Government Chatbot Social Characteristics and Citizen Preferences: Evidence from a Discrete Choice Experiment in China

Abstract: Government chatbots have become increasingly popular as artificial-intelligence-based tools to improve communication between the government and its citizens. This study explores the interaction mode design of a trustworthy government chatbot, which involves multiple social characteristics from the user-centric perspective. A discrete choice experiment was conducted in the context of Chinese government chatbots to examine the effects of various social characteristics on citizen preferences. Participants utilized a crowdsourcing survey platform to report their preferences for interaction processes designed with distinct sets of social characteristics. Valid data were obtained from 371 participants and analyzed using a multinomial logit model. The results indicate that (in order from highest to lowest impact) emotional intelligence, proactivity, identity consistency, and conscientiousness significantly influence the citizens' preferences. Identity consistency has a negative effect, whereas the other factors all have positive impacts. It was also determined that some of these correlations are influenced by the participants' individual characteristics, such as age, gender, and prior experience with chatbots. This work provides empirical evidence for the relative importance of social characteristics and its impact on user perception, expands the service dimension scope of information provision/communication (one of five categories of digital interaction), and facilitates the identification and operationalization of the social characteristics. We provide a theoretical framework to understand the interaction model design of a trustworthy government chatbot and also offer practical recommendations for government chatbot designers, for enhanced policy implications.

Keywords: Government chatbot; Social characteristics; Interaction mode; Citizen preferences; Discrete choice experiment

1 Introduction

In recent years, many countries have employed artificial intelligence (AI) technologies to transform their digital government services. Mechanisms have been established at the national level (e.g., agencies, projects, pilot initiatives) to fully exploit the potential of AI for policy making and the design of government service programs. The 2020 United Nations E-Government Survey reported that the number of countries that use chatbots (i.e., AI-enabled user-interaction applications) in their national portals doubled from 28 in 2018 to 59 in 2020. Government chatbots act as virtual civil servants that are available around the clock. They use AI-related algorithms, such as natural language processing (NLP), deep learning, knowledge graphs, and decision trees, to analyze citizen inquiries and respond instantly and accurately. They also have the capability of continually “learning” about citizens’ needs in order to optimize their responses. This study focuses on text-based chatbots that provide consultations regarding government services, rather than voice-based or physical bots.

With the advent of new chatbots such as GPT3 (invented by OpenAI), it is argued that chatbots are competent to change the world, as they are capable to chat exactly like humans. However, despite the impeccable communication abilities, trust still remains a critical issue with these advanced chatbots (New York Times, 2022). Further, industry reports suggest that there are already a billion users of text or voice-based conversational chatbots (Singh, 2021). Hence, it is likely that over time, chatbots will be universally adopted by multiple people to interact with the government, thus it is vital to understand the interaction model design of a trustworthy government chatbot. This is the focus of our study.

By the end of November 2019, about 70% of the provincial governments in China had launched chatbots on their portals. These chatbots exhibited varying levels of performance in the interaction model design (see more in Table 3). For example, some chatbots use an official language style (e.g., response to citizen: Sorry, I can't find the results for your query.), while others use an unofficial language style (e.g., response to citizen: Your question is so difficult that I can't answer it. I've written it down and tell you in a few days!). When dealing with a relatively complex inquiry, some chatbots use multi-turn dialogue to gradually ascertain a citizen’s needs, whereas others use single-turn dialogue to solve the query all at once. Therefore, the pertinent question becomes: which design can better help governments interact with citizens? This issue has clearly not received enough attention from the government. Instead, public administrations usually focus on technologies and existing processes during public e-service development, rather than thinking of the preferences of the end-users, namely citizens (Rose, Flak, & Sæbø, 2018). The resulting e-services, which ignore user preferences, often lead to low adoption rates (Fakhoury & Aubert, 2015) and low service quality evaluations (Buckley, 2003). Actually, individual preferences should be central to research regarding e-service success factors (Wirtz & Kurtz, 2019). A user-centric approach, resulting in the development of e-services from an end-user’s perspective, must be sufficiently explored (Högström et al., 2016). Specifically, governments should evaluate citizens’ preferences in order to ensure that citizens receive the services provided by the government chatbots more effectively, thereby engendering a sense of satisfaction toward their government (Lin & Doong, 2018).

However, research into user-centric service design in the context of e-government is still in its infancy. Based on the five categories of digital interactions proposed by Jansen and Ølnes (2016), Pleger et al. (2020) identified seven possible characteristics of public service, including registration, infrastructure, communication, data security/data protection, processing status, time expenditure, and price. Further, they tested user preferences for these aspects through a public survey with conjoint analysis. Among the five categories of digital interactions, the interaction between the chatbot and a citizen evaluated in our study represents a type of information provision/communication. While, Pleger et al. (2020) identified only one general service characteristic for this interaction — communication — which alone cannot fully encompass the characteristics of the complex human-like interactions between a government chatbot and a citizen. Moreover, the chatbots are capable to exhibit eleven possible social characteristics that benefit human-machine interactions, such as proactivity, conscientiousness, communicability, damage control, thoroughness, manners, moral agency, emotional intelligence, personalization, identity, and personality Chaves & Gerosa, 2021). Therefore, we aim to address two key research questions intended to shed light on citizens' preferences in terms of the social characteristics of a government chatbot: (i) what are the crucial social characteristics of a government chatbot, and (ii) how do they affect a citizen's preferences for the interaction?

The remainder of this paper is organized as follows. Section 2 reviews the existing literature on the social characteristics of government chatbots and citizen preferences. Sections 3–5, respectively, describe the hypotheses informed by the presented literature review, present the details of the applied research method, and report the empirical findings of this study. Section 6 discusses the theoretical and practical implications, as well as the limitations of this study. Section 7 presents the conclusions drawn based on the results discussed in this article.

2 Literature Review

2.1 Digital interactions between a government chatbot and a citizen

Government-to-citizen (G2C) e-government refers to government systems using information and communication technology (ICT) to better serve their citizens. It aims to simplify and improve transactions, improve public service delivery, and provide benefits to end-users (Al-Hujran et al., 2015; Moon, 2002; Axelsson, Melin, & Lindgren, 2013). Recently, there has been growing interest regarding the potential of government-focused digital solutions (Buckley, 2003; Veeramootoo, Nunkoo, & Dwivedi, 2018). Governments at the federal, state, and local levels are actively exploring the use of AI to facilitate the transformation of digital government services. To date, AI case studies involving citizen services have generally comprised five categories, including AI-enabled question-answering, document completion, request routing, translation, and document drafting (Mehr, Ash, & Fellow 2017). The government chatbots evaluated in the present study represent the AI-enabled question-answering application.

The digital services (also known as e-services or online services) provided by the government chatbot can be considered as digital interactions between the government and a citizen, which adds some value to the end-user (Jansen & Ølnes, 2016; Pleger et al., 2020). According to the five categories of digital interaction (e.g., information provision/communication, secure interaction/transaction, secure contraction, complete transaction process, and support functions) proposed by Jansen and Ølnes (2016), the interactions between a government chatbot and a citizen represent a type of information provision/communication. In contrast to search engines or active push systems that provide information, a chatbot is expected to communicate naturally with behavior mimicking the tone and sensitivity of a human being (Jenkins et al., 2007); otherwise, users must adapt their own behavior in the interaction, which drives down their engagement and satisfaction. The chatbot is also expected to provide more useful, productive, and convenient services than human beings (Tavanapour & Bittner, 2018), otherwise it's perceived wasteful and disappointing.

In fact, the interaction preferences of users are influenced by the chatbot's characteristics, and although this aspect has not been studied in the field of government services, it has been explored in other fields. For example, Jain et al. (2018) conducted a study of 16 chatbot users who interacted with eight chatbots; the authors analyzed chat logs and user interviews, which revealed that users preferred chatbots that clarified their own chat capabilities, sustained the conversational context, handled dialogue failures, and ended conversations gracefully. Dohsaka et al. (2014) recruited 64 adults to experimentally study thought-evoking multi-party dialogues between multi-users and multi-agents. Their results demonstrate that empathic expression by the agents significantly increased user satisfaction and improved the users' ratings of the agents. Ho et al. (2018) recruited 128 college students to conduct an emotional conversation with a chatbot and found that chatbots with the ability to process emotions provided users with emotional, relational, and psychological benefits as human interactions. These studies identified various characteristics that likely influence user preferences and tested the significance of several of these factors, thus providing a theoretical basis for the present study. However, further systematic analysis is needed to determine the key characteristics of chatbots in the context of government services, and whether they have a significant impact on user preferences, which is the focus of our study.

