



AI-based self-service technology in public service delivery: User experience and influencing factors

Tao Chen^a, Wenshan Guo^a, Xian Gao^{b,*}, Zhehao Liang^a

^a College of Public Administration, Huazhong University of Science and Technology, Wuhan, Hubei, China

^b Department of Political Science, California State University, Los Angeles, Los Angeles, CA 90032, United States of America

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ABSTRACT

Public sectors are utilizing AI-based self-service technology (SST) at an accelerating rate, given its potential for improving work efficiency and user experience, reducing service costs, and relieving human workloads. However, there is a limited understanding of the factors influencing citizens' user experience when services supported by AI-based SST are provided. Thus, with insights from the Consumer Value Theory, this paper aims to explore the factors that are important to AI-based SST user experience and the conditional role of trust in government. The on-site survey of 379 citizens in a public service center in China indicates that user experience positively relates to personalization and aesthetics and negatively associates with perceived time spent on the AI-based self-service machines. In addition, the results suggest that citizens with more trust in government are more likely to have a pleasant experience coming from AI-based SST's personalization and aesthetics. Public managers should ensure that the AI-based SST is aesthetically appealing and should be able to personalize the delivery of the right contents to the right person at the right time. Furthermore, they should always prioritize cultivating more trust from citizens to achieve a more positive user experience.

1. Introduction

With the rapid development of artificial intelligence (AI), smart self-service technologies (SSTs) provide unprecedented opportunities for governments to improve public services and strengthen their interaction with citizens. SSTs refer to technological interfaces that enable users to avail of services mostly independent of direct service employee involvement (Meuter, Ostrom, Roundtree, & Bitner, 2000). While SSTs have been widely used in almost all service industries, the integration of AI technologies and SSTs is an emerging tendency. Compared with conventional SST, AI-based SST has unique attributes (Table 1). First, intelligent features like natural language processing, face recognition, machine learning, recommendation algorithm, and OCR recognition are integrated into the AI-based SST to provide users with 24-h self-service. Second, AI-based SST collects and processes data based on previous business transactions (Rijdsdijk, Hultink, & Diamantopoulos, 2007). As AI can learn by itself, the accuracy of the algorithms will increase if more transactions are processed. Therefore, by using the recommendation algorithm, AI-based SST contributes to a personalized, seamless, and improved user experience. Third, AI-based SST could provide users with more consistent, timely, and effective services with the support of its

advanced data storage capabilities, high processing speed, and accurate personalization capabilities (West, Clifford, & Atkinson, 2018). In contrast, conventional SST primarily emphasizes the interaction between channels and users and lacks flexibility, which limits users to handle their business within a fixed period.

Government agencies are utilizing AI-based SST at an accelerating rate, given its potential for improving work efficiency and user experience, reducing service costs, and relieving human workloads (Buell, Campbell, & Frei, 2010). However, we know little about what influences citizens' user experience when they are provided with AI-based services. A knowledge gap like this could significantly prevent the quality improvement of AI-based service. At worst, it may trigger citizens' service dissatisfaction, which may ultimately impede governments from pursuing AI-innovations.

This case study thus focuses on investigating factors that influence citizens' user experience with AI-based SST. We looked at the use of AI-based SST in the Wuhou Administrative Approval Bureau (Wuhou AAB) in China. Starting from 2018, Wuhou AAB introduced AI-based self-service machines in its public service center. These self-service machines integrate AI technologies, such as natural language processing, face and fingerprint recognition, and big data analysis, to provide citizens and

* Corresponding author.

E-mail address: xgao9@calstatela.edu (X. Gao).

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Table 1
Key differences between conventional SST and AI-based SST.

Attributes	Conventional SST	AI-based SST
Space	Physical	Bridging physical and digital
Core technology	Button	Natural language processing, face recognition, recommendation algorithm
Nature of interactivity	User to machine	User to machine Machine to machine (touchpoint to touchpoint) User to user User to government officials
Nature of experience	Offline experience	New personalized and seamless user experience
Service provision	Fixed service	Always-on and always-responsive services

enterprises with 24/7 self-service consultation, self-check, self-service handling, self-service pickup, and more. With embedded tools, such as suction ID card reader, QR code scanner, high-resolution camera, binocular live camera embedded in AI-based self-service machines, citizen users are also allowed to self-print documents like social security certificates, business licenses, and permits. Thus, they may find it more efficient to engage in business transactions with the government. During the time we conducted this research, the introduction of AI-based self-service machines was widely welcomed by citizens, with the number of users exceeding 30,000.

To achieve and sustain the expected long-term AI benefits, it is necessary to ensure that the AI-based SSTs produce pleasant user experiences for all relevant user groups, including those who are elderly, less educated, or with disabilities. Therefore, at this early stage of AI-based SSTs' adoption, the machine design team and the government may want to work collaboratively to identify elements that affect user experience and adjust the machine quality, functionality, and aesthetic design accordingly. The goal is to enhance citizens' AI-based service experience and to be more efficient and enjoyable.

Another interest of this study lies in citizens' trust in government. In 1958, 75% of citizens in the United States reported a good level of trust in government, but this number fell to 40% by the beginning of the 21st century (The Council for Excellence in Government, 2004). Restoring trust is one of the common reasons for governments around the world to invest in IT innovations (Belanger & Hiller, 2006; Parent, Vandebeek, & Gemino, 2005). A series of empirical studies showed that citizens reported more trust in governments that are efficient, open, transparent, and responsive (Bannister & Connolly, 2011). In using AI-based SST, a fixed set of business processes has been embedded, which reduced human interference and increased accuracy and equity to a certain extent. Transparency and efficiency levels have also been increased because citizens now have access to timelier and personalized information and services. However, it remains unclear how trust in government affects citizens' feelings about using public services. In other words, there is a lack of empirical evidence on how the effect of AI-based SST attributes on user experience could be conditioned by citizens' trust level.

Therefore, the current study attempts to investigate the relationship between citizens' levels of trust in government and AI-based SST attributes and user experience. It focuses on two questions: (1) What are the key factors affecting the user experience of AI-based SST? (2) How does trust in government influence the relationship between AI-based SST attributes and user experience?

We have structured this paper as follows. Section 2 reviews the relevant literature on AI, SST, user experience, and Consumer Value Theory (CVT). This is followed by a discussion of the research model and hypotheses. In Sections 4 and 5, we describe in detail the data analysis procedures and results. Then, in Section 6, we discuss the findings, implications, limitations, and future research directions. Section 7 concludes this paper.

