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Research Article

Public and private value creation using artificial intelligence: An empirical study of AI voice robot users in Chinese public sector

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ABSTRACT

Despite significant theoretical and empirical attention on public value creation in the public sector, the relationship between artificial intelligence (AI) use and value creation from the citizen perspective remains poorly understood. We ground our study in Moore's public value management to examine the relationship between AI use and value creation. We conceptually categorize public service value into public value and private value. We use procedural justice and trust in government as indicators of public value and, based on motivation theory, we use perceived usefulness and perceived enjoyment as indicators of private value. A field survey of 492 AI voice robot users in China was conducted to test our model. The results indicated that the effective use of AI voice robots was significantly associated with private value and procedural justice. However, the relationship between the effective use of AI and trust in government was not found to be significant. Surprisingly, the respondents indicated that private value had a greater effect on overall value creation than public value. This contrasts with the common idea that value creation from the government perspective suggests that social objectives requiring public value are more important to citizens. The results also show that gender and citizens with different experiences show different AI usage behaviors.

1. Introduction

Artificial intelligence (AI) can be defined as "a system's ability to process data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (Haenlein & Kaplan, 2019, p. 5). With the advancement of big data and computing power (e.g., natural language processing, computer vision, and voice recognition), AI has the potential to not only enrich our lives in many ways (e.g., innovations such as image recognition, smart medical, and self-driving car) (Bag, Pretorius, Gupta, & Dwivedi, 2021; Borges, Laurindo, Spínola, Gonçalves, & Mattos, 2021; Grover, Kar, & Dwivedi, 2020; Makridakis, 2017; Nishant, Kennedy, & Corbett, 2020; Shareef et al., 2021), but also has the power to transform businesses (Ågerfalk, 2020; Coombs et al., 2021; Coombs, 2020; Dwivedi, Rana, Jeyaraj, Clement, & Williams, 2019; Pillai et al., 2021; Pillai, Sivathanu, & Dwivedi, 2020; Zhang, Pee, & Cui, 2021; Brynjolfsson & McAfee, 2017). Further, by 2030, AI will contribute as much as $15.7 trillion to the global economy (PWC, 2019). Due to its high efficiency and adaptability, AI has been widely adopted in various industries, including automotive, electronics, medical, pharmaceutical, catering, and food and beverage, and agriculture (Demlehner, Schoemer, & Laumer, 2021; Duan, Edwards, & Dwivedi, 2019; Dubey et al., 2020; Kar & Dwivedi, 2020; Sharma, Yadav, & Chopra, 2020; Xiao & Kumar, 2021).

Similar to the business sector, the public sector is beginning to use AI to improve their services. Extant research has shown that AI has significant potential in the area of public sector governance and discretion (e.g., König & Wenzelburger, 2020; Bullock, 2019; Young, Bullock, & Lecy, 2019), for example, reducing discretion, increasing the efficiency of monitoring, and improving democratic policies. Utilizing resources (such as AI voice robots) to create value by improving public service performance (e.g., offering new services, providing new service channels, and reducing costs) is a significant challenge faced at all levels of government around the world (Bryson, Crosby, & Bloomberg, 2014; Cabral, Mahoney, McGahan, & Potoski, 2019; Yang, 2016). Citizens' personalized service needs are increasing and becoming unpredictable, and the large-scale use of AI just meets this demand (Venkatesh,Thong,

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Chan, & Hu, 2016). AI technologies are increasingly adopted in the public sector areas, such as education, social policy, government regulations, and public healthcare (Sun & Medaglia, 2019). Public service managers expect AI to provide values like increased effectiveness, efficiency, fairness, and response time, although reality might be different (Bullock, 2020).