2.2 Social characteristics of government chatbots

According to the Media Equation theory, individuals treat computers as social actors and naturally respond to social situations when interacting with them (Reeves & Nass, 1996; Fogg, 2003; Nass et al., 1994). Mimicking person-to-person conversations as realistically as possible is therefore an important aspect of chatbot design (Brandtzæg & Følstad, 2017; Nguyen & Sidorova, 2018). As a result, researchers have continually highlighted the importance of social abilities as interactional goals for chatbots (Jain et al., 2018; Liao et al., 2018). Chaves and Gerosa (2021) derived a conceptual model of chatbot social characteristics that effect user perceptions and behavior based on analyzing disembodied, text-based chatbot literature across various domains. They identified eleven social characteristics from three dimensions: (i) conversational intelligence (i.e., a chatbot's ability to effectively converse beyond the technical capability of achieving a conversational goal), which involves social characteristics including proactivity, conscientiousness, and communicability; (ii) social intelligence (i.e., a chatbot's ability to exhibit adequate social behaviors, such as responding to social cues, accepting differences, managing conflicts, and expressing emotions for the purpose of achieving the desired goals), which involves social characteristics including damage control, thoroughness, manners, moral agency, emotional intelligence, and personalization; (iii) personification (i.e., a chatbot's ability to assign personal traits, such as physical appearance and emotional states, to chatbots), which involves social characteristics including identity and personality (Chaves & Gerosa, 2021). These three dimensions comprise a universal model that can enhance our understanding of the social characteristics of government chatbots.

Research efforts to date have not directly investigated the social characteristics of government chatbots; however, prototype design research has indirectly revealed the social characteristics that should be prioritized in practice. The prototype design typically follows design science research methodology to formulate design principles (e.g., what functionality it should have and what business logic it should follow) for emerging IT artifacts, based on practical requirement analysis and constrains from technical and theoretical knowledge (Von Alan et al., 2004). According to relevant literature as well as specialists' knowledge, scholars have prototyped two chatbot applications in the contexts of policy making and open government data (Tavanapour et al., 2019; Porreca et al., 2018). The design principles of the two prototypes follow the conceptual requirements of certain social characteristics because they are formulated to satisfy designated social behavior requirements. In other words, these principles are expressions of desirable social characteristics of government chatbots. According to the conceptual model of chatbot social characteristics (Chaves & Gerosa, 2021), the key social characteristics of government chatbots can be identified from analyzing the design principles of the two prototypes. Specifically, considering process- and task-related behavioral requirements, Tavanapour et al. (2019) and Porreca et al. (2018) argued that the chatbot should be designed to "proactively" lead and adhere to a conversational framework in order to achieve conversational capabilities that ensure goal-oriented operations. Additionally, the chatbot should have the capacity to convey the conditions of an ideal interactive dialogue, which means that it requires the characteristic of "communicability" (Tavanapour et al., 2019; Porreca et al., 2018). Furthermore, the chatbot should have NLP capabilities that are sufficient to recognize users' utterances and pose follow-up questions (thereby exhibiting "conscientiousness"), and to respond in simple and understandable language (thereby exhibiting "identity") (Tavanapour et al., 2019; Porreca et al., 2018). Finally, relationship-related behavior requirements indicate that the government chatbot should have sufficient socio-emotional cues to resemble a social actor; it should build a personal relationship with users to address their needs while providing comfort during the interaction (thus presenting "emotional intelligence") (Tavanapour et al., 2019; Porreca et al., 2018).

Additionally, the professional code of civil servants is also an important basis for the judgement of key social characteristics of government chatbots(because a trustworthy chatbot should conform as closely as possible to the behavioral characteristics of the particular social actor it represents). The National Vocational Skills Standards issued by China's Ministry of Human Resources and Social Security points out that the civil servants engaged with comprehensive government services should abide by the professional codes, which includes: 1) behave politely and service enthusiastically, 2) love job and keep secrets, 3) operate under standard and provide high-quality and high-efficient services, 4) do own duty and follow orders, and 5) comply with the law and be honest in performing duty. Here codes 1,3 and 4 focus on civil servant's attitude and service ability, which map to the social characteristics of chatbots. Specifically, the social characteristics of "proactivity" and "emotional intelligence" enable chatbots to present service enthusiasm like civil servants. "Communicability" and "conscientiousness" enable chatbots to provide high-quality and high-efficient service. "Conscientiousness" is consistent with the requirement of doing own duty for civil servants. Further, there is no correspondence between identity and the professional code because identity(as a characteristic of personification) describes how a chatbot realistically mimics a human, rather than some humanoid behavioral characteristics.

Based on above discussion, proactivity, conscientiousness, identity, communicability, and emotional intelligence represent the key aspects for a trustworthy government chatbot design(especially in China). The five social characteristics are defined in Table 1. **"Proactivity"** refers to the capability of a chatbot to autonomously act on behalf of users, i.e., by exhibiting dialogue initiation, additional information provision, or follow-up question behavior to conveniently complete interactive tasks (Salovaara & Oulasvirta, 2004; Tennenhouse, 2000; Chaves & Gerosa, 2021). **"Conscientiousness"** is the capacity of the chatbot to demonstrate attentiveness to the conversation at hand, which requires an understanding of the context and interpretation of each user's utterance as a meaningful part of the entire interaction (Dyke et al., 2013; Morrissey & Kirakowski, 2013; Chaves & Gerosa, 2021). **"Communicability"** is the chatbot's capacity to convey its underlying features and embedded interactive principles to users (Prates et al., 2000). Chatbot interactions are more effective when the user has a strong understanding of the available functionalities of the chatbot and how it can be utilized (Valério et al., 2017). **"Emotional intelligence"** is the capability to appraise and express feelings, regulate effective reactions, and harness emotions to solve a problem (Salovey & Mayer, 1990); this characteristic enables the chatbot to recognize and control users' feelings and demonstrate respect, empathy, and understanding, thereby improving the interactive relationship (Li et.al, 2017). **"Identity"** refers to the capability of a chatbot to present itself as a particular social actor (Stets & Burke, 2000). The designers embed this characteristic in the chatbot by defining its manner of speech and behavior (Cassell, 2009). A chatbot can express its identity by conveying a certain gender, age, name, or language style to users (Chaves & Gerosa, 2021).

Table 1. Key social characteristics of government chatbots

Dimension	Characteristic	Definition	Source
Conversational intelligence	Proactivity	The capability of a chatbot to autonomously act on behalf of users	Salovaara & Oulasvirta, 2004; Tennenhouse, 2000; Chaves & Gerosa, 2021
	Conscientiousness	The capacity of a chatbot to demonstrate attentiveness to the conversation at hand	Dyke et al., 2013; Morrissey & Kirakowski, 2013; Chaves & Gerosa, 2021
	Communicability	The capacity of a chatbot to convey its underlying features and interactive principles to users	Prates et al., 2000
Social intelligence	Emotional intelligence	The capability of a chatbot to appraise and express feelings, regulate effective reactions, and harness emotions to solve problems	Salovey & Mayer, 1990; Li et.al, 2017
Personification	Identity	The capability of a chatbot to present itself as a particular social actor	Stets & Burke, 2000

3 Hypotheses

This study systematically identifies five key social characteristics of government chatbots, which enable government chatbot design to better meet practical requirements (Tavanapour et al., 2019; Porreca et al., 2018). These key features also encompass the three necessary dimensions of the conceptual model of chatbot social characteristics (Chaves & Gerosa, 2021), thus highlighting the uniqueness of chatbots in digital interactions (compared with other e-government services). Based on previous research regarding citizen satisfaction and e-government service quality, this section theoretically analyzes the influence of social characteristics on interaction perception and proposes relevant theoretical hypotheses.

3.1 Proactivity

Government chatbots have various means to convey proactivity, such as initiating dialogue, providing additional information, or proposing follow-up questions to maintain dynamic conversations with users (Salovaara & Oulasvirta, 2004; Tennenhouse, 2000; Chaves & Gerosa, 2021). Simply put, proactivity adds value to chatbot-user interactions. For example, a chatbot that shares useful information elicited or inferred from the conversation results in a statistically significant increase in the user’s enjoyment and reduces the effort he or she spends in the interaction relative to a chatbot that does not provide additional information (Avula et al., 2018). Moreover, a chatbot that formulates follow-up questions based on the content of previous messages results in higher perceived user engagement (Schuetzler et al., 2018). Proactivity also improves conversational productivity. For example, a chatbot that asks follow-up questions can reduce the search space and save time in achieving the user's goals (Avula et al., 2018; Jain et al., 2018).