2. Theoretical background

Three research streams form the theoretical base of this study. First, we briefly introduce the research on AI and its applications in government. We also review the evolution and research status of SST empowered by AI. Second, we discuss those studies on user experience that are most relevant to our research background. Third, we review the CVT that enlightens the development of our research model and hypotheses.

2.1. AI, SST, and AI-based SST in government

AI technology is typically goal-oriented and enables a device to perceive its environment and take action to maximize the chances of success (Russell & Norvig, 2016). Exemplary methods used in data-based AI are cognitive mapping (CM) (McJohn, 1998), machine learning (ML) (Smola & Vishwanathan, 2008), and natural language processing (NLP) (Liddy, 2001). AI technology encompasses enriched databases and advancements in computing power, which results in faster data processing and interpretation (Newell & Marabelli, 2015) and enables the performing of routine and nonroutine tasks (Brynjolfsson & Mitchell, 2017; Frey & Osborne, 2017). AI components mostly include voice interaction, personalization, and face recognition. Regarding voice interaction, Hoy (2018) clarified: the voice assistant installed in the machine uses NLP and machine learning to interpret and understand the user's language and process the responses in real-time. Therefore, the user can have a conversation with the voice assistant and execute the requests, for example, search for information, purchase products, etc. Personalization means the provision of personally relevant content, products, and services based on the users' unique characteristics and needs (Xiao & Benbasat, 2007). Personalized functions are increasingly favored by users as they "treat different users differently" and alleviate the cognitive burden of users. Face recognition systems use distinguishing facial features like eyes, mouth, forehead, nose, or other spatial geometry features to differentiate one user from the other (Jayaraman, Gupta, Gupta, Arora, & Tiwari, 2020). Given the advantages like noncontact, nonintrusive, fast, and convenient collection and expandability, face recognition products have been widely used for identity verification in fields such as public security, border inspection, medicine, and education.

AI technology has become a flexible go-to tool for service innovations, yet many research focuses on information systems (IS) and private sectors. Optimizing IS has the advantages of enhancing system stability, improving user experience, reducing hardware costs, and improving operation and maintenance support capabilities. For example, Pawar, TarunKumar, Vittal, and P. (2020) proposed Intelligent Smart Energy Management Systems (ISEMS) based on ML to predict the energy consumption of residents. Yang and Lam (2019) studied typical Intelligent Parking Information Systems to find out the important factors that affect Willingness-to-Pay. Then, municipal governments can make their decisions based on the estimation of the driving factors' benefits for effective deployment of ICT resources to achieve the intelligence, convenience, and environmental protection of the parking lot. Li, Deng, and Cai (2020) analyzed the intelligent vehicle network system with advanced technologies, such as intelligent control and ASOS. By using distributed and parallel computing to extract useful information, intelligent traffic control is achieved to avoid traffic jams and ensure traffic safety.

Regarding the application of AI in private sectors, business managers believe that their organizations are showing a tendency toward human-computer cooperation, particularly in the organizational decision-making process characterized by uncertainty, complexity, and ambiguity (Jarrahi, 2018). Senior managers were suggested to promote a culture of cost awareness and service excellence, as well as accelerating the development, deployment, and integration of AI to achieve a balance between cost-effectiveness and excellent services (Wirtz, 2019).

Entrepreneurs tended to adopt big data analysis powered by artificial intelligence to achieve superior operational performance (Dubey et al., 2019). Besides, they can use AI technology to predict employee knowledge-hiding behavior and create an atmosphere of knowledge sharing to alleviate this behavior and improve team creativity and cohesion (Abubakar, Behraves, Rezapouraghdam, & Yildiz, 2019). Other organizational interventions, such as support from leaders, have been found to mitigate the impact of hotel employees' AI and robotics awareness on their turnover intention (Li, Bonn, & Ye, 2019).

The implementation of AI projects in the public sector aims at promoting public interest and providing public value; however, empirical studies on the applications of AI in the government are still scarce. To list a few, based on the viewpoints of stakeholders in the public health field, Sun and Medaglia (2019) proposed four sets of guidelines for the governance of public sectors' AI adoption. Similarly, de Sousa and colleagues put forward a framework for the public sectors' AI solutions (de Sousa, de Melo, Bermejo, Farias, & Gomes, 2019). In 2019, Greek government agencies utilized chat robots based on NLP and ML methods to improve communication between the government and citizens (Androutopoulou, Karacapilidis, Loukis, & Charalabidis, 2019). Noriega (2020) adopted AI in interrogations to create an unbiased environment that promotes voluntary confession by criminal suspects.

Before being integrated with AI technology, conventional SST was widely used across service industries, such as hospitality (Shin & Perdue, 2019) and retail (Weijters, Rangarajan, Falk, & Schillewaert, 2007). Research on SST has seen it as a platform of value co-creation. For example, Kelly, Lawlor, and Mulvey (2017) explored the role of SST in tourism by using a service-led logic. Their results showed that the customers' value creation experience helped explain the experience continuum. In contrast, Plé & Cáceres, (2010) found that value co-destruction can occur when SST systems were used in inappropriate ways. Therefore, ensuring that the customers have the required knowledge and skills to operate SST systems is the key to successful value creation.

In addition, previous studies have examined the factors affecting the adoption of conventional SST. For example, Meuter, Ostrom, Bitner, and Roundtree (2003) found that technical anxiety was the main factor influencing consumers to use SST repeatedly. Weijters et al. (2007) found that perceived ease of use, usefulness, and reliability are the determinants of adopting SST. Moreover, personal attributes (Beatson, Lee, & Coote, 2007), situational factors (Dabholkar, Bobbitt, & Lee, 2003), technical readiness (Bitner, Ostrom, & Meuter, 2002), and demographic factors (Kim & Qu, 2014) have also been found to explain SST adoption.

Regarding the continuous utilization of SST, researchers and practitioners believe that positive user experience generally determines users' revisit intention (Lallemant, Gronier, & Koenig, 2015; Verhoef et al., 2009). For example, Wang, Harris, and Patterson (2012) found that user experience had a strong impact on the users' attitudes toward and behaviors on SST systems than any other factors. Wei, Torres, and Hua (2016) theorized SST experience and confirmed its impact on consumers' commitment.

The integration of conventional SST and AI technology has emerged in the public field, such as the AI-based self-service machines that aim to provide effective public services and improve the user experience. AI-based SST opens a new possibility for human-computer cooperation that potentially improves service efficiency and public values. This opportunity is critical to the government, given the increased labor cost, high employee turnover rate (Buell et al., 2010), and a rise in the citizens' demands for a personalized experience. In China, local governments, such as that in Chengdu and Shanghai, have installed AI-based SST in the government service hall to serve citizens' needs.