However, there is still a lack of theoretical and empirical framework in the mechanisms by which AI helps the public sector to create value. Although there are a large number of academic studies on public value, empirical research on public value is scarce (Hartley, Alford, Knies, & Douglas, 2017). Give that public value creation is the public sector's aim (Tantalo & Priem, 2016), a significant number of scholars have contributed to this topic (e.g., Moore, 1995; Alford, 2002; Bryson et al., 2014; Bozeman, 2019; Cabral et al., 2019). Generally, extant research on value creation in the public sector can be broadly categorized into two main categories depending on whether the research examines the supply or demand side of the phenomenon (Lim, Tan, Cyr, Pan, & Xiao, 2012). The supply side of value creation examines the actions taken by the public sector in rolling out public services, while the demand side examines citizens' individual views on the creation of public value. The former is concerned with how the public sector creates value to improve government performance and satisfy the needs of citizens (Bryson, Sancino, Benington, & Sørensen, 2017; Moore & Khagram, 2004). For example, past studies had introduced the concept of public value management (e.g., defining public value and identifying its characteristics) (Alford & O'Flynn, 2009; Moore, 1995), illustrated the process of value creation based on different theories (Cabral et al., 2019), measured public value (Crosby, 't Hart, & Torfing, 2017; Moore, 2014), and used public value to guide public management (Alford & Hughes, 2008; O'Flynn, 2007).

The demand side of value creation examines citizen perception of the value of public services (e.g., Bozeman, 2019). For example, past studies had defined public value from a citizen perspective (e.g., Alford, 2002), measured public value based on citizen perception (e.g., Scott, DeLone, & Golden, 2016), and designed public service systems to meet citizen needs (e.g., Grimsley & Meehan, 2007). These studies have provided important insights into the process of value creation.

However, most of these insights remain somewhat limited for advancing public value in the public sector. As pointed out by extant studies (e.g., Wang, 2012; Ju, Liu, & Feng, 2019), value creation related to the supply side overemphasizes public attributes of the services (e.g., social well-being, justice, and trust) (Grimsley & Meehan, 2007), while value creation related to the demand side pays more attention to the needs and satisfaction of citizens. Actually, the value that citizens acquire from the public sector has a dual nature (Nabatchi, Sancino, & Sicilia, 2017; Ju et al., 2019). Citizens are motivated to participate in certain public activities due to the service value created during the engagement process. One part of this acquired value may meet their motivation for participation (e.g., usefulness, enjoyment), whereas the other part may indirectly increase the welfare of society (e.g., justice, trust in government) (Wang, 2012). Although extant research has a metaphor for the dual attributes of public value (e.g., Lyons, Duxbury, & Higgins, 2006; Scott et al., 2016), to our knowledge, relatively little research defines this dual role of value. Even though some studies have pointed out the existence of this attribute, which is called "public value creation and private value acquisition" (e.g., Mills, Carter, & Belanger, 2010; Ju et al., 2019), these studies have not clearly pointed out the dual connotation of value. This will make it difficult for the government to understand citizens' specific needs and designs and provide public services for citizens. Therefore, *the first gap in existing research* is that the dual role of public service value is not taken into account in empirical research from the citizen perspective.

Moreover, information technology (IT) is becoming the primary means for citizens to access public services and the source of service innovation in the public sector. Hence, governments expect to leverage IT to provide public services to citizens, thereby improving public value. Examples often include websites (e.g., Karkin & Janssen, 2014; Samoilenko & Osei-Bryson, 2019), e-government (Cordella & Bonina, 2012; Seltsikas & O'keefe, 2010), social media (Criado, Sandoval-Almazan, & Gil-Garcia, 2013; Grube, 2017), and mobile government (Walravens & Ballon, 2013; Wang, 2014). Although AI has been widely used in the private sector and extant research has confirmed the positive impact of AI on value creation (e.g., Riikkinen, Saarijärvi, Sarlin, & Lähteenmäki, 2018; Luo, Tong, Fang, & Qu, 2019), the role of AI in value creation is still unclear in the public sector. Further, while some studies have theoretically pointed out the impact of AI on public value creation (e.g., Wirtz & Müller, 2019), there is still a lack of a theoretical and empirical framework to examine the effect of AI on value creation in the public sector. Consequently, the impact of the use of AI on public value creation is still unclear. Therefore, *the second gap in existing research* is that there is a dearth of empirical research on the specific impacts of AI use on value creation in the public sector.