"Proactive" service and information delivery are necessary for enhancing the administrative efficiency of e-government services, and they were notably considered in Taiwan's fourth e-government strategy (Linders et al., 2018). A proactive government chatbot is user-friendly and requires limited user effort, which align with the concept of "ease of use" that drives user satisfaction with e-government services (Papadomichelaki & Mentzas, 2012; Nguyen et al., 2020). The rationale behind ease of use is that users are generally concerned about complexity and effort required when carrying out e-services, and a poorly designed government chatbot that is difficult to use can thus incite further frustration (Meuter et al., 2000; Nguyen et al., 2020). Therefore, when a high level of proactivity is embedded in the government chatbot, citizens have greater preference for participating in such interactions because of the relative ease of use. Hence, we outline our first hypothesis:

H1. Proactivity embedded in the government chatbot has a positive impact on citizens' preferences for interacting with the chatbot.

3.2 Conscientiousness

The conscientiousness of a chatbot lies in its ability to track conversations and maintain a sense of conversational continuity over time (Jain et al., 2018). A conscientious chatbot aligns with the purpose of the interaction and moves the conversation toward its final goal in an efficient, productive manner (Ayedoun et al., 2017). As the complexity of a given goal increases, more turns are required to successfully achieve that goal. A chatbot with an integrated multi-turn conversation workflow design can anticipate the resolution of the interaction, thereby reducing the effort required from the user to achieve his or her goal (Jain et al., 2018).

Similar to its proactivity, the conscientiousness of a government chatbot helps citizens reduce the effort required to utilize e-services by maintaining the conversation in such a way to promote greater user satisfaction (Papadomichelaki & Mentzas, 2012; Nguyen et al., 2020). Additionally, a conscientious chatbot providing automatic and professional conversation moving toward the final goal demonstrates two key abilities, i.e., prompt replies to citizens' inquiries, and knowledge to answer users' questions, which are two dimensions of the support system that enhances citizens' satisfaction with e-government services (Delone & McLean, 2003; Papadomichelaki & Mentzas, 2012; Nguyen et al., 2020). Conscientiousness, therefore, is assumed to have a positive effect on citizens' preferences.

H2. Conscientiousness embedded in the government chatbot has a positive impact on citizens' preferences for interacting with the chatbot.

3.3 Communicability

Chatbots are communicative by nature because they depend on exchanging messages with users to achieve their goals. It is therefore crucial for the chatbot to convey its underlying design intent and interactive principles to users at the onset of the conversation (Prates et al., 2000). Communicability involves defining the available functions and operation principles of the chatbot to the user (Jain et al., 2018; Valério et al., 2017), which further clarifies the learnability of the chatbot program (Grossman et al., 2009). Communicability also helps manage users' expectations; first-time users tend to have higher expectations than repeat users if they do not know the capabilities and limitations of the chatbot prior to the interaction. First-time users also tend to feel more frustrated over chatbot failures than repeat users (Jain et al., 2018).

A government chatbot with effective communicability is considered reliable as introducing design intent (i.e., telling citizens what can be asked) and interactive principles (i.e., telling citizens how to ask) to citizens before a conversation, helps reduce the likelihood of interaction failure and enhances the user's confidence toward the chatbot concerning correct and timely delivery of the service (Papadomichelaki & Mentzas, 2012; Nguyen et al., 2020). In fact, reliability is an essential component of the SERVQUAL (service quality) performance expectation model (Parasuraman et al., 1991), and it directly affects user satisfaction. Hence, we expect embedded communicability to have a positive impact on citizens' preferences for chatbot interactions.

H3. Communicability embedded in the government chatbot has a positive impact on citizens' preferences for interacting with the chatbot.

3.4 Emotional Intelligence

Although chatbots do not have genuine emotional capacity, they are often endowed with some form of human emotions. They can demonstrate attention to users' feelings by showing respect, empathy, and understanding, or they can make emotional self-disclosures or express reciprocity (Li et al., 2017; Lee & Choi, 2017). An emotionally intelligent chatbot develops a stronger relationship with its users than a non-emotional chatbot (Li et al., 2017). For example, empathic expressions significantly improve user satisfaction and ratings of the chatbot in terms of intimacy, compassion, amiability, and encouragement (Dohsaka et al., 2014). Additionally, users are more likely to engage with emotionally intelligent chatbots. Empathic phrases have been demonstrated to encourage users to engage and provide non-answer statements, such as feedback about the success or failure of an interaction (Dohsaka et al., 2014).

In contrast to showing conscientiousness, an emotionally intelligent government chatbot contributes to another dimension of citizen support, namely, showing sincere interest or empathy in solving a citizen's problems (Nguyen et al., 2020; Papadomichelaki & Mentzas, 2012). It has been determined that good user support, such as asking and responding to citizens' complaints in conversations, leads to pleasant interaction experiences for users (Nguyen et al., 2020). Hence, we expect that:

H4. Emotional intelligence embedded in the government chatbot has a positive impact on citizens' preferences for interacting with the chatbot.

3.5 Identity Consistency

The identity of a chatbot is imparted by its designers (intentionally or not) when programming its speech and behavior (Cassell, 2009). Aspects that convey identity include the gender, age, language style, and name of the chatbot. The identity perceived by users gives rise to new processes and expectations, and ultimately impacts the outcome of the interaction (Ho et al., 2018). Compared with a machine-like identity, a chatbot using a human-like language style, a human name, and greetings associated with human communication resulted in significantly higher user reviews in terms of "naturalness" (Araujo, 2018). However, certain identity elements tend to generate negative effects. For example, gender and race may reinforce certain users' negative stereotypes of the group represented by the chatbot (De Angeli et al., 2001; Marino, 2014; Schlesinger et al., 2018). The impact of chatbot identity on the user's perception of an interaction depends on the context. To manage this expectation, chatbots should give explicit signals of their personification and behave consistently throughout agent-oriented conversations (Liao et al., 2018; Neururer et al., 2018; Toxtli et al., 2018). An explicit personal identity helps to decrease users' efforts in establishing common ground, and thus, improves their willingness to engage (De Angeli et al., 2001).

In our study, identity consistency refers to the fact that government chatbots present identity elements that embody common key characteristics of civil servants (e.g., fairness, professionalism, seriousness, politeness, etc.) rather than personal characteristics (i.e., gender, race, etc.). Because these identity elements clearly portray government chatbots as civil service agents, identity consistency reduces the effort required for a citizen to establish common ground with the chatbot (De Angeli et al., 2001; Papadomichelaki & Mentzas, 2012; Nguyen et al., 2020). In other words, identity consistency embedded in the government chatbot increases its ease of use, which has a positive impact on citizens' preference for the interaction. Hence, we expect that:

H5. Identity consistency embedded in the government chatbot has a positive impact on citizens' preferences for interacting with the chatbot.

4 Method

4.1 Discrete choice experiment

The discrete choice experiment (DCE) is a widely-used research method in the marketing, public administration, and information systems fields (Jensen & Pedersen, 2017; Cantarelli et al., 2020; Van Puyvelde et al., 2016; Richard et al., 2012). The DCE method was employed in this study because it allows decisions made by subjects to resemble their real-world decision-making process more closely than in other methods of evaluating individual preferences (Raghavarao et al., 2010). This strategy can reveal valuable information regarding the attributes that contribute to individual choice behaviors. There are five steps involved in conducting a DCE: (i) identifying the attributes; (ii) assigning attribute levels; (iii) generating alternatives; (iv) determining choice sets and obtaining preference data; (v) analyzing the choice data (Van Puyvelde et al., 2016).

DCE was used in this study to elicit citizens' preferences for government chatbots and to determine how various social characteristics embedded in the chatbots contribute to those preferences. Participants were asked to select their most preferred government chatbot (i.e., an alternative) from two designs (i.e., the choice set) with distinct social characteristics (i.e., attributes). Each participant was exposed to several choice sets and he/she selected the one that they most preferred from each choice set. According to the DCE maximum utility assumption, citizens assigned a utility to each design in the choice set and chose the one with the maximum utility (Raghavarao & Wiley, 2006). This selection process resembles an actual decision-making process; therefore, analyzing participants' choices can reveal useful insights regarding how chatbot social characteristics influence user perceptions in practice (Obrien, 2012).