2.2. User experience

User experience is associated with a variety of concepts, including functional, emotional, affective, experiential, hedonic, and aesthetic

aspects of human-product interaction (Hassenzahl & Tractinsky, 2006; Lallemant et al., 2015; Law, Roto, Hassenzahl, Vermeeren, & Kort, 2009). Although there is no universal agreement on its nature and scope, user experience typically contains three essential elements: the user, the system, and the context. For example, in 2008, the International Organization for Standardization (2010) defined user experience as "a person's perceptions and responses that result from the use or anticipated use of a product, system or service." In line with this definition and based on the scientific as well as practical views of 275 user experience researchers and practitioners, Law and his colleagues scoped the term to be "products, systems, services, and objects that a person interacts with through a user interface" (Law et al., 2009, p. 727).

Corresponding to the previously mentioned essential elements, studies have investigated the dynamic, context-dependent, and subjective user experience from three major perspectives. The first thread focuses on the instrumental and noninstrumental (e.g., aesthetic and hedonic) needs of users. For instance, Hassenzahl, (2001) confirmed the importance of products' usability and hedonic quality for subjective judgments of product appeal. The second addresses affective and emotional aspects of the interaction, such as a user's expectation, motivation, and mood. The third thread emphasizes the situatedness and temporality of the experience, for example, the context within which the interaction occurs (Verhoef et al., 2009). An integration of these perspectives demonstrates that user experience is a consequence of "a user's internal state (predispositions, expectations, needs, motivation, mood, etc.), the characteristics of the designed system (complexity, purpose, usability, functionality, etc.), and the context (or the environment) within which the interaction occurs (organizational/social setting, meaningfulness of the activity, voluntariness of use, etc.)" (Hassenzahl & Tractinsky, 2006, p. 95).

User experience has been considered to be the antecedent of brand equity (Sheng & Teo, 2012) and consumers' frequency to use (McLean, Al-Nabhani, & Wilson, 2018). Enhancing the user experience has become an integral part of corporate marketing strategies that are significant to success. Thus, it is unsurprising to see research on user experience in the retail context (Verhoef et al., 2009), and brand and product design context (Gentile, Noci, & Spiller, 2007; Sheng & Teo, 2012). Besides, user experience has been a core concept of Human-Computer Interaction (HCI) for more than a decade (McLean et al., 2018; McLean & Wilson, 2016). The advancement of the Internet of Things and interactive technologies has further promoted the interest of researchers. For example, Shin (2017) developed a conceptual model of quality of experience to understand the impact of consumer experience on the perceived quality of the Internet of Things. Öztürk and Rızvanoğlu (2011) investigated how the user interface and the capabilities and constraints of different mobile applications could affect user experience in social networking sites.

Additionally, a small number of studies were found in the public service context. For instance, in Das, Das, & Mackenzie, 1996 surveyed customer satisfaction with local public services in Canada and found that satisfaction levels varied depending on the user experience level and homogeneity of consumers' needs. In Foth & Schroeter, 2010 introduced how the real-time passenger information system deployed in Australia's public transportation system can provide a core platform to improve commuters' user experiences. Kumar, Sachan, and Mukherjee (2017) interviewed 31 Indian citizens to investigate their experience when using e-Gov services and how the experience affects their behaviors. Lallé, Conati, and Carenini (2017) turned their focus to individual differences and showed how individual differences affect user experience with a real-world visualization interface for public engagement. Madariaga, Nussbaum, Marañón, Alarcón, and Naranjo (2019) developed and tested a classification and monitoring framework by using online surveys and interpreted the user experience of government documents from dimensions like interaction goals, information volume, and ease of understanding. Overall, there is still a lack of user experience research in the public service context, not to mention empirical research

explicitly focusing on the user experience of smart products.

2.3. Consumer value theory

The New Public Management approach tends to define citizens as customers of government agencies. In addition, it emphasizes consumer sovereignty. Through management reforms, government departments improve public services, organizational efficiency, and provide services that meet consumer demands (Aberbach & Christensen, 2005). In reviewing the literature, we found CVT benefited our understanding of the use of AI-based SST by citizens in the public service context. CVT believes that consumers choose to buy or not to buy (use or not to use) specific products after evaluating a variety of value components, including functional values, emotional values, epistemic values, social values, and conditional values (Sheth, Newman, & Gross, 1991). These values may be the potential factors that stimulate consumers to buy products and services or enhance their intention to use them. Therefore, they shed light on our understanding of the use of AI-based SST.

CVT has been used to explain how consumer values promote users' continuous use of social networking sites (Chen & Sharma, 2013), the adoption of hedonic digital products (Turel, Serenko, & Bontis, 2010), the adoption of online services (Omigie, Zo, Rho, & Ciganek, 2017), and the delight of using SST (Collier & Barnes, 2015). In our study, AI-based SST is an environment-friendly and sustainable technology that provides 24/7 self-service, supported by human ID verification, intelligent guide office, material intelligence review, and others. Compared to conventional SST, AI-based SST has a greater potential in producing public values and bringing a better experience to users. Therefore, it is appropriate to use CVT to explain the user experience component of AI-based SST.

CVT suggests that the relative importance of value components may vary with the changing context. In our study, we contextualize the value components to fit the characteristics of AI-based SST. Specifically, functional value always relates to performance (Sheth et al., 1991). The functional value of AI-based SST comes from a series of facts, for example, face recognition embedded in the self-service machine can recognize user's face quickly, voice interaction can offer timely responses to user's inquiries, and personalization can accurately recommend relevant service contents according to user's needs. For ease of

operation, we contextualize the functional value of AI-based SST as personalization. Emotional value refers to the perceived utility in improving feelings (Sheth et al., 1991). Aesthetics is a key element of AI-based SST, typically capturing color, shape, and material. Thus, we used aesthetics to indicate the emotional value of AI-based SST. Epistemic value, on the other hand, refers to the "perceived utility acquired from an alternative's capacity to arouse curiosity, provide novelty, and/or satisfy a desire for knowledge" (Sheth et al., 1991). The users' product knowledge plays an important role in helping them decide whether to use new products. Moreover, the epistemic value of AI-based SST is related to perceived time spent on the self-service machine. Thus, we use the perceived time spent on the AI-based SST machines to indicate the epistemic value. This study excludes social and conditional values as they do not show direct correlations with the use of AI-based SST (Teng, 2018). More specifically, citizens dealing with their business in the public service center are not familiar with each other; thus, they are free of social bonds. Additionally, their use of AI-based SST machines is not restricted by the surrounding environment in the service center.

