need had lower communication capability perceptions compared to ones with weak human interaction need ($M_{high} = 3.133 < M_{low} = 3.191$). That is, strong/weak human interaction need will reduce/increase consumers' perception of communication capability in the use of the chatbots (see Fig. 4), which validated H12.

Discussion. The effect of service agent type on perceived accuracy (H8), and perceived communication capability (H12) were moderated by the effect of the need for human interaction. Specifically, in the case where the service agent type were human beings, consumers with strong human interaction need had higher accuracy and communication capability perceptions compared to weak human interaction need. In the case where the service agent type was a chatbot, consumers with strong human interaction need had weaker accuracy and communication capability perceptions compared to weak human interaction need; thus strong/weak human interaction need will increase/decrease the requirement for perceived accuracy in the use of human beings as service agent. Strong/weak human interaction need will decrease/increase consumers' communication capability perceptions in the use of chatbots. The moderating influence of need for human interaction on the relationship between agent tupe and customers' risk perceptions is examined next in Experiment 5.

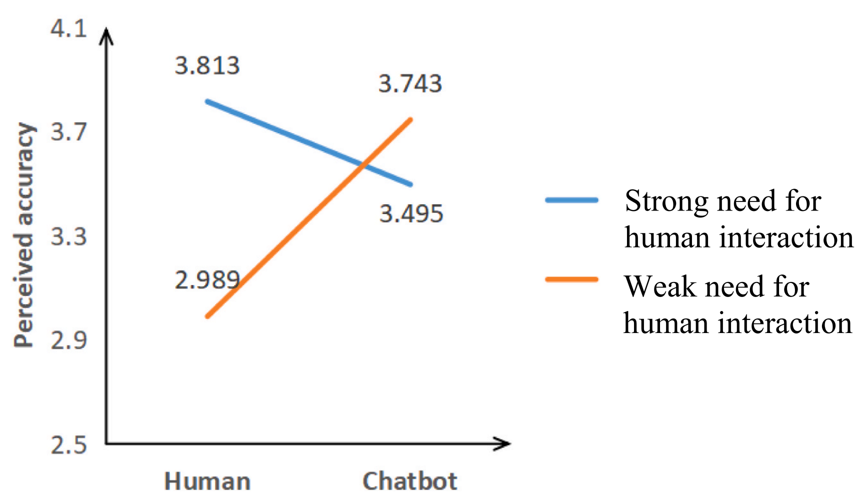

Fig. 3. Effect of service agent type and need for human interaction on perceived accuracy.

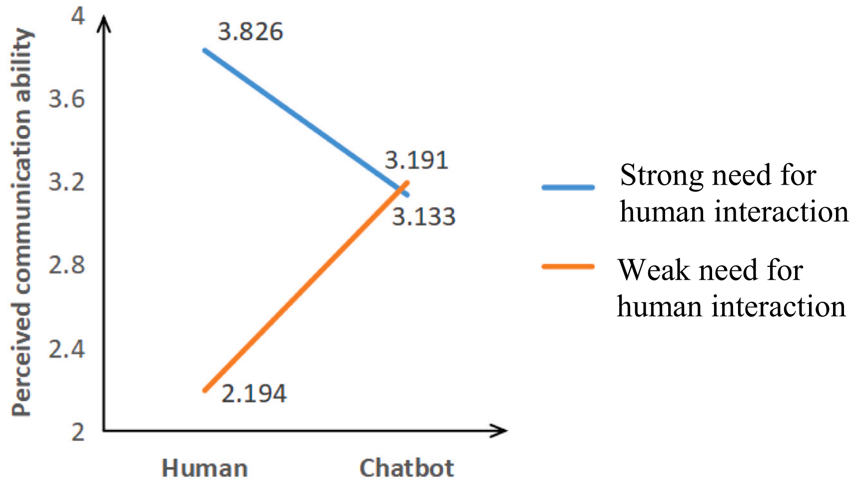

Fig. 4. Effect of service agent type and need for human interaction on perceived communication capability.