4.2 DCE design

4.2.1 Experimental background

In China, digital government strategies, especially those involving AI-related technologies, have been prioritized in recent years in an effort to improve the efficiency, accessibility, and openness of the government. The Guidelines on Government Website Development, issued by the General Office of the State Council of China was published in 2017, and these guidelines require government departments at various levels to embed chatbots on their websites to help address citizens' inquiries as a supplement to manual services. By the end of November 2019, about 70% of the provincial government portals among 34 provinces had implemented AI-enabled government chatbots, including "Jingjing" of Beijing and "Government Waiter" of Zhejiang Province.

4.2.2 Attributes and levels

According to the literature review presented in Section 2, five essential social characteristics of government chatbots that impact citizen interaction preferences were established: proactivity, conscientiousness, communicability, emotional intelligence, and identity consistency. These were also identified as attributes in the DCE. Defining the levels within each social characteristic is challenging because they are often difficult to measure or quantify. Based on the definition of each social characteristic and the performance of provincial government chatbots in China, two ordinal levels were assigned to each of the five social characteristics, as presented in Table 2.

In practice, all chatbots could proactively initiate conversations and formulate follow-up questions; however, they perform differently in terms of providing additional information. According to the definition of proactivity, we defined “low proactivity” as a chatbot that does not provide additional information and “high proactivity” as one that does. An e-government application that provides appropriate detailed information is viewed as efficient, thus improving user satisfaction (Nguyen et al., 2020).

Government chatbots generally use two modes to conscientiously track and maintain conversations. One is the single-turn conversation mode, wherein citizens choose the most relevant option from several large-information-granularity options provided by the chatbot, and then obtain the final answer from the chatbot after one round of conversation. The other is the multi-turn conversation mode, wherein the chatbot gradually guides citizens to identify their problems through multiple rounds of conversation with two or three small-information-granularity options in each round till a final answer is provided. Considering that multi-turn conversation design can better anticipate the resolution of the interaction and reduce a user’s efforts (Jain et al., 2018), a chatbot in single-turn conversation mode represented low conscientiousness, and a chatbot in multi-turn conversation mode was determined to have high conscientiousness.

These chatbots also perform differently in terms of communicability. Some chatbots introduce their features and interactive principles in the first message, which we define herein as “high-communicability” chatbots. Chatbots that provide no such introduction therefore exhibit low communicability.

Some chatbots manage citizens’ emotions mainly by paying attention to their feedback. Therefore, a chatbot that pays attention to citizens’ feedback is considered to have high emotional intelligence, and otherwise, it has low emotional intelligence.

Compared with gender, age, and name, a chatbot’s language style is generally a more stable and effective tool to convey identity consistency in a government chatbot (e.g., the fairness, professionalism, seriousness, and politeness of civil servants) (De Angeli et al., 2001; Marino, 2014; Schlesinger et al., 2018). Thus, government chatbots using an official language style were considered to show high identity consistency because they effectively mimic a civil servant. In contrast, a chatbot using unofficial language exhibits low identity consistency.

Table 2. Government chatbot attribute levels

Attribute	Low level	High level
Proactivity	Not providing additional information	Providing additional information
Conscientiousness	Single-turn conversation mode	Multi-turn conversation mode
Communicability	Not introducing features and interactive principles	Introducing features and interactive principles
Emotional intelligence	Not paying attention to citizens' feedback	Paying attention to citizens' feedback
Identity consistency	Using unofficial language style	Using official language style

Table 3 summarizes the performance of chatbots from 23 Chinese provincial governments in terms of five social characteristics (as of November 2019). It shows that these chatbots performed differently across the various evaluated attribute levels, and every level of those attributes was derived from practice. Table 3 reflects government practices in terms of chatbot interaction design, but it does not represent citizens' preferences and perceptions of the interactions. We are not sure whether these designs can help governments interact with citizens, as mentioned in Introduction. It is therefore necessary to test the significance and directionality of the impact of these social characteristics on citizens' interaction preferences.

Table 3. Performance of 23 Chinese provincial government chatbots

	Proactivity		**Conscientiousness**		**Communicability**		**Emotional intelligence**		**Identity consistency**	
	Low	High	Low	High	Low	High	Low	High	Low	High
Beijing	√		√			√		√	√	
Shanghai		√		√	√		√			√
Hebei	√		√		√			√		√
Shanxi	√		√		√		√			√
Inner Mongolia	√		√		√			√		√
Heilongjiang	√		√		√			√		√
Jiangsu	√		√		√			√		√
Zhejiang	√		√		√		√			√
Anhui		√		√	√		√			√
Fujian	√		√		√		√		√	
Jiangxi	√		√		√			√		√
Shandong	√		√		√		√			√
Henan	√		√		√			√		√
Hubei	√		√		√			√		√
Guangdong	√		√		√		√		√	
Hainan		√		√	√			√		√
Guizhou	√		√			√	√		√	

Yunnan	√		√		√		√			√
Tibet		√	√			√		√		√
Shaanxi	√		√		√		√			√
Qinghai	√		√		√		√		√	
Ningxia	√		√		√		√			√
Xinjiang	√		√		√		√			√

4.2.3 Alternatives and choice sets

There are 32 distinct alternatives (i.e., 32 possible chatbot designs) for the two levels (high and low) of the five attributes evaluated herein. Considering subjects' cognitive limitations and time constraints, we generated 16fold-over choice sets designed using SAS (SAS Institute Inc.) (Street et al., 2005), which can achieve the four properties of good design: level balance, orthogonality, minimal overlap, and utility balance (Huber & Zwerina, 1996).

Each participant compared two chatbots, Chatbot A and Chabot B, simultaneously in the experiment. Each chatbot was defined by the five social characteristics (i.e., attributes), where each characteristic had different levels, and other aspects were consistent. This is the basis for a fold-over design, so Chatbot A and Chatbot B differ in *every* characteristic: proactivity (no vs. yes to providing additional information), conscientiousness (single- vs. multi-turn conversation mode), communicability (no vs. yes to introducing features and interactive principles), emotional intelligence (no vs. yes to paying attention to citizens' feedback), and identity consistency (using unofficial vs. official language). For example, if Chatbot A provides additional information, applies a single-turn conversation mode, and uses official language, then Chatbot B does not provide additional information, applies a multi-turn conversation mode, and uses unofficial language. In short, subjects were asked to choose between two government chatbots in each choice set that were mirror images of each other. Chatbot A and Chatbot B made up a dual choice set, within which, the subjects indicated one preference.

4.2.4 Experimental procedure and data collection

In the experiment, the participants were first briefed with a scenario (Figure 1, top) wherein a citizen lost his or her identity (ID) card and hoped to obtain a new one in Beijing, although his or her registered residence was not in Beijing. The citizen consulted Jingjing, the government chatbot on the Beijing Municipal Government Service website, regarding cross-regional ID card reissuance. The cross-regional ID card reissuance was selected as the experiment scenario because this is a sub-service of ID card issuance, and ID card issuance is the second most frequent government service consulted by citizens using Jingjing. Moreover, the associated consulting process met the design requirements of the five embedded social characteristics.

Next, the two chatbot designs in the choice set were described in a simple table (Figure 1, second part), which is the common method used in most DCE studies (Jensen &

Pedersen, 2017; Cantarelli et al., 2020; Van Puyvelde et al., 2016). To clearly define the meaning of each attribute level in order to make the experimental selection more closely resemble real-world decision-making processes (Raghavarao et al., 2010), a social application (i.e., WeChat) was used to simulate the user-chatbot conversation for each alternative. We designed a fixed conversation text and expression for each attribute level to reflect its meaning. Each alternative was thus a combination of the fixed conversation texts and expressions corresponding to the attribute levels contained therein. For example, as shown in the third part of Figure 1, the fixed design for the single-turn conversation mode is that the chatbot asks one question with five options one time, and the participant gives one answer. The fixed design for the multi-turn conversation mode is that the chatbot asks a question three times, with three, two, and two answer options, respectively, and the participant gives answers three times. According to the attribute levels in each alternative, we simulated the conversation processes whereby a chatbot embodying the corresponding social characteristics attempts to resolve the cross-region ID card reissuance problem. The preferred chatbot was then selected by the participant (fourth part of Figure 1).

Overall, 16 choice sets were generated following the procedures described above. In each choice set, two conversations were illustrated side-by-side. The participants could then select their preferred chatbot from the set without any time pressure. Considering possible cognitive fatigue, each participant was randomly assigned to one of four experimental sessions derived from the 16 choice sets. Additionally, the second choice set presented in each experimental session was intentionally replicated as the fifth choice set, and participants were asked to repeat their selection as a validation check; thus, each participant evaluated five choice sets in total.