3. Research model and hypotheses

In our research model, personalization, aesthetics, and perceived time spent on the AI-based SST machines are seen as the value factors that affect user experience. Meanwhile, we regard trust in government as a moderator that influences the relationship between the above factors and user experience. Fig. 1 displays this study's model.

3.1. Personalization and user experience

Benefiting from machine learning and data mining technology, personalization can be defined as the provision of personally relevant content, products, and services based on the users' unique characteristics and needs (Xiao & Benbasat, 2007). Zhang and Sundar (2019) considered personalization to be a practical variable affecting user experience by offering advice to the users. Bhalla (2014) argued that personalization is the top criteria for evaluating customer experience in a digital retail environment. Personalization can recommend products and services that customers might be interested in based on historical data and thus help customers in making informed decisions and

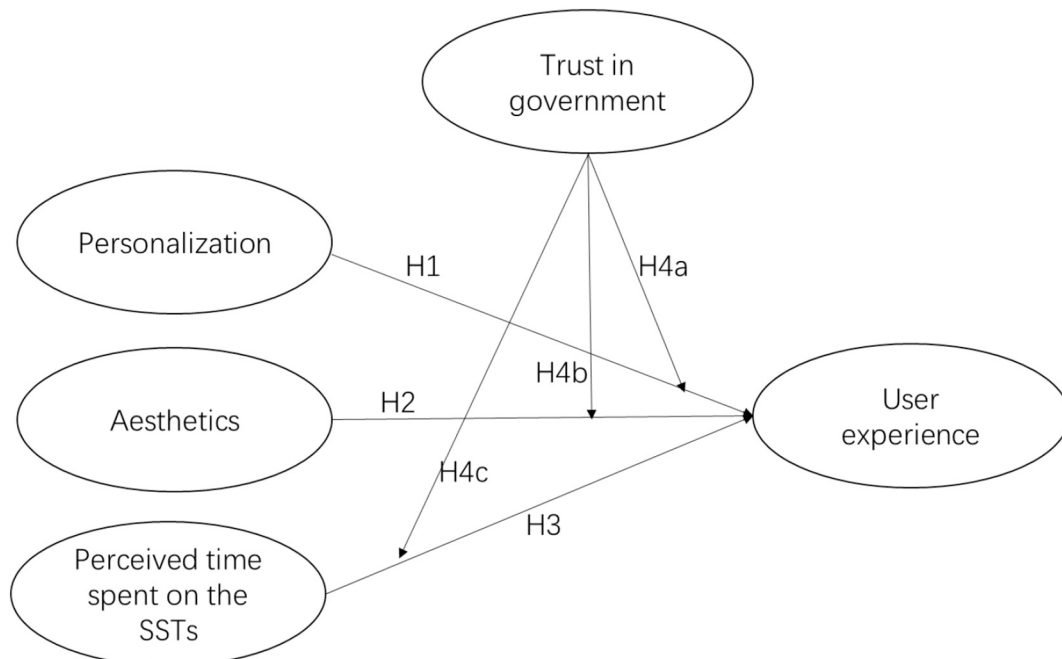


Fig. 1. Research model.

reducing risks and uncertainties (Shi, Wang, Chen, & Zhang, 2020). In our study, AI-based SST with integrated citizen information database may improve user experience by reducing knowledge/skill barriers, mitigating users' cognitive load, and automatically providing personalized services recommendations that align with users' interests and needs. This way, users will have more autonomy to create their unique experiences (Roy, Balaji, Sadeque, Nguyen, & Melewar, 2017). Thus, we hypothesize as follows:

H1. Personalization is positively related to the user experience of AI-based self-service machines.

3.2. Aesthetics and user experience

Aesthetics refers to the sensory experience induced by the product and the extent to which it conforms to personal goals and preferences (Rafaeli & Vilnai-Yavetz, 2004). When individuals use smart products, product aesthetics influences their perceptions and behaviors. Postrel (2002) believed that aesthetics was an important method to ensure the uniqueness of the products and enhance user experience. Coursaris and van Osch (2016) tested the influence of aesthetics and usability dimensions on user satisfaction from a cognitive-affective standpoint. Their study divided aesthetics into classical aesthetics and expressive aesthetics. The results showed that classical aesthetics had a stronger influence on user satisfaction. Sheng and Teo (2012) emphasized that individuals made product choices based on aesthetic values. In this study, we extend product aesthetics to the field of public service and assume that aesthetics can activate citizens' cognitional and emotional experience. Aesthetics plays a particularly important role in building relationships between users and products and closely relates to established users' viewpoints, such as trust (Li & Yeh, 2010) and loyalty (Cyr, Head, & Ivanov, 2006). Therefore, we believe that the user experience of AI-based SST can be affected by the aesthetics of the product, such as color, material, shape, etc. Accordingly, we propose the following hypothesis:

H2. Aesthetics is positively associated with the user experience of AI-based self-service machines.

3.3. Perceived time spent on AI-based SST and user experience

Thus far, the impact of users' willingness to spend time on AI-based SST on their user experience is still unclear. Previous studies have highlighted telepresence and time disruption as key components of positive customer experience (Hoffman & Novak, 2009), where customers were unaware of the time spent on a website. However, Klaus (2013) argued that the customer experience is context-specific and that the customer may be time-conscious in a goal-oriented utilitarian activity. In another study, McLean and Wilson (2016) highlighted that customers were time-conscious when using the website: the time spent on it significantly affected their experiences. In addition, McLean et al. (2018) found that if the customers felt that the time taken to complete an activity in an m-commerce mobile application was too long, they tended to report a negative user experience. In this study, the nature of AI-based SST and the citizens' business-oriented SST usage may arouse their awareness of the time spent. Therefore, we assume that the prompt accomplishment of business will result in a positive user experience. With this, we propose,

H3. The perceived time spent on the AI-based SST is negatively correlated with user experience.

3.4. Trust in government and user experience

Trust in government refers to "the level of confidence that citizens have in their government (both politicians and public officials) to 'do the right thing,' and to act appropriately and honestly on behalf of the

public" (Barnes & Gill, 2000, p. 4). Citizens develop trust when they are aware that their government's initiatives are responsive, transparent/open, and efficient. These beliefs are valued as key indicators for assessing trust in government (Bannister & Connolly, 2011).