4.5. Experiment 5 the moderating role of need for human interaction in service agent type on perceived privacy risk

4.5.1. Design of experiment

Experiment 5 used a single factor (service agent type: chatbot vs. human beings) within-subject group experimental design. The manipulation of service agent types were used as in Experiment 1, and was achieved through textual materials and chat log pictures. Participants were divided as in Experiment 4 into high and low groups based on the mean value on the need for interaction scale.

4.5.2. Procedure of experiment and variable measurement

As with all prior experiments, Experiment 5 was conducted as a situational experiment with a questionnaire. The participants were recruited using an invitation to participate in the study posted onto the portal. 149 participants were randomly assigned to the two experimental contexts. Subsequent to reading the experimental design materials, the success of the independent variable manipulation was first tested by asking subjects about the type of service agency perceived. Second, subjects completed the need for human interaction scale at the end of the attention measure, with items as per Experiment 4 (Ashfaq et al., 2020). This was followed by the scale of perceived privacy risk and finally the demographic characteristics. A total of 149 questionnaires were obtained. The demographic results showed that female and male subjects accounted for 61.1% and 38.9% of the total number of subjects respectively. In addition, 63.1% of subjects shopped online more than 5 times monthly on average, 67.1% used customer service more than 3 times when shopping online, and 57.7% encountered chatbots more than 3 times, indicating that subjects were more familiar with online shopping and could better experience the shopping environment, thus making the experimental data more realistic.

4.5.3. Results and discussion

Manipulation test. The familiarity with the event was designed as a question "Would I be familiar with such an experience?", and the data showed that $M = 4.34$ ($SD = 0.98$) [$t = 16.745$, $p < 0.001$], which was greater than the median of 3, indicating that subjects were relatively familiar with the experimental situation, which subsequently laid the foundation for the integration of the experimental situation. The immersion level of the question "Would I imagine myself as the main character in the above scenario?" showed that $M = 4.34$ ($SD = 1.03$) [$t = 15.982$, $p < 0.001$], indicating that subjects were able to integrate well into the pre-defined situation. One-sample *t*-test results for the independent variable manipulation test question showed significant results that $M_{\text{human beings}} = 4.56$, $M_{\text{chatbots}} = 1.34$. The results of the two independent sample *t*-test showed that $M_{\text{human beings}} = 4.56 > M_{\text{chatbots}} = 1.34$ ($t_{(147)} = 23.8$, $p < 0.001$), indicating that the manipulation test was successful. The Cronbach's α coefficient of the need for human interaction scale was greater than 0.8 ($\alpha = 0.884$), therefore, a good reliability was confirmed.

Hypothesis test. Chatbots and human beings were set as dummy variable 1 and dummy variable 2 respectively. The results of the 2 × 2 ANOVA with perceived privacy risk as the dependent variable showed that there was a significant interaction effect of service agent type and need for human interaction on perceived privacy risk ($F = 9.673$, $p < 0.001$). This indicated the effect of service agent type on perceived privacy risk was moderated by need for human interaction. Specifically, in the case where the service agent type were human beings, the privacy risk perception was weaker for consumers with strong human interaction need than ones with weak human interaction need ($M_{\text{high}} = 2.757 < M_{\text{low}} = 2.860$). In the case where the service agent type was a chatbot, the perceived privacy risk would have still been weaker ($M_{\text{high}} = 2.962 < M_{\text{low}} = 3.848$). That is to say, people with weak human interaction need have the highest perception of privacy risk in the use of chatbots as compared to human agents (see Fig. 5). This interaction effect is different to expectations for H13.

Discussion. The effect of service agent type on perceived privacy risk is moderated by the need for human interaction as suggested in H13, however the effect differs from the expectation that consumers with strong human interaction need would perceive the greatest risks in chatbot interaction. Specifically, the privacy risk perception is lower for consumers with strong human interaction than weak human interaction need in both cases where the service agent type is either a human being or chatbot. The results of Experiment 3 show that compared with chatbots, consumers believe that interacting with human agents has higher privacy risk perceptions. This was possibly because consumers perceive a chatbot to have no incentive to leak information. Those results however seem to be different from the result of Experiment 5, which show chatbots as having higher risk perceptions. Thus, we can conclude that the need for human interaction as the moderating variable, changes the direction and intensity of the relationship between service agent type and consumers' perception of privacy risks such that consumers have lower perceived privacy risk in using human agents after the moderation of the need for human interaction.