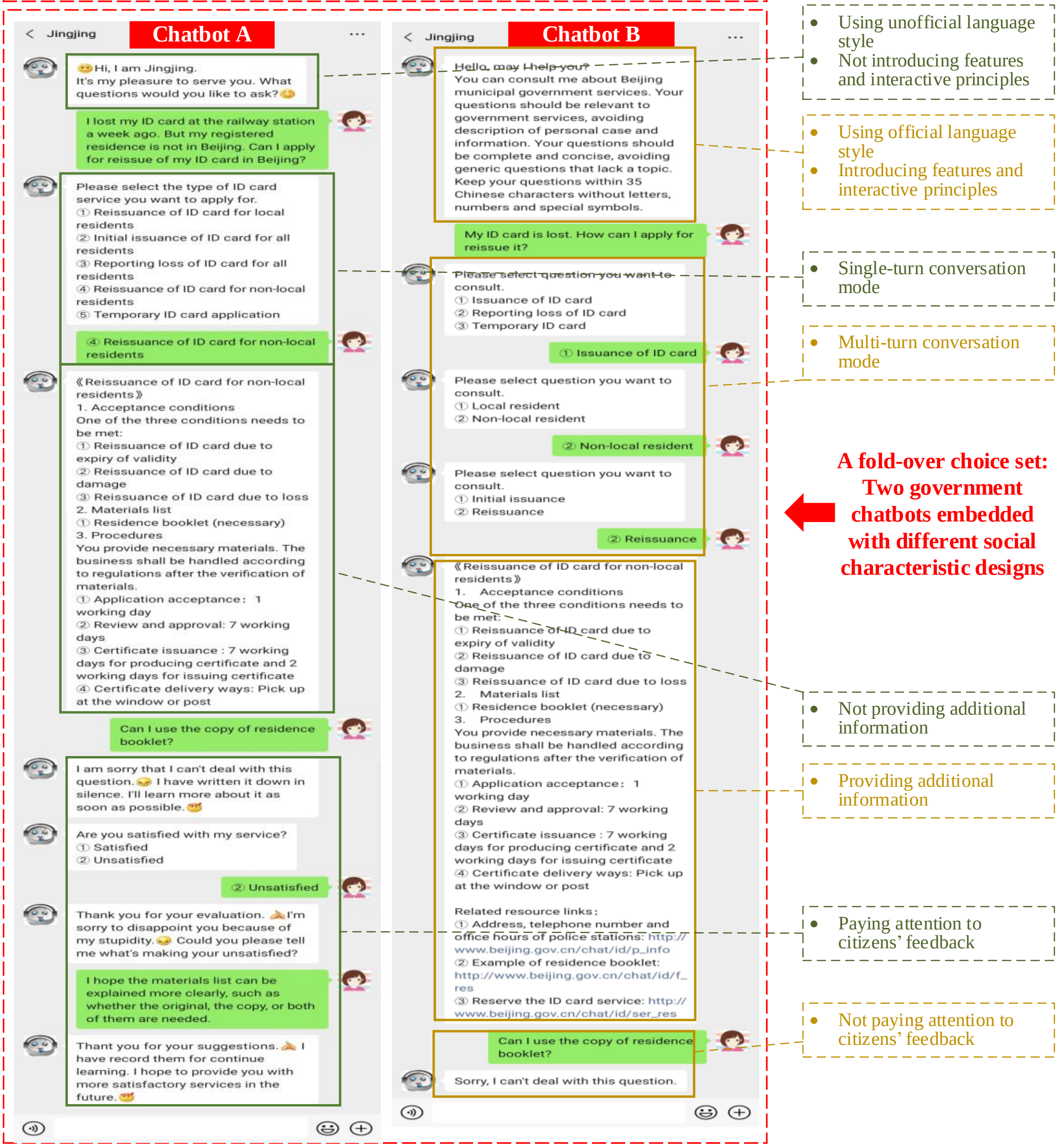
Because every Chinese person represents a potential user of all provincial chatbots, we randomly recruited participants across China through a professional crowdsourcing survey platform (www.wjx.cn). Ultimately, 428 participants were obtained through random recruitment across the country, covering 90% of China's provinces. Each of the 16 choice sets was evaluated by about 100 participants. After finishing the evaluations, the participants answered several demographic questions regarding their age, gender, education, and chatbot usage experience. Each participant was limited to one experimental session lasting approximately five minutes, for which they were paid 5 RMB.

(Simulated scenario) You lost your ID card at the railway station a week ago. Now you want to reissue a new one in Beijing. But your registered residence is not in Beijing. So, you plan to consult Jingjing, the government chatbot on the Beijing Municipal Government Service website, about the process of cross-regional ID card reissuance application. Here are two chatbots with different social characteristics serving you and the following two screenshots describe your conversation processes with them, respectively. Please choose which chatbot you prefer.

Scenario introduction

Social characteristics	Chatbot A	Chatbot B
Provide additional information links in the business processing introduction	No	Yes
Identify your needs in single- or multi-turn conversation mode	Single	Multiple
Introduce its features and interactive principles to you	No	Yes
Pay attention to your feedback	Yes	No
Interact with you in unofficial or official language style	Unofficial	Official

Attribute levels comparison between two chatbots



Options: ○ Chatbot A ○ Chatbot B

Preference choice

Figure 1. Sample choice set and DCE process

4.3 Data analysis

Following a preliminary validity screening of the 428 survey responses, any data with inconsistent answers between the second and fifth choice sets were omitted (see more in the Appendix 1), and we obtained valid data from 371 participants. The multinomial logit model was employed to analyze this data set because this model represents the most common technique for analyzing DCE results (Raghavarao et al., 2010; Chen & Chitturi, 2012). The applied strategy is capable of deducing the probabilities of each alternative based on the values of independent variables. Assuming that the probability of selecting each alternative (i.e., chatbot interaction mode design) is a function of the attributes (i.e., social characteristics) specific to that alternative, the multinomial logit model can estimate the probability of each alternative being chosen as the exponential of the utility of that alternative. The *mlogit* package of R was used to analyze the data collected in this study, and the statistical details of the applied multinomial logit model are presented in the Appendix 2.

5 Results

The survey sample comprised a broad range of participants. As shown in Table 4, 93% of the participants were between 18 and 40 years old, 47% were male, 74% had bachelor's degrees, 11% had graduate degrees, and 15% did not have any university degree. The majority of our sample participants are young and have a certain level of education. Because this population is more likely to become the early adopters of chatbots (Jain et al., 2018; Kasilingam, 2020), we believe that it is reasonable to evaluate their preferences as sample groups to study the design of early chatbot-user interaction modes, similar to previous studies (Nguyen et al., 2022; Ho et al., 2018; Avula et al., 2018). Up to 93% of the participants had some level of previous experience with using chatbots; specifically, 53% only used non-government chatbots (e.g., on shopping platforms or service consulting platforms), 12% only used government chatbots, and 28% used both.

Table 4. Demographic profile of participants

Variable		Count	Percentage
Age	18-30 (code as 1)	184	50%
	30-40 (code as 2)	160	43%
	40-50 (code as 3)	21	6%
	>50 (code as 4)	6	2%
Gender	Male (code as 1)	176	47%
	Female (code as 2)	195	53%
Education	High school (code as 1)	7	2%
	Community college (code as 2)	50	13%
	Bachelor's degree (code as 3)	274	74%

	Graduate degree (code as 4)	40	11%
Usage Experience	Neither (code as 1)	24	6%
	Only non-government chatbot usage (code as 2)	198	53%
	Only government chatbot usage (code as 3)	46	12%
	Both (code as 4)	103	28%

Table 5 presents the multinomial logit estimation results for the survey data. For each attribute, Table 5 displays the estimated coefficient (β), as well as the associated standard error (SE), z-score (z), and p-value. The high level of each attribute is coded as 1, and the low level is coded as 0; therefore, if an estimated coefficient is significantly positive, then the high level of that attribute positively contributes to the alternative being chosen. In other words, citizens prefer to experience this attribute at its high level, rather than at its low level. Similarly, if an estimated coefficient is significantly negative, then the high level of this attribute negatively contributes to the alternative being chosen, i.e., citizens prefer to see this attribute at its low level.