IT infrastructure development has become a top strategy employed by governments to restore the citizens' trust (Androutsopoulou et al., 2019). Information technology, to a certain extent, can help organizations rebuild business processes, reduce the interference of human factors, and increase transparency and fairness (Wang, 2014). Evidence shows that citizens who trust the government are more likely to share personal information while using online services, based on which the government can recommend relevant services and contents to meet citizens' needs better (Beldad, de Jong, & Steehouder, 2011). This enhances citizens' user experience of online services. Moreover, citizens who trust the government tend to be more excited about government service innovations, which leads to greater government motivation in designing IT aesthetics and incorporating the assessment of required service time into innovation management. Thus, in our opinion, trust in government may conditionally affect the relationships between personalization, aesthetics, and perceived time and AI-based SST user experience. Therefore, we predict that

H4a. Trust in government positively moderates the impact of personalization on user experience.

H4b. Trust in government positively moderates the impact of aesthetics on user experience.

H4c. Trust in government positively moderates the impact of the perceived time spent on the AI-based SST on user experience.

4. Methods

4.1. Data collection

To test the hypotheses, we surveyed AI-based self-service machine users at Wuhou AAB. The reasons for choosing the Wuhou District are as follows: First, a decade ago, Wuhou District took the lead in launching the national reform of the administrative approval system, based on the idea of Whole of Government. Now, the Wuhou AAB is introducing the "Do it yourself" public services with the help of big data and AI technologies. Therefore, it is an ideal research site for studying AI applications in public service delivery. Second, AI-based self-service machines provide a new service channel at Wuhou AAB. The government and citizens are at their early stage of adopting and exploring this new channel. Research that focuses on citizens' user experience could help the government and its technology suppliers to improve the design and enhance the performance of the AI-based SST.

Before sending out the questionnaire, we invited experts in the field of information systems to review it and suggest modifications. We also collected revision advice from 15 government employees that manage AI-based self-service machines at Wuhou AAB. Based on their comments, we revised the questionnaire and conducted a pilot test with 30 AI-based self-service machine users at Wuhou AAB, in the summer of 2019. Cronbach's alpha, above the 0.70 cut-off, was used for measuring the reliability of survey items (Cronbach, 1970). Based on users' feedback, we further modified the questionnaire to address issues such as ambiguous wording and terminology.

The final questionnaires were sent out by trained research assistants (excluding the authors) to citizens who have just accomplished their business by using AI-based self-service machines at the government service hall. The survey time was from 9:00 am to 5:00 pm on weekdays, from August 15 to September 15, 2019. The compensation for taking the survey was a gift costing 5 RMB (roughly 0.8 US dollars). To ensure valid responses, we used the trap questions technique to reverse questions' wording and outliers. After data cleaning, 379 out of the 500 collected questionnaires were identified as valid and then used in the final data

analyses. Table 2 shows the demographic information of the survey respondents.

Of the 379 samples collected, men accounted for 30.6% (116) and women accounted for 69.4% (263) of the samples. About half of the respondents are between the ages of 18 and 24 (47%), with an income less than 2000 RMB (42%) per month. Most of the respondents are employees of small and medium-sized enterprises (82.6%) and have a college degree (86.5%). The sample was random in nature, yet the representativeness of participants could be difficult to justify, given the lack of a users' dataset. With that, we are not trying to generalize the research findings to other contexts. Rather, this research is better to be seen as a preliminary investigation on this topic that provides factual evidence of how the user experience of AI-based SST might be influenced, at the early stage of adoption in public service delivery.

4.2. Measures

The conceptualization of personalization was measured through five items derived from previous research. In 2016, Lee and Rha explored consumers' response to the personalization–privacy paradox caused by using location-based mobile commerce and investigated the factors influencing consumers' psychological and behavioral responses to the paradox. In 2017, Roy et al. applied personalization to the context of smart retail technology to explore the impact of factors constituting smart retail technology's experience on smart technology, customer, and retailer-level results. The five items used in the current study have been modified in line with the context of government services.

The conceptualization of aesthetics was measured through five items derived from Sheng and Teo (2012). In 2012, Sheng and Teo studied the mediating role of mobile users' customer experience on the relationship between product attributes and mobile brand equity. Since mobile phones and smart self-service technologies are both tangible products, we adopted these survey items for our research.

The conceptualization of perceived time spent on the AI-based SST was measured through three items derived from McLean and Wilson (2016). In 2016, McLean and Wilson studied whether customers need online customer support; in addition, they also studied the impact on customer experience when users spend a long time searching for information and services on the business support website. As this study also measures the impact of perceived time spent on the AI-based SST on user experience in a utilitarian context, we draw on these three items to conduct the current study.

We created nine items to capture the multidimensionality of user

Table 2
Demographic information of respondents.

Variables	Categories	Frequency	Percentage
Gender	Men	116	30.6
	Women	263	69.4
Age	18–24	178	47.0
	25–34	146	38.5
	35–44	45	11.9
	45–54	9	2.4
	55–60	1	0.3
Education	Junior high school	7	1.8
	High school	42	11.1
	College	328	86.5
	Master's degree	2	0.5
Nature of enterprise	Large enterprise	12	3.2
	Small and medium-sized enterprise	313	82.6
Monthly income (RMB)	Self-employed person	54	14.2
	2000 or blow	161	42.5
	2001–3999	63	16.6
	4001–5999	55	14.5
	6001–7999	38	10.0
	8001–9999	30	7.9
	Over 10,000	32	8.4

experience. These measures can be attributed to Schmitt (1999) and Gentile et al. (2007). In 1999, Schmitt proposed a modular conceptualization of customer experience in five aspects: sensory experiences (sense), affective experiences (feel), creative cognitive experiences (think), physical experiences, behaviors, and lifestyles (act), and social-identity experiences (relate). In 2007, Gentile, Noci, and Spiller extended Schmitt's modules and identified the sensorial, emotional, cognitive, pragmatic, lifestyle, and relational components of the customer experience. The nine survey items used in our study did not try to measure all these components; instead, they focused on the emotional, cognitive, lifestyle, and relational dimensions of user experience.

In addition, we used four items to measure trust in government. These four items are derived from Teo, Srivastava, and Jiang (2008). In 2008, Teo et al. used the updated DeLone and McLean IS success models as a theoretical framework to study the role of trust in the success of e-government. They concluded that trust in government is positively related to trust in e-government websites. Since e-government websites and smart self-service technologies are oriented to provide public services and meet citizen's needs, we modified the research items to measure citizens' trust in government. All variables were assessed through a 7-point Likert scale, which anchors at value 1 as Strongly Disagree and at 7 as Strongly Agree. Table 3 summarizes the measures.