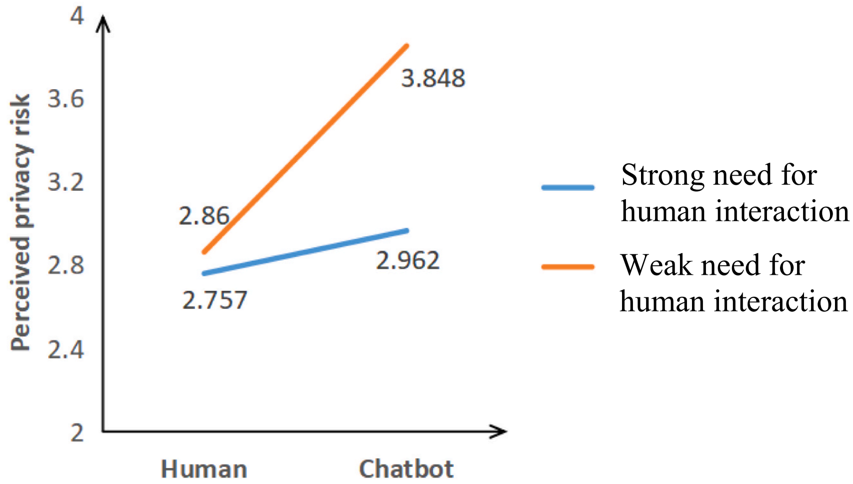

Fig. 5. Effect of service agent type and need for human interaction on perceived privacy risk.

5. Conclusions and implications

5.1. Research findings

The main goal of this study was to examine how the type of service agent (chatbots vs. human beings) affects consumer perceptions of the interaction process. This is important to find an appropriate service balance between robot and human collaboration, and take into account the efficiency of the robot and the empathy of human. First, it is found that different service agent types have a direct impact on consumers' adoption intention, and consumers are more willing to accept human beings as service agents than chatbots. According to the uncanny valley hypothesis, consumers' willingness to accept chatbots may have an inverted U-shaped relationship with the level of anthropomorphism, and people feel discomfort when they find robot highly similar to human (Mori et al., 2012). Second, this study found that consumers have a higher communication capability perception for human beings than chatbots. Users generally perceive that human beings understand them and have a better experience with the interaction; however, although the accuracy perception of human beings is higher than that of chatbots, the service accuracy of human beings is still known to diminish with increasing work time and intensity (Luo et al., 2019). Therefore, chatbots could be particularly useful as a first support to provide basic services to avoid human beings becoming tired and distracted to save human agents time and energy spent on basic repetitive service interaction tasks. Additionally, customers' trust in chatbots varies at different stages of the shopping journey (Rese et al., 2020). Through our scenario, this study discovered that consumers' credibility perception of chatbots was lower at the time of purchase; however it has been noted that consumers' pre-purchase (browsing stage) trust in personalized recommendations from chatbots is higher (Rese et al., 2020). Taken together with our results, it might be better for the use of human beings to be reduced and investment in chatbots increased in the pre-purchase phase but with investment in human agents higher in the purchase phase. The main attraction of chatbots for customer service is the ability to provide easy-to-understand answers in real-time, and when they fail to provide services that meet users' need and consumers perception, the attraction of chatbots become weaker, thus providing a path for users to communicate with human may enhance the user's experience. Third, the effect of service agent type on perceived accuracy and perceived communication capability is also moderated by the need for human interaction. Specifically, strong/weak human interaction need will increase/decrease the requirement for perceived accuracy in the use of human beings, and strong/weak human interaction need will decrease/increase consumer perceptions of communication capability of chatbots. Fourth, from Experiment 3, we see that users' willingness to accept service agents is also enhanced if they perceive lower privacy risks during the interaction. Contrary to expectations, consumers appeared to perceive that human beings have higher privacy risk perceptions compared to chatbots. Users may tend to believe that human beings are more likely to be motivated by subjective interests to disclose users' privacy. Thus suggesting that merchants may switch chatbots to interact with users when sensitive information is involved. This is already known to occur in some banking applications. However, Experiment 5 suggests that chatbots may still be perceived as high risk among some consumer groups, such as those without a strong need for human interaction. Consumers with less need for human interaction may be more familiar with computer agents and computer interaction and they might better understand how computer agents are able to store user data thus increasing their risk perceptions.