Considering that citizen perceptions of public value have become the core of public governance (Bozeman, 2019), we focus our study on the citizen perspective. To address the above gaps, we propose the research question: *How do citizens' effective use of AI affect value creation in the public sector?* To answer this question, we utilize the public value creation theory to build a research model of AI voice robot use and value creation to illustrate the mechanism of value creation in the public sector. The model argues that citizens' effective use of AI voice robots will enhance public value and private value, and ultimately add to the total public service value.

This study contributes to the extant literature by highlighting why citizen use of the AI voice robot is related to value creation in the public sector. First, we contribute to value creation theory by categorizing public service value into public value and private value. Moreover, we use perceived usefulness and enjoyment to measure private value. We use procedural justice and trust in government to measure public value, as these represent the two most important strategic goals of the government. Second, we offer a theoretical and empirical framework that links the AI voice robot use to public service value creation. Third, we test our proposed model with AI voice robot services, which is different from extant empirical studies using text-based chatbots or voice-based virtual (intangible computer programs) chatbots.

The paper is organized as follows. The following section introduces the public value creation theory, briefly reviews prior studies on AI voice robot services, value creation theory, and develops our research model. The next section addresses the data, measurements, statistical techniques used to test the research hypotheses, and present the empirical results. Finally, findings, implications, and conclusions are presented.

2. Conceptual and theoretical background

2.1. The evolution of AI

AI began in the 1950s and is a revolutionary tool for using computers to simulate and display intelligence (Russell & Norvig, 2016). The root of AI, and indirectly robots, can be traced back to Turing (1950) early work, who presented the famous Turing test, which describes how to create intelligent machines and how to examine their intelligence. Even today, the Turing test is still regarded as the benchmark to measure the intelligence of artificial systems (Haenlein & Kaplan, 2019; Kumar, Dwivedi, & Anand, 2021). However, the word "artificial intelligence" was introduced by John McCarthy at a workshop at Dartmouth College in 1956 (McCarthy, 1988), which marks the arrival of AI Spring. In the next two decades (1956–1973), AI entered the summer period, and its iconic results were ELIZA computer program and General Problem Solver program. Unfortunately, AI entered the winter period (1974–1996) for more than two decades due to AI development that fails to meet expectations (Buchanan, 2005). However, AI experienced a short period of prosperity in the 1980s because Japan and the United States increased their investment in AI and created smart computers and

3D printers (McCorduck, 2004). Since 1997, AI has entered the harvest period, as illustrated by the following three landmark events. First, IBM's computer system "Deep Blue" defeated the world chess champion Kasparov in 1997. Second, Hinton's breakthrough in the field of deep learning in neural networks in 2006, and the third is that AlphaGo (a computer program designed by Google) defeated the world champion Jie Ke in the board game Go in 2016 (Haenlein & Kaplan, 2019). Currently, with the development of supercomputing power, machine learning, and big data technologies, AI has become the most important general-purpose technology that is effective and increasingly used (Brynjolfsson & McAfee, 2017; Gursoy, Chi, Lu, & Nunkoo, 2019). For example, AI is widely used in a variety of industries, such as self-driving vehicles, medical diagnostics, home care, service robots, virtual agents, online advertising and marketing, and image recognition (Nasirian, Ahmadian, & Lee, 2017).