5. Data analysis and results

Stepwise hierarchical moderated regression analysis was used to test the proposed model through a three-step process. Before that, a confirmatory factor analysis (CFA) was performed to evaluate the adequacy of the measurement model based on its reliability, convergence validity, and discriminant validity. Then, we implemented the stepwise hierarchical moderated regression method, in accordance with the steps proposed by Baron and Kenny (1986), to examine the hypothesized relationships between variables. The statistical analysis was carried out on SPSS 24.

5.1. Confirmatory factor analysis

Confirmatory factor analysis (CFA) examines the relationship between the observed variables and their underlying latent variables. It was used to assess the loadings of items on a specific factor. In this study, the values of factor loadings were displayed in Table 4, which demonstrated acceptable loadings of all items except for the user experience variable. Among the items measuring user experience, those with lower factor loadings (below 0.70) were excluded from further analysis. Following the directive of Cronbach's alpha coefficient proposed by Nunnally and Bernstein (1994), all the alpha values were greater than 0.70, which provided strong evidence of internal consistency (Hair, Ringle, & Sarstedt, 2011).

In addition, the average variance extracted (AVE) values (Table 4) for all constructs showed desired convergent validity (Fornell & Larcker, 1981). As shown in Table 5, the square root of all constructs' AVE is greater than that between itself and other constructs, indicating toward the expected discriminative validity (Hair et al., 2016). These results warranted further analysis in the form of stepwise hierarchical moderated regression analyses.

5.2. Regression analysis

The hypothesized relationships among variables in our model are examined through regression analysis. Specifically, to check the hypotheses containing moderation effect, we adopted a stepwise hierarchical regression method borrowed from Baron and Kenny (1986).

The assumptions of multi-collinearity and residual means have been discussed separately for each hypothesis. Table 6 shows the statistical figures used to determine the effect of independent variables on user

Table 3
Measures of variables.

Constructs	Items	Source
Personalization	P1. Smart self-service machine offers me personalized services.	Lee & Rha, 2016, Roy et al. (2017)
	P2. Smart self-service machine understands my specific needs.	
	P3. Smart self-service machine offers recommendations that match my needs and the situation.	
	P4. Smart self-service machine is customized to my needs.	
	P5. By using smart self-service machine, I can get personalized information that is tailored to my interests and needs.	
Aesthetics	A1. The design of this smart self-service machine is appealing.	Sheng and Teo (2012)
	A2. I like the shape of this smart self-service machine.	
	A3. This smart self-service machine makes me happy.	
	A4. This smart self-service machine can give me a sense of superiority.	
	A5. The design of the smart self-service machine can inspire my positive emotions.	
Perceived time spent on the AI-based SST	T1. I spent more time than I should on the smart self-service machine.	McLean and Wilson (2016)
	T2. It took longer than I expected to find the information on the smart self-service machine.	
	T3. It took too long searching for the information on the smart self-service machine.	
	UX1. This smart self-service machine tries to be emotional.	
	UX2. This smart self-service machine tries to be affective.	
User experience	UX3. This smart self-service machine tries to intrigue me.	Schmitt (1999) Gentile et al. (2007)
	UX4. This smart self-service machine tries to stimulate my curiosity.	
	UX5. This smart self-service machine makes me think creatively.	
	UX6. This smart self-service machine tries to make me think about my lifestyle.	
	UX7. This smart self-service machine gets me to think about my behavior.	
Trust in Government	UX8. This smart self-service machine tries to make me think about bonds.	Teo et al. (2008)
	UX9. I can relate to other people through this smart self-service machine.	
	TG1. I feel that the government acts in citizens' best interests.	
	TG2. I feel comfortable interacting with the government because the government generally fulfills its duties efficiently.	
	TG3. I always feel confident about relying on the government to do its part when I interact with it.	
	TG4. I am comfortable relying on the government to meet its obligations.	

experience, along with the moderation effect of trust in government (Hypotheses 1, 2, and 3). In Table 6, the values indicate that all the factors proposed in our model (including personalization, aesthetics, and perceived time spent on AI-based SST) significantly affect citizens' user experience. Specifically, personalization and aesthetics are found to be positively associated with user experience. One unit increase in personalization and aesthetics leads to increased user experience by 0.249 and 0.441 units, respectively. As is hypothesized, the perceived time spent on AI-based SST is found to be negatively affecting citizens'

Table 4
Measurement scale properties.

Constructs/items	Item loadings	Cronbach's alphas	AVE	CR
Personalization (P)		0.885	0.620	0.889
P1	0.789			
P2	0.836			
P3	0.803			
P4	0.803			
P5	0.667			
Aesthetics (A)		0.880	0.602	0.883
A1	0.737			
A2	0.865			
A3	0.865			
A4	0.717			
A5	0.720			
Perceived time spent on the SSTs (T)		0.798	0.588	0.808
T1	0.737			
T2	0.902			
T3	0.755			
User experience (UX)		0.884	0.459	0.884
UX1	0.639			
UX2	0.624			
UX3	0.737			
UX4	0.725			
UX5	0.766			
UX6	0.622			
UX7	0.666			
UX8	0.580			
UX9	0.633			
Trust in government (TG)		0.967	0.882	0.968
TG1	0.919			
TG2	0.914			
TG3	0.967			
TG4	0.954			

Notes: N = 379.

Table 5
Discriminant validity.

Construct	P	A	T	UX	TG
Personalization (P)	0.787				
Aesthetics (A)	0.384	0.776			
Perceived time spent on the AI-based SST (T)	-0.099	-0.175	0.767		
User experience (UX)	0.424	0.520	0.063	0.678	
Trust in government (TG)	0.307	0.378	-0.233	0.326	0.939

Notes: N = 379.

Table 6
Multiple regression analysis.

Variables	β	Std. error	t	Sig
User experience				
Personalization	0.259	0.043	6.002	0.000
Aesthetics	0.441	0.045	9.825	0.000
Perceived time spent on AI-based SST	-0.154	0.039	3.994	0.000

Notes: N = 379. β = Standardized regression coefficient.

user experience: an increase of one unit of perceived time spent on AI-based SST will result in a decrease of 0.154 units of user experience. It implies that the longer a user spends on the self-service machine, the worse his or her experience will be. Thus, Hypotheses 1, 2, and 3 are supported.