Table 5. Multinomial logit model predictions of citizens' chatbot preferences

Hypothesis	Attribute levels	β	SE	z	p (>|z|)
H1: Proactivity has a positive impact on citizens' decisions to interact with the government chatbot	**Proactivity** ▸ Low (0): Not providing additional information ▸ High (1): Providing additional information	0.50	0.06	8.69	0.000***
H2: Conscientiousness has a positive impact on citizens' decisions to interact with the government chatbot	**Conscientiousness** ▸ Low (0): Single-turn conversation mode ▸ High (1): Multi-turn conversation mode	0.24	0.06	4.19	0.000***
H3: Communicability has a positive impact on citizens' decisions to interact with the government chatbot	**Communicability** ▸ Low (0): Not introducing features and interactive principles ▸ High (1): Introducing features and interactive principles	0.02	0.06	0.42	0.68
H4: Emotional intelligence has a positive impact on citizens' decisions to interact with the government chatbot	**Emotional intelligence** ▸ Low (0): Not paying attention to citizens' feedback ▸ High (1): Paying attention to citizens' feedback	0.64	0.06	11.02	0.000***
H5: Identity consistency has a positive impact on citizens' decisions to interact with the government chatbot	**Identity consistency** ▸ Low (0): Using unofficial language style ▸ High (1): Using official language style	–0.43	0.06	-7.46	0.000***
No. subjects			371		
No. observations			1484		
log(likelihood)			–895.21		

Notes: * denotes $p < 0.05$; ** denotes $p < 0.01$; *** denotes $p < 0.001$

As shown in Table 5, the estimated coefficients of proactivity, conscientiousness, emotional intelligence are positive and significant ($\beta = 0.50$, $p < 0.001$, $\beta = 0.24$, $p < 0.001$, and $\beta = 0.64$, $p < 0.001$, respectively), implying that participants preferred government chatbots that provided additional information, used multi-turn conversation mode, and paid attention to their feedback. Specifically, when all other parameters were consistent, the odds that citizens would choose a government chatbot increased by 0.50 times when it exhibited higher-level proactivity, by 0.24 times when it had higher-level conscientiousness, and by 0.64 times when it presented a higher-level of emotional intelligence. The coefficient of identity consistency is negative and significant ($\beta = -0.43$, $p < 0.001$), implying that participants preferred government chatbots that used an unofficial language style. The odds of preferring a government chatbot decreased by 0.43 times when it had a higher-level of identity consistency (i.e., using official language style). The coefficient of communicability is not significant ($p = 0.68$), which implies that with all other characteristics being the same, whether or not the chatbot introduced features and interactive principles did not appreciably affect citizens' preferences. Overall, the data in Table 5 seem to support hypotheses 1, 2, and 4 while failing to support hypothesis 3 and 5.

To investigate possible preference heterogeneity in the tested sample population, further analysis was conducted by incorporating socio-demographic variables (i.e., age, gender, and education) and individual experience (i.e., chatbot usage experience). As shown in Table 6, proactivity and conscientiousness have significant impacts on interaction preference when all these socio-demographic variables are considered ($\beta = 2.3$, $p < 0.001$, and $\beta = 1.47$, $p < 0.01$, respectively). Age, gender, and usage experience did reveal some preference heterogeneity, whereas education did not. Specifically, age has a negative heterogeneity effect on proactivity and conscientiousness ($\beta = -0.32$, $p < 0.001$, and $\beta = -0.23$, $p < 0.05$, respectively), which implies that older participants were less sensitive than the younger ones to the increase in interaction preference resulting from proactivity and conscientiousness. Gender has a negative heterogeneity effect on proactivity ($\beta = -0.43$, $p < 0.001$), implying that female participants tended to be less sensitive than the male ones to the increase in interaction preference resulting from proactivity (male code as 1 and female code as 2). While, usage experience has a positive heterogeneity effect on proactivity ($\beta = 0.13$, $p < 0.05$), implying that participants with more usage experience tended to be more sensitive to the increase in interaction preference resulting from proactivity, than the ones lacked of experience.

Table 6. Multinomial logit model predictions of preference heterogeneity

Variable	*β*	SE	*z*	*p* (>|*z*|)
Proactivity	2.3	0.55	4.19	0.000***
Conscientiousness	1.47	0.54	2.71	0.007**
Communicability	0.98	0.55	1.77	0.076
Emotional intelligence	0.57	0.54	1.07	0.286
Identity consistency	–0.30	0.53	–0.56	0.578
Heterogeneity – Age				
Proactivity: Age	–0.32	0.09	–3.53	0.000***
Conscientiousness: Age	–0.23	0.09	–2.54	0.011*
Communicability: Age	–0.05	0.09	–0.59	0.557
Emotional intelligence: Age	0.04	0.09	0.42	0.675
Identity consistency: Age	0.04	0.09	0.47	0.638
Heterogeneity – Gender				
Proactivity: Gender	–0.43	0.12	–3.48	0.000***
Conscientiousness: Gender	–0.17	0.12	–1.34	0.179
Communicability: Gender	–0.13	0.12	–1.07	0.286
Emotional intelligence: Gender	–0.05	0.12	–0.45	0.654
Identity consistency: Gender	–0.08	0.12	–0.7	0.484
Heterogeneity – Education				
Proactivity: Education	–0.16	0.10	–1.60	0.109
Conscientiousness: Education	–0.17	0.10	–1.74	0.081
Communicability: Education	–0.19	0.10	–1.93	0.053
Emotional intelligence: Education	–0.03	0.10	–0.32	0.748
Identity consistency: Education	–0.06	0.10	–0.62	0.533
Heterogeneity – Usage Experience				
Proactivity: UsageExperience	0.13	0.06	2.01	0.044*
Conscientiousness: UsageExperience	0.10	0.06	1.62	0.104
Communicability: UsageExperience	0.05	0.06	0.76	0.446
Emotional intelligence: UsageExperience	0.08	0.06	1.19	0.235
Identity consistency: UsageExperience	0.04	0.06	0.72	0.471
No. subjects		371		
No. observations		1484		
log(likelihood)		–871.65		

Notes: * denotes $p < 0.05$; ** denotes $p < 0.01$; *** denotes $p < 0.001$

6 Discussion and Implications

6.1 Discussion

We hypothesized that proactivity embedded in the government chatbot would positively impact the citizens' preferences for interacting with the chatbot (H1). As shown in Table 5, the impact of this social characteristic is significant; therefore, H1 is supported by the experimental data. Our theoretical explanation for the significance of this impact is that a government chatbot with high-level proactivity (i.e., one that provides additional information) is more successful in attracting citizens because this characteristic adds value and improves conversational productivity (Avula et al., 2018; Jain et al., 2018). In fact, proactive service is an effective way to solve various problems involving cumbersome service forms and service triggers that rely on citizen requests. Both the proactive e-governance framework that aims to shift the service delivery model from the "pull" to "push" (Linders et al., 2018) and the e-government stage model that extends from the "one-stop shop" to the "no-stop shop" (Scholta et al., 2019) conceptually demonstrates the inevitable trend of proactive services under a service-oriented government strategy. The findings presented herein provide empirical evidence supporting the benefits of this trend from the perspective of citizens.

We also hypothesized that conscientiousness embedded in the government chatbot would be positively correlated with the likelihood of a citizen preferring to interact with the chatbot (H2). As shown in Table 5, the impact of conscientiousness on citizens' decision-making was both positive and significant; therefore, H2 is supported by the data. We believe that a chatbot employing multi-turn conversation mode is perceived as exhibiting greater conscientiousness in terms of tracking and driving the conversation, relative to a government chatbot that adopts the single-turn conversation mode. Consistent with findings reported by Jain et al. (2018), we observed that users preferred chatbots with a familiar turn-based messaging pattern. Jain et al. (2018) conducted a study of 16 first-time chatbot users interacting with eight chatbots from various domains (e.g., travel, entertainment, shopping, news, games, etc.), whereas most of the subjects in this study had used chatbots, and the chatbot of interest was in the domain of government service. Therefore, our study contributes to the generalization of this finding.

It is clear from Table 5 that H3 is not supported by the empirical results of this study. We believe that one possible reason is that the effect of communicability on user preferences is influenced by communicative strategies. Among the 11 strategies identified by Valério et al. (2017), S1 (i.e., presenting the main feature(s) in the first message) and S3 (i.e., suggesting next actions to the user) are the main strategies adopted by most Chinese provincial government chatbots to convey communicability. However, we found that the communicability (using S1 and S3) does not have a significant effect on user preferences. The communicability based on other strategies, such as S2 (guiding the user through a small tutorial during the first messages), S4 (having a persistent menu with main features), or S5 (having a main menu with main features), may have different effects. In particular, using S4 may have a significantly positive impact (Jain et al. (2018) found that it was beneficial to provide a persistent view of the chatbots capabilities during the interaction). In addition, our study suggested that the communicability (using S1 and S3) may not significantly improve citizens' perception of the reliability of government chatbots in terms of e-government service quality.