As one of the important applications of AI, Chatbots have attracted significant interest of researchers and practitioners in recent years (e.g., Luo, Tong, Fang, & Qu, 2019; Xiao & Kumar, 2021). An AI chatbot can be divided into voice-based chatbot and text-based chatbot and can be defined as "computer programs that simulate human conversations through voice commands or text chats and serve as virtual assistants to users" (Luo, Tong, Fang, & Qu, 2019, p. 1). A similar definition has been introduced by others like Riikkinen et al. (2018) and Krämer, Lucas, Schmitt, and Gratch (2018). Another way is to define AI robot broadly as tangible intelligent mechanical machines or intangible computer programs that "perform rule-based work, and tend to be configurable with basic features like authentication, security, auditing, logging, and exception handling" (Xiao & Kumar, 2021, p. 3; Wilson, 2015, p. 2). Current empirical research on chatbots has primarily focused on virtual chatbots, especially text-based chatbots (e.g., Chattaraman, Kwon, & Gilbert, 2012; Zhou, Mark, Li, & Yang, 2019). A few empirical studies were based on voice-based chatbots (e.g., Son & Oh, 2018; Yokotani, Takagi, & Wakashima, 2018) with the exception of Luo, Tong, Fang, & Qu, 2019, who used experimental research methods. To our knowledge, there is a lack of field survey research on the effect of voice-based mechanical chatbot applications on the service value of emerging AI technology in the public sector. At present, governments are increasingly providing public services to citizens through multiple channels to improve value creation (Wirtz & Langer, 2017; Yang, Jiang, Yao, Chen, & Wei, 2018), and tangible chatbots have been increasingly introduced in on-site services. Hence *voice-based mechanical chatbot* (termed AI voice robot) are used as IT-artifact in this paper. The AI voice robot facilitates service applications, especially those that perform citizen-oriented service.

2.2. AI services in the public sector

Recently, with the increase of citizens' demand for efficiency and personalization of public services, the public sector of governments at all levels in countries around the world has continued to increase investment in new AI-based technologies (de Sousa, de Melo, Bermejo, Farias, & Gomes, 2019). For example, as early as 2017, China released a 3-year development plan for AI (2018–2020). Under the guidance of this plan, local governments at all levels in China have successively issued similar AI development plans, with the goal of making AI-related industries investing 10 trillion yuan by 2030 (China, 2017). Similarly, Europe has spent up to 700 million euros on AI for robotics and public-private partnerships (Wirtz & Müller, 2019). Likewise, IDC estimated the US government's investment in cognitive and artificial intelligence technologies will grow at a CAGR of 54.3% from 2018 to 2021 (Bharadwaj, 2019).

Research in AI in the public sector remains limited, although there are some exceptions (Dwivedi et al., 2019; Kankanhalli, Charalabidis, & Mellouli, 2019). AI can result in benefits like improved efficiency and faster delivery of services, and possibly more rational decisions. However, there are many challenges in adopting and implementing AI in the public sector (Kankanhalli, Charalabidis, & Mellouli, 2019). For example, AI algorithms can introduce inadvertent bias, reinforce historical discrimination, favor a particular political orientation or reinforce undesired practices (Janssen & Kuk, 2016). Key application areas of government AI mainly include general public service, economic affairs, and environmental protection (de Sousa et al., 2019). There are studies on AI trust (e.g., Aoki, 2020), AI governance (Janssen, Brous, Estevez, Barbosa, & Janowski, 2020; Kuziemski & Misuraca, 2020), the relationship between AI and discretion or bureaucracy (Bullock, 2020). Overall, research on AI needs to be in-depth, especially on AI and public sector value creation.

2.3. Value creation in the public sector

Existing studies (e.g., Sun & Medaglia, 2019; Dwivedi et al., 2019) have mentioned that the use of AI might have a positive impact on value creation in the public sector. In a similar vein as the goal of private companies (for profit) is to create private (economic) value, the goal of government agencies is to create public value. Moore (1995) suggested that public value should not be evaluated from the perspective of individual consumers' economic market but should be evaluated within the scope of the political will of citizens and the collective decision-making of representative democratic institutions. Grounded in Moore's statement on the nature of public value, Kelly, Mulgan, and Muers (2002) identified that citizens' value in three categories: *services, outcome, and trust*. This classification provides a useful way to conceptualize the dimensions of public value in terms of solving internal problems at the management level (services), creating public value at the social level (outcomes), and improving citizen-government interaction at the political level (trust) (Wang, Liu, & Fang, 2016).