To test Hypothesis 4a, the variable *Personalization* was entered at Step 1 (Table 7) while controlling for demographic variables of respondents. The total variance explained by the model was 18% ($F(1, 377) = 82.518, p < .001$). Results show that perceiving the personalized

Table 7

Moderating effect of trust in government on personalization and user experience.

Model	β	Std. error	ΔR^2	t	Sig
DV: User experience					
Step 1 for H4a					
Personalization	0.407	0.045	0.180	9.084	0.000
Step 2					
Personalization	0.343	0.046		7.477	0.000
Trust in government	0.214	0.047	0.043	4.534	0.000
Step 3					
Personalization	0.354	0.046		7.726	0.000
Trust in government	0.255	0.050		5.080	0.000
Moderator	0.062	0.027	0.011	2.307	0.022

features of AI-based self-service machine could positively and significantly enhance the user's experience ($\beta = 0.407, p < .001$). After adding the variable *Trust in Government* in Step 2, the results indicated that the model accounted for 22.3% of the variance in *User Experience*. *Trust in Government* was significantly and positively related to *User Experience* ($\beta = 0.214, p < .001$); therefore, people with higher levels of *Trust in Government* reported better *User Experience*. Interestingly, the effect of personalized features of AI-based self-service machines on citizens' user experience was reduced after the addition of *Trust in Government* ($\beta = 0.343, p < .001$). This result further explained an additional 4.3% of the variance beyond the variance accounted for by *Personalization* ($F(2, 376) = 52.678, p < .001$). Then, in Step 3 of the regression analysis, the "Personalization $\times$ Trust in Government" interaction was entered to assess the moderating effect of *Trust in Government* on the *Personalization* - *User Experience* relationship. The result showed that 23.4% of the variation in the dependent variable could be explained by the main effects and the interaction effects ($F(3, 375) = 37.970, p < .001$). This interaction effect, although significant, accounted for a minimal incremental effect beyond the direct effects of perceived gender discrimination and work autonomy ($\Delta R^2 = 0.011, p < .05$). Therefore, H4a is supported in that the relationship between perceived personalized features of AI-based self-service machines and user experience was positively moderated by citizen's trust in government ($\beta = 0.06, p < .05$).

We used the previously explained method in testing Hypotheses 4b and 4c. Specifically, Table 8 displays the statistics about the relationships between *Aesthetics*, *Trust in Government*, and *User experience*. Results show that perceiving the aesthetic features of AI-based self-service machines can significantly enhance user's experience ($\beta = 0.514, p < .001$). After introducing *Trust in Government*, the effect of *Aesthetics* on *User Experience* is reduced in a lower margin ($\beta = 0.458, p < .001$). The model further explained an additional 2% of the variance, which is minimal but still significant, beyond the variance accounted for by *Aesthetics* ($F(2, 376) = 76.665, p < .001$). Then, the analysis indicated that 29.3% of the variation in the dependent variable could be explained by the main effects and interaction effects. Therefore, the results in Table 8 support H4b in that citizens' trust in government could

Table 8

Moderating effect of trust in government on aesthetics and user experience.

Model	β	Std. error	ΔR^2	t	Sig
DV: User experience					
Step 1 for H4b					
Aesthetics	0.514	0.044	0.270	11.810	0.000
Step 2					
Aesthetics	0.458	0.046		9.848	0.000
Trust in government	0.150	0.046	0.020	3.223	0.001
Step 3					
Aesthetics	0.458	0.046		9.906	0.000
Trust in government	0.201	0.052		3.866	0.000
Moderator	0.064	0.030	0.009	2.155	0.032

positively influence the effect of aesthetics on their experience of AI-based SST ($\beta = 0.064, p < .05$).

Table 9 shows the results of the hypothesized relationship between *Trust in Government*, *Perceived Time Spent*, and *User Experience*. In Step 1, the perceived time spent on AI-based self-service machines is not significantly related to citizens' user experience ($\beta = 0.058, F(1, 377) = 1.521, p > .05$). After adding *Trust in Government* in Step 2, the effect of perceived time spent on AI-based self-service machines on *User Experience* significantly increased ($\beta = 0.135, p < .001$). In Step 3, the "Perceived Time Spent $\times$ Trust in Government" interaction was entered to assess the moderating effect of *Trust in Government* on the *Perceived Time Spent* - *User Experience* relationship. The analysis found no significant increase of explained variance of *User Experience* was accounted for by *Perceived Time Spent* ($\Delta R^2 = 0.008, F(3, 375) = 19.562, p > .05$), which rejected H4c.

6. Discussion

The continuous progress of AI technologies helps governments in making constant adjustments to meet the growing demands and expectations of citizens. In this study, a new public service delivery method, namely AI-based SST, attracted our attention. This novel digital channel bridges the physical world with the digital world, making it easier for citizens to find needed information and services. Previous research on conventional SST has mostly focused on traditional attributes, such as ease of use and usefulness. Compared with conventional SST, AI-based SST is empowered by NLP, ML, big data mining, and other technologies, and functionalized by face recognition, voice interaction, and personalization. These technologies and functions ensure an increased integration of historical transaction data into the AI-based self-services, which could quickly and accurately identify users, properly respond to user inquiries, and efficiently provide personalized recommendations to fulfill users' needs. The AI-based SST has far more functions than the conventional SST; the latter is limited to simple queries.

When conducting this research project, we realized there had been a steady increment in the number of AI-based self-service machine users, for example, in cities like Chengdu and Shanghai in China. To achieve and sustain the expected AI advantages and benefits in the long run, it is necessary to ensure that the AI-based SSTs bring pleasant and satisfying user experience. Yet our knowledge about factors affecting AI-based SST user experience is limited. Consequently, this paper attempts to investigate the use of AI-based self-service machines in the government service hall in Wuhou AAB.

This study took a preliminary step to investigate the roles of potential factors that influence the user experience of AI-based SST. We also contextualized the analyses within the levels of citizens' trust in

Table 9

Moderating effect of trust in government on perceived time spent on AI-based SST and user experience.