5.2. Theoretical contributions

Research on human–computer interaction in the service domain is relatively new, but much research has already been carried out into customer perceptions and adoption of service agents. These past works help scholars and practitioners grasp the role of service agents in online customer service, yet there are still valuable research gaps in understanding human–computer interaction and how collaboration between human and computer service agents can improve the service experience. To fill these gaps, the theoretical significance of this study is mainly reflected in the following four points:

(1) Based on the CASA paradigm, this study comprehensively examines the difference between human–computer interaction and human interaction as well as the psychological mechanisms affecting that difference in terms of the five dimensions of perceived communication quality and the inclusion of perceived privacy risk. It makes up for the shortcomings of the past studies of human–computer interaction by adding a theoretical basis for achieving the maximum desired effect of human and computer collaboration in service provision.
(2) The study finds that consumers have higher communication quality perceptions with human beings compared to chatbots, which is inconsistent with Chung et al. (2020)'s finding that using chatbots for e-services improves customer satisfaction with brands, and Cheng and Jiang's (2020) finding that chatbots can meet consumer expectations in interactions. This study fills a gap

left by past studies which had focused on the advantages of chatbots in customer service while ignoring consumer demand for high quality communication and empathetic service experience. By focusing on the latter, our study extends research into the chatbot-service experience.

(3) Based on social response theory (Nass et al., 1996), this study investigates the impact of perceived privacy risk on customer adoption intentions during human interaction and human−computer interaction, and the differences in perceived privacy risk under different service agent types. The study confirms that people can react to chatbots with caution and perceived them as creating privacy risks and that these risk perceptions can influence chatbot-based service adoption. Chatbots are thus not neutral agents.

(4) Previous studies have focused on the effects of user need for human interaction on robot anthropomorphism and adoption intention. Sheehan et al. (2020) found that the stronger the human interaction need, the stronger the relationship between anthropomorphism and adoption intention. In contrast, this study introduces the need for human interaction as a moderating variable in the study of service agent type on adoption intention and finds that strong/weak human interaction need will increase/decrease the perceived accuracy of human agent communications, and strong/weak human interaction need will decrease/increase consumer perceptions of communication capability of chatbots. The findings expand on the moderating factors in the study of service agent types.

5.3. Management significance

Although the use of chatbots can save costs and improve service efficiency for companies, these benefits are obtained based on the success of their services, as well as consumer's poor experience when using them when the synergy of human beings is still needed. Therefore, this study provides insights into the use of chatbots in service marketing and offers guidance and strategies for the continued use of chatbots services with the following management implications for successfully promoting the coexistence of human beings and robots in the workplace to achieve the maximum effect of human−robot collaboration:

(1) Encourage the use of a tiered approach to customer service. Merchants can use chatbots as the first support to answer simple, basic customer questions. When rendered ineffective, the merchant would provide a path to human customer service through the chatbots, in order for the user to easily to seek assistance to human beings, especially when a need for communication accuracy and capability becomes more important and consumers have higher need for human interaction. By providing such path, the service failure of the chatbots will not damage the customer experience, but would complements humans as the service interface, achieving the maximum effect of human−robot collaboration. Therefore, we suggest using a tiered approach to allow chatbots and human beings to work together, with chatbots acting more as a supplement to human beings than as a replacement, to meet the diverse need of users.

(2) When developing robot e-service systems, companies should pay attention to the need for such systems to provide accurate, trustworthy, personalized and timely information in order to ensure the quality of consumer perceived communication in human−computer interaction, and for enterprise service providers to apply a friendlier, open and dynamic approach to defining conversation styles to reduce the psychological distance from customers. If customers do not get the information they want from chatbots, they will consider the system useless and will still desire the intervention of human beings. In this case, chatbots can negatively affect the consumer adoption intention. In addition, chatbots' provision of repetitive, mechanical information, does not only distracts customers, but also increases the cost and effort of information processing, more importantly, time spent by customers reading useless information. Therefore, the development of robot electronic systems that provide high-quality information is the key to ensuring the quality of human−computer interaction communication and enhancing consumer adoption. It is also the key for companies to save costs and successfully promote the continued use of chatbots services.