Services are designed to meet a relatively enduring need, for example, provision of education, technology, healthcare, and policing. These services are preferably cost-effective and high-quality services because a cost-effective provision of high-quality services benefits the achievement of desired outcomes. *Outcomes* refer to the achievement of desirable end results after receiving the service. Some direct service-related outcomes mainly involve high efficiency, good urban sanitation, high employment rates, and low crime rates. More general outcomes may include social inclusion, community well-being, environmental and economic sustainability (Grimsley & Meehan, 2007). *Trust* refers to the relationship between citizens and government. Individuals are always in some institutions in society, and the basis for maintaining relationships with these institutions depends on the level of trust. Generally, citizens' high trust in the government indicates that the government has effectively realized its various service goals related to citizens, and its legitimacy will be strong (Try & Radnor, 2007). Services can directly affect outcomes and trust.

At the same time, other researchers have also carried out research on the classification of public value in the context of e-government. Bannister and Connolly (2014) believe that the classification of public values can be classified into three categories: duty-oriented (e.g., responsibility to the citizen), service-oriented (e.g., effectiveness), and social-oriented (Justice). Rose, Persson, Heeager, and Irani (2015) proposed four value positions relevant to e-Government: professionalism, efficiency, service, and engagement. Twizeyimana and Andersson (2019) classified three domains of public value through literature review: improved public services, improved administration, and improved social value, and further subdivided them into six types based on these three categories. Generally, these classifications are similar to Kelly, Mulgan, & Muers (2002) in that the value divisions all reflect the technical service methods of e-government, and the effectiveness, efficiency, and social value of e-government services. Given that Moore (1995) triangular model of public value has been widely accepted, and Kelly's (2002) division of public value is partially derived from Moore, our division of public service value (private value and public value) adopts Kelly's research results (services, outcome, and trust).

2.4. Private and public value creation

Research on the impact of IT on value creation, whether in e-commerce or e-government, has attracted the interest of many researchers. For example, Amit and Zott (2001) identified the four driving factors, e.g., efficiency, complementarities, lock-in, and novelty that could enhance the value creation potential of e-commerce. Zhu, Kraemer, and Dedrick (2004) stated that the value creation of e-commerce mainly includes three types of impacts: the impact on commerce, internal efficiency, and coordination. Haile and Altmann (2016) believed that system availability, service types and personal connectivity are the main determinants of providing value to users on mobile software service platforms. Generally, value creation in the business field focuses on the impact on individuals' and companies' profitability, which is different from the value creation of the public sector.

Since the concept of public value (or creating public value) was proposed by Moore (1995), there has been continuing interest in this topic for both administration scholars and practitioners (Williams & Shearer, 2011). Moore initially regarded public value in the public sector as equivalent to shareholder value in the private sector. Moore's work focuses primarily on the value added by public organizations and public managers, and many subsequent studies continue in this vein (Hartley, Parker, & Beashel, 2019). Generally, there are three main categories of public value in the existing literature—public value, public sphere or public realm, and creating public value (Bryson et al., 2014). The first two are concerned with the societal level or policies, and the last focuses on the individual level (e.g., public managers). Given that our study adopts the citizen perspective, we follow Moore (1995) definition of public value and view value from the citizen perspective.