Model	β	Std. error	ΔR^2	t	Sig
DV: User experience					
Step 1 for H4c					
Perceived time spent on AI-based SST	0.058	0.047	0.004	1.233	0.218
Step 2					
Perceived time spent on AI-based SST	0.135	0.045		2.978	0.003
Trust in government	0.357	0.049	0.123	7.279	0.000
Step 3					
Perceived time spent on AI-based SST	0.125	0.046		2.730	0.007
Trust in government	0.381	0.051		7.546	0.000
Moderator	-0.054	0.028	0.008	-1.898	0.059

government, which is an essential element that governments worldwide care about. The findings underscore the importance of personalization, aesthetics, and perceived time spent on AI-based SST. Specifically, citizen users believe that the personalized services provided by AI-based SST contribute to a smooth and positive experience. Moreover, the simple and attractive appearance of AI-based SST makes it aesthetically appealing for users. Besides, users are aware of the time it takes to use AI-based SST. Therefore, timely completion of tasks results in a positive user experience. Additionally, the predictions that personalization and aesthetics have positive impacts on user experience and that trust in government positively moderates these relationships are accepted. This result suggests that citizens with more trust in government are more likely to have a pleasant experience from AI-based SST's personalization and aesthetics. Public managers should ensure that the AI-based SST is aesthetically appealing and personalize the delivery of the right contents to the right person at the right time to achieve a more positive user experience. Besides, they should work on cultivating more trust from citizens, for example, by providing citizen-centric services, increasing government transparency, engaging citizens in service coproduction, and making evidence-based decisions.

6.1. Theoretical implications

AI technology-based services are becoming a popular tool for governments to enhance service quality, interactivity, accuracy, and efficiency. Despite the rapid implementation of AI technology, there has been little focus on the citizens' experience when using AI technology in public services. This research contributes to the literature of AI, SST, trust in government, and user experience. It identifies the antecedents that affect citizens' user experience of AI-based SST. For instance, the results show that personalized services, attractive appearance, and service efficiency significantly influence citizens' experience of AI-based SST. This research also contributes to our knowledge of CVT. It demonstrates the importance of functional value (personalization), emotional value (aesthetics), and epistemic value (perceived time spent on AI-based SST) in associating with citizens' user experience.

McLean et al. (2018) highlighted that more attention should be paid to moderator variables while studying the factors affecting user experience. The present research responds to this line of thought and contributes to the literature on user experience by introducing trust in government as a moderating variable. Furthermore, this study examines how the combination of AI-based SST attributes and trust in government affects the citizens' user experience. The findings suggest that the positive relationship between personalization, aesthetics, and user experience will be strengthened when citizens place more trust in their government. Since this research was the first attempt to determine the moderating role of trust in government in the relationship between critical attributes and AI-based SST user experience, it has significant theoretical implications.

6.2. Practical implications

This study has important practical implications for public managers and AI service contractors. First, the study highlights the unique nature of AI-based SST user experience. Personalization and aesthetics appear to enhance a positive user experience. Therefore, the government and its AI service contractors should work collaboratively to strengthen personalized functions that allow easy customization of activities, i.e., recommend related services and contents, according to the characteristics and needs of users. In line with this, the government might want to extend the inclusiveness of its "24/7" AI-based self-service, to ensure accessible, efficient, and timely services for diverse demographic groups. Moreover, the aesthetic design of AI-based SST seems to result in a strong emotional feeling for the users, thereby affecting their experience. A neatly designed AI-based SST would reduce the cognitive workload required to process visual stimuli. Thus, continuous tests

should be conducted on these variables to safeguard an optimal user experience.

The results of this study also outline the citizens' time awareness with AI-based SST in the government service hall. Contrary to the previous research on telepresence and time disruption that led to positive customer experience, this study further emphasizes the nature of user experience based on a specific context and outlines to the government that the time citizens spend on AI-based SST is for business-oriented practical activities. Since spending more time than expected will lead to negative user experience, public managers and AI service contractors may want to incorporate the required service time assessment into usability tests to ensure prompt services.

Finally, the results of this study indicate that trust in government improves citizens' user experience. Therefore, the government should take action to strengthen the citizens' trust and improve their satisfaction. This could be attained by improving their information, system, and service quality (Santa, MacDonald, & Ferrer, 2019). In addition, public managers may want to act in a manner that would build up the government's reputation, such as actively opening service datasets, being transparent in decision-making, and engaging citizens in service coproduction. Meanwhile, they can achieve workplace safety by controlling technical (privacy), time, and financial risks. Evidence shows that such an approach by the government would lead to an increase in the citizens' trust (Beldad, van der Geest, de Jong, & Steehouder, 2012).

6.3. Limitation and future research

This research has some limitations. First, data were collected from residents of Wuhou District, Chengdu City, so it is unclear whether the results apply to other regions or countries that are interested in adopting AI-based self-service technology in public services. In the future, it would be beneficial to conduct cross-sectoral research as well as international investigations to test the generalizability and validity of the model. Second, future research may collect longitudinal data to comprehensively discover and trace the influencing factors of user experience dynamics over time. Third, the model presented in this paper should be further expanded to capture the importance of factors like user perception of privacy and information security.

7. Conclusion

By using on-site survey data, this study finds that personalization, aesthetics, and perceived time spent on the AI-based SST have significant impacts on user experience. Moreover, it shows that trust in government moderates the relationship between personalization, aesthetics, and user experience. Citizens with more trust in government are more likely to have a pleasant experience from AI-based SST's personalization and aesthetics. Based on the findings, we suggest that public managers should ensure that the AI-based SST is aesthetically appealing. Besides, they should be able to personalize the delivery of the right content to the right person at the right time to achieve a more positive user experience. In addition, they may want to steadily build up citizens' trust to improve citizens' service experience, for instance, by providing citizen-centric services, increasing government transparency, engaging citizens in service coproduction, and making evidence-based decisions. This study improves our theoretical understanding of AI-based SST user experience in public service delivery. It also has significant managerial implications for governments' AI-based SST adoption and implementation. The results of this study can serve as the launching pad for future exploration of AI innovations in government, given the continuous advancements in AI technology and the changing needs of the public.

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Tao Chen is a professor at the College of Public Administration, Huazhong University of Science and Technology, China. He is interested in e-government, smart city, open data, and artificial intelligence.

Wenshan Guo is a doctoral student at the College of Public Administration, Huazhong University of Science and Technology, China. His research focuses on user experience in digital age, e-service, and artificial intelligence.

Xian Gao (Corresponding author) is an assistant professor at the Department of Political Science, California State University, Los Angeles. She had her Ph.D. from the School of Public Administration, University of Nebraska at Omaha. Her research interests include digital governance, collaborative governance, performance management, and smart city.

Zhehao Liang is a doctoral candidate at the College of Public Administration, Huazhong University of Science and Technology, China. His work focuses on how public sectors in developing nations can better use technology to meet citizens' needs.