Emotional intelligence positively and significantly affected citizens' preferences for interacting with the government chatbot; therefore, H4 is supported by the data. The results of this study indicate that a government chatbot with a high level of emotional intelligence (i.e., one that pays attention to citizens' feedback) assists citizens by expressing empathy, which enhances citizens' interaction experiences. This finding is consistent with previous studies (Li et al., 2017; Dohsaka et al., 2014) suggesting that emotional intelligence has a positive impact on user perception. In addition, showing sincere interest or empathy in solving a citizen's problems provides an additional dimension of citizen support (Delone & McLean, 2003; Papadomichelaki & Mentzas, 2012), and this aspect is represented as paying attention to citizens' satisfaction and feedback in this study. Therefore, these results provide insights for further research on how chatbot interaction design affects the quality of its service.

The results of this study also showed that identity consistency significantly and negatively impacted citizens' preferences for interacting with the government chatbot; therefore, H5 is not supported. Although an official language style is more in line with the communication characteristics of civil servants than the unofficial language style, it does not necessarily generate better citizen-chatbot interactions. One possible reason is that the official language style reinforces some users' negative stereotypes of the group represented by the chatbot, similar to gender- and race-based perceptions (De Angeli et al., 2001; Marino, 2014; Schlesinger et al., 2018). In fact, some government departments now prefer to use informal language to interact with citizens in public channels (Stone & Can, 2020). The significantly positive effect of the unofficial language style may be related to the greater perceived social presence. A recent study indicated that a chatbot's informal communication style led to a higher perceived social presence, which positively influenced the quality of the interaction (Liebrecht, Sander, & Van Hooijdonk, 2020). In our study, the unofficial language style using emojis and emotional language to express empathy more directly and effectively increased the social presence of the chatbot perceived by citizens and thus enhanced their interaction experiences.

This work involved evaluating the relative impacts of various social characteristics on citizen preferences. According to the coefficients in Table 5, the social characteristics can be ranked in order from high to low importance: emotional intelligence > proactivity > identity consistency > conscientiousness. Overall, emotional intelligence was the most effective social characteristic for enhancing citizen preferences.

We also found that certain individual factors significantly amplified or weakened the effects of social characteristics on citizen preferences. As shown in Table 6, age weakened the positive effects of proactivity and conscientiousness on citizens' preferences, and female gender also weakened the positive effect of proactivity on citizens' preferences. Citizens with more chatbot usage experience had a significantly greater preference for chatbots exhibiting proactivity rather than other characteristics.

Previous research findings also support the results presented herein. For example, proactivity has been shown to lead to information overload for certain users. Information literacy, i.e., the ability to recognize the information required to reach personal goals, decreases the citizen's perceived information overload; experiencing information overload generally decreases the perceived usefulness of a government website (Lee, Lee, & Lee-Geiller, 2020). Participants in this study who had more experience with chatbots prior to the experiment are arguably more information-literate, meaning they could more easily overcome the information overload created by chatbot proactivity, which then increased their positive perception of the chatbot (e.g., its usefulness).

Some previous studies have also shown that advanced age and gender (female) affect information overload adaptability (Sasaki et al., 2015; Holton & Chyi, 2012), such that older and/or female participants (i.e., those who perceive more information overload) express lower preferences for chatbots embedded with proactivity. Older participants also prefer the single-turn conversation mode, which has greater information granularity and fewer interactions than the multi-turn mode. This finding was also supported by Van Deursen et al. (2011), who found that age positively contributed to content-related Internet skills (e.g., understanding complex interactive content), but negatively affected medium-related Internet skills (e.g., frequently interacting with chatbots) (Van Deursen et al., 2011).

6.2 Theoretical implications

Our study has four theoretical contributions. First, our results provide guidelines for the interaction model design of a trustworthy government chatbot. We establish a theoretical basis for understanding the relative importance of social characteristics of chatbots. Although studies in other fields have begun to examine the impact of social characteristics on user interactions, they generally focus on one characteristic a time; for example, Dohsaka et al. (2014) focus on conscientiousness, and Ho et al. (2018) focus on emotional intelligence. Our study provides an innovative exploration of the relative importance of social characteristics, which contribute to the design of a trustworthy government chatbot and also establish the quality assessment framework of government chatbot service. . In addition, we provide empirical evidence on mechanism design by which some social characteristics influence user perception. Specifically, our findings in the context of government service align with those presented in existing literature, including results regarding proactivity (Avula et al., 2018; Jain et al., 2018), conscientiousness (Ayedoun et al., 2017; Jain et al., 2018), and emotional intelligence (Li et al., 2017; Lee & Choi, 2017; Dohsaka et al., 2014). The results inconsistent with the existing research will trigger new theoretical discussions. For example, unsupported hypothesis about communicability could inspire further research question, as to whether communicability presented via different strategies (Valério et al., 2017) leads to different user perceptions. In other words, it is necessary to refine the research regarding the effect of communicability on user perceptions on the basis of various distinct communicative strategies. The results described herein are also not consistent with the assumption that explicit personal identity increases user engagement (De Angeli et al., 2001), and this too inspires further discussion regarding potential identity elements that reinforce users' negative stereotypes. Apart from gender and race (De Angeli et al., 2001; Marino, 2014; Schlesinger et al., 2018), language style seems to be a new identity element that can generate negative stereotypes of users.

Second, this study focuses on the user-centric digital government service design, clarifying the service characteristics (namely, social characteristics of chatbot) and the mechanism by which they impact intelligent human-computer interaction preferences. The interaction between the chatbot and a citizen represents a type of information provision/communication. Previous literature identified only one general service characteristic (i.e., communication) for this category of digital interaction (Pleger et al., 2020), which is not sufficient for the complex chatbot-citizen interaction. Our study extends the service characteristic of information provision/communication from a single dimension to five dimensions (i.e., proactivity, conscientiousness, communicability, emotional intelligence, and identity). As analyzing the service characteristics of digital interactions is beneficial for constructing a model to assess the quality of e-services (Jansen & Ølnes, 2016),thus the refined service characteristics contribute to the establishment of intelligent government service quality assessment framework, by providing richer theoretical evidence. Additionally, our empirical results related to the mechanism of social characteristics provide a more persuasive theoretical basis for government chatbot prototype research (e.g., Tavanapour et al. 2019 and Porreca et al. 2018), especially for determining its design principles.

Third, this study is the first to examine the social characteristics of government chatbots. Our identification and operationalization of the social characteristics provides a reference for future research on the impact of social characteristics on citizen perception. However, it should be pointed out that the identification and operationalization are contextualized (i.e., they are based on the professional codes of Chinese civil servants and practical cases of Chinese government chatbots). When studying government chatbots in other countries, the potential influence of different social and cultural backgrounds should be taken into account (Aladwani, 2013). Our methods of identifying and manipulating social characteristics can be directly adopted, but the basis of identification and the results of operationalization may vary across countries. For example, a high level of "identity consistency" refers to the use of an official language style, because this operationalization is in line with the Chinese government's manner of maintaining a serious image on any occasion or through any channel. However, this operationalization may not be consistent with government codes of conduct in other countries. A recent study by Stone and Can (2020) found that the Twitter accounts of United States municipalities with higher tweet frequencies were more likely to use an informal language style to interact with citizens on social media platforms. This suggests that, if these municipalities do so in additional public channels, it will lead citizens to believe that using unofficial language represents their identity. When chatbots and participants from these municipalities are selected to study, a high level of "identity consistency" should be represented by the use of an unofficial language style, which is contrary to our study.

6.3 Practical implications

Based on the results of this study, we propose three practical recommendations for government chatbot designers. First, they should empower the chatbot to provide additional information, use multi-turn conversation mode, pay attention to citizens' feedback, and use an unofficial language style because proactivity, conscientiousness, and emotional intelligence have significant positive impacts on citizen preferences, and identity consistency has a significant negative impact. Second, if all of the aforementioned social characteristics cannot be implemented in a single chatbot design, we suggest that priority should be given to the ability to pay attention to citizens' feedback, and other characteristics (e.g., providing additional information, using an unofficial language style, and applying a multi-turn conversation mode) could be introduced later if possible. This recommendation is based on the relative importance of these social characteristics. Emotional intelligence has the largest impact on citizen preferences ($\beta = 0.64$; Table 5). Paying attention to citizens' feedback helps the chatbot show empathy and mitigate citizens' disappointment following failed interactions. Furthermore, feedback data from citizens contribute to the improvement of chatbot design, especially in the initial application phase. Third, it is not necessary to let the chatbot introduce features and interactive principles in the first message because the communicability strategies, i.e., S1 (presenting the main features in the first message) and S3 (suggesting next actions to the user), had no significant effect on citizen preferences. However, designers could try to implement other strategies, e.g., S4 (having a persistent menu with main features), in order to demonstrate the communicability of the chatbot.