(3) The findings suggest that privacy risk is a major factor in reducing willingness to accept service agent types. Compared with chatbots, consumers perceive a higher privacy risk in using human agents. However, the need for human interaction as the moderating variable, changes the direction and intensity of the relationship between the mediating variable and independent variable. Consumers with low human interaction need may be more familiar with computers and thus perceive higher privacy risks when using chatbots than human agent. Thus, it is necessary to mitigate and control these perceptions of risks. Enterprise developers should design interfaces that convinces users that they are interacting with secure information systems, that all service agents (human and chatbots) respect human privacy concerns, and the security of user data obtained from all service agent interactions is closely monitored and secured.

(4) For people with strong human interaction need, it is not enough for chatbots to provide simple answers; what they need is a more anthropomorphic robot system. Even though users tend to find the current service provided by chatbots satisfactory, they will look forward to interacting with human beings more. Therefore, for consumers with strong human interaction need, companies should try to prioritize human beings to provide service for them.

(5) Our studies show users trust in chatbots does not differ from human agents. Companies can continue to build trust between their users and chatbots by using artificial intelligence to achieve 24/7 service response and create better learning opportunities for users, while allowing users to understand how chatbots work, making the system more transparent and giving users more autonomy and control over their decisions. By building trust, users can more comfortably take advantage of chatbots and companies can more easily delegate a large number of repetitive tasks to them, freeing human agents up to better meet more complex communication and interaction need. As a result, robots can become true partners of human in service scenarios, and human−robot collaboration can enhance service efficiency.

6. Research limitations and prospects

The study focuses on the effect of the type of service agents on consumer adoption intention in the online retail industry, and the findings can only be applied to the retail industry. In subsequent future application to other fields, further studies need to be done to validate the findings to enhance the generalizability of the findings. Most of the chatbots used in the study are text-based chatbots, and presently, human-like robots are increasingly used. The study does not segment the degree of anthropomorphism of the chatbots to discuss the impact on adoption intentions. Future studies may consider segmenting the degree of anthropomorphism of chatbots for further exploration. In addition, the scope of the experimental subjects in this study is limited, and the popularity of chatbots varies with culture and country. Future research should focus on groups from different countries or cultural backgrounds.

Founding information

This work was supported by Natural Science Foundation of China (Project No.72062015), Hainan Provincial Natural Science Foundation (Project No. 620RC561), Hainan Education Department (Project No.

Hnky2019-13).

Appendix A

Variable		Item
Perceived communication quality	Accuracy	I feel the customer service replies me timely.
		I feel the customer service replies me accurately.
		I feel the customer service replies me completely.
	Credibility	I feel the customer service replies me sincerely.
		I feel the customer service replies me reliably.
	Openness	I can easily have a free communication with customer service.
		I can express what I want to express with customer service.
		I can easily understand the replies from customer service.
	Attraction	I feel the customer service attitude is very friendly.
		I want to continue communication with customer service.
		I can make the right purchase decision based on my conversations with customer service.
		I don't think the customer service can solve the problem well.
	Communication capability	I feel this kind of customer service can deal with complex problems more efficiently than offline stores.
		I feel this kind of customer service can deal with complex problems more efficiently than other forms of service.
		I feel this kind of customer service has saved me a lot of decision-making time.
Perceived privacy risks		I'm worried about personal information being leaked and sold to third parties.
		I'm worried about the misuse of my personal information.
		I'm concerned about personal information being obtained by unknown individuals and companies without authorization.
Adoption		I'm willing to accept this kind of customer service in the future.
		I'm happy to interact with this kind of customer service.
		I'm willing to continue to interact with this kind of customer service.
Need for human interaction		I enjoy the process of communicating with human service agent.
		Personalized response from customer service is very important to me.
		I like communicating with human service agent.
		Interacting with robot service agent bothers me more than human service agent.

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