This study also has some policy implications. For example, we suggest that the national governmental departments should issue relevant policies to give specific, informed guidance regarding the design of government chatbot interaction modes. This would contribute to the overall improvement of chatbot service quality, as well as help inexperienced departments avoid ineffective attempts. It is clear from Table 3 that Chinese provincial government chatbots generally performed poorly based on the social characteristics that enhance citizens' preferences; specifically, 80% of the chatbots did not exhibit high-level proactivity, high-level conscientiousness, and low-level identity consistency. To address this issue, the government department responsible for the construction of e-government services throughout the country (e.g., the E-government Office of the State Council) can advocate for the chatbot construction specifications in the relevant policy documents to require provincial governments to uniformly adopt design parameters to develop chatbots that provide additional information, use a multi-turn conversation mode, pay attention to citizens' feedback, and use an unofficial language style.

Our study provides a theoretical framework to understand the interaction model design of a trustworthy government chatbot, including the key social characteristics and their effective design principles. Thus, another practical implication of our study is that our framework can be generalized to other countries, if integrated well with their specific social and cultural aspects.

6.4 Limitations and future research

Our study has certain limitations. First, we conducted the experiments with a limited set of attributes because of the inherent constraints of the DCE method. Specifically, we did not account for social characteristics that are involved in the conceptual model but not often considered in previous government chatbot prototype design research efforts. We do not claim to provide a holistic model of all social characteristics that may impact citizens' chatbot preferences.

Second, since research efforts to date have not directly investigated the social characteristics of government chatbots, this study determines key social characteristics based on the conceptual model of chatbot social characteristics and the relatively limited prototype design research of government chatbots, which may have the problem of insufficient supporting basis. With the wide application of government chatbots to facilitate interactions between a government and its citizens, it is becoming increasingly crucial to improve the quality of human-computer interactions. Future research should focus on exploring the impact of each social characteristic on the interaction in the context of government services to provide a more solid foundation for the selection of key characteristics.

Third, research regarding citizen preferences for government chatbot social characteristics is still in an exploratory stage, and the present study only provides an exploratory result. To eliminate the possible influence of the experimental scenario on the results and to improve the generalizability of the conclusions, future studies should aim to conduct experiments in various categories of scenarios and conduct further comparative analysis. Adding another government service task to our experiment cannot fundamentally solve the problem of generalization.

7 Conclusions

We are entering in an era where it is increasingly becoming difficult to identify chatbots from humans (Singh, 2021). Thus, it is crucial to understand the interaction model design of a trustworthy government chatbot for its enhanced efficacy. In the current study, we investigate the key social characteristics of government chatbots and understand how they impact citizen preferences., We have identified five important social characteristics (i.e., proactivity, conscientiousness, communicability, emotional intelligence, and identity) according to the conceptual model and prototype design research on government chatbots. Then, a DCE was conducted to examine how each of these characteristics impact citizens' preferences. Based on a preliminary investigation of Chinese provincial government chatbots, two levels (high vs. low) were defined for each characteristic, and 32 distinct alternatives (16fold-over choice sets) were generated for the five social characteristics (attributes) and two levels (high vs. low). The user-chatbot conversations corresponding to the 32 alternatives were simulated on WeChat, and 428 participants assigned via a crowdsourcing survey platform randomly joined the experiment and reported their preferences for five pairs of simulated conversations. Valid data was obtained from 371 participants, and these datasets were then subjected to multinomial logit model analysis. The results indicated that (in order from highest to lowest importance) emotional intelligence, proactivity, identity consistency, and conscientiousness embedded in the government chatbot all had significant effects on citizen preferences; identity consistency had a negative impact, whereas the other features had positive effects. We also determined that these effects were influenced by individual factors. Specifically, older age weakened the effects of proactivity and conscientiousness on citizen preferences, and both female gender and limited chatbot usage experience weakened the effects of proactivity on their preferences.

Appendix 1

In this study, an experimental session consists of five choice sets, in which the second choice set was intentionally replicated as the fifth choice set. For example, the repeated choice set in a certain session is shown below.

- Chatbot A: providing additional information, applying a single-turn conversation mode, not introducing features and interactive principles, paying attention to citizens' feedback, and using official language.
- Chatbot B: not providing additional information, applying a multi-turn conversation mode, introducing features and interactive principles, not paying attention to citizens' feedback, and using unofficial language.

Participant A completed the five selections in the session. We found that the choice given by the participant for the second choice set was Chatbot A, that is, Participant A preferred the interaction mode design of Chatbot A. However, the choice given by the participant for the fifth choice set was Chatbot B, that is, Participant A preferred the interaction mode design of Chatbot B. Thus, Participant A gave contradictory answers to the same choice question at a very short interval, implying that Participant A has no clear preference for this choice set, or they have not taken the survey seriously. In either case, all survey data about Participant A should be deleted to avoid affecting the model estimation result.

Appendix 2

The most commonly used model applied to DCE is the multinomial logit model. By collecting consumer's choices regarding certain questions (i.e., choice sets), the coefficients in the multinomial logit model representing the relative importance of each social characteristic can be estimated.

According to random utility theory, when a subject evaluates a chatbot, there is a latent utility perceived by the subject, but not observable by the researcher. This latent utility can be decomposed into two components: a systematic element, which is determined by the social characteristics of the chatbot along with their covariates, and a random component, which accounts for all other nondeterministic factors that influence the choice.

Assuming that subject s evaluates chatbot j, then according to random utility theory, the utility of service j perceived by subject s (U_{js}) can be expressed as follows,

$$\mathrm{U_{js}} = \mathrm{V_{js}} + \varepsilon_{\mathrm{js}} \quad \text{(A-1)}$$

where V_{js} is the deterministic part of the perceived utility, and ε_{ij} denotes the random component of the perceived utility. When a subject is presented with a choice set of two chatbots, he/she will choose his/her favorite, i.e., the service that maximizes his/her perceived utility. Therefore, the chance that service j is chosen from choice set C by subject s ($P_i(j|C)$) can be expressed as follows:

$$\mathrm{P}_i(\mathrm{j}|\mathrm{C}) = \mathrm{P}\big(\mathrm{U}_{js} > \mathrm{U}_{is}, \forall \mathrm{i} \in \mathrm{C}\ \&\ i \neq j\big)$$

$$= \mathrm{P}\big(\varepsilon_{is} - \varepsilon_{js} < \mathrm{V}_{js} - V_{is}, \forall \mathrm{i} \in \mathrm{C}\ \&\ i \neq j\big) \quad \text{(A-2)}$$

By assuming each ε independently follows a Gumbel distribution (type-I distribution), the probability relationship in Eq. (A-2) can be further developed into the expression in Eq. (A-3) (Street and Burgess, 2007),

$$\mathrm{P}_s(\mathrm{j}|\mathrm{C}) = \frac{\exp(\mathrm{V}_{js})}{\sum_{i=1}^{n}\exp(\mathrm{V}_{is})} \quad \text{(A-3)}$$

where n is the number of chatbots in choice set C. Usually, it is the preference of a target group that is of interest, rather than the preference of any individual; therefore, for all notations hereafter, the subscript s specifying the subject has been removed.

The deterministic part of the utility (V_j) is typically expressed as an additive function of the social characteristics of the chatbot. When each chatbot has only two levels (e.g., high or low level of proactivity), V_j can simply be modeled as follows,

$$\mathrm{V}_j = \alpha_\mathrm{j} + \beta_{proactivity} X_{proactivity,j} + \beta_{conscientiousness} X_{conscientiousness,j} + \beta_{communicability} X_{communicability,j} + \beta_{EI} X_{EI,j} + \beta_{consistency} X_{consistency,j} \quad \text{(A-4)}$$

where X values are dummy variables (0–1) representing whether a social characteristic is present at its high level for chatbot j, and β coefficients represent the main effect of those social characteristics to the deterministic part of the utility. In other words, these coefficients indicate how much each social characteristics would contribute to the subject's preference if included. Combining Eqs. (A-3) and (A-4) yields the multinomial logit model. Once the experiment is completed and choices are collected from the subjects, the β coefficients can then be estimated accordingly.

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