There are two different perspectives of value creation in the public sector: value in exchange and value in use (Petrescu, 2019). The former is the supply-side value creation based on the provider service logic or logic for provision (e.g., the public manager's perspective), which means that value creation occurs when the government provides services to citizens (Grönroos, 2011). A typical example is Moore's conceptualization of public value (Moore, 1995) as efficiency, effectiveness, social outcomes (e.g., procedural justice), etc. (e.g., Moore, 1995, 2013; Moore & Khagram, 2004). Based on the provider service logic, the public sector has no direct control over how the citizen use public services (Grönroos, 2019), which may result in services with the greatest value in the exchange but little or no value in use (Vargo, Maglio, & Akaka, 2008).

The latter is the demand-side value creation based on the customer's service logic or logic for usage (e.g., the citizen perspective), suggesting that value creation happens when the citizen acquires public services from governments (Grönroos, 2011). Based on the logic for usage, the experience of individual value depends on the satisfaction of its basic needs (Bryson et al., 2014). A typical example reflecting this logic is Meynhardt (2009) conceptualization of public value as being closely related to the basic needs of psychological theory and welfare economics. This conceptualization contains four dimensions, value related to moral-ethical, value related to political-social, value related to utilitarian-instrumental, and value related to hedonistic-aesthetical (Bryson et al., 2014).

It is widely recognized that value in exchange based on the logic for provision is regarded as public value (e.g., Moore, 1995), while value in use, based on the logic for usage in the public sector, is not uniformly regarded in extant studies. For example, value in use is sometimes considered to be the same as perceived value (e.g., Yang et al., 2018; Wang, 2014), whereas it is regarded as public value in other studies (e.g., Grimsley & Meehan, 2007 ; Scott et al., 2016). Osborne (2018) argued that the definition of value is not clear enough and requires urgent consideration in public management. The inconsistency of expression may stem from the value in use exhibiting private and public aspects, as well as individual and collective features (Petrescu, 2019). Hence, Petrescu (2019) stated that value in use consists of two correlated parts—public value and private value. Private value is consumed by individual citizens who use public services, while public value is consumed collectively by all citizens, even if he does not consume public services (Alford & Greve, 2017; Alford & Yates, 2014; Hartley et al., 2017). Other studies also suggested that value in use involved the co-existence and complementary nature of public value and private value (Ju et al., 2019; Wang, 2012).

We follow the extant research (e.g., Moore, 1995; Bannister & Connolly, 2014; Rose et al., 2015; Twizeyimana & Andersson, 2019; Ju et al., 2019) stating that citizens acquire both private and public value when acquiring public services. We define *private value* as the benefits citizens gain when using AI voice robot services to satisfy their motivations (their own needs) and enhance individual welfare. This is in line with motivation theory, which is generally concerned with the reasons (or motivation) behind choices humans make. Further, such reasons can be internally driven (i.e., intrinsic motivation) or externally driven (i.e., extrinsic motivation) (Deci & Ryan, 1985). Hence, we use extrinsic motivation (i.e., perceived usefulness) and intrinsic motivation (i.e., perceived enjoyment) to measure private value. *Public value* refers to the benefits that users gain when using AI voice robot services that increase the welfare of the society (or other citizens indirectly gain benefits). Further, according to the definition of public value and the main social goals of public service (e.g., procedural justice, trust), we use procedural justice (Moore,1995; Bryson et al., 2014; Petrescu, 2019) and trust in government (Grimsley & Meehan, 2007; Wang & Wan Wart, 2007; Lim et al., 2012) to measure public value.

3. Research model and hypotheses

Public value theory provides us with a useful framework for analyzing public value (e.g., Grimsley et al., 2007). However, some researchers have pointed out that there are some shortcomings. First, public value consists of three parts, and the three elements lack a sense of hierarchy in this model (Wang et al., 2016). For example, generally speaking, citizens can feel the effect of the service only after receiving the service, which in turn produces different levels of trust. Second, elements of public value (e.g., services and outcomes) are very general and applicable in a wide number of contexts. Third, the categories overlap, for example, as trust might be judged as another example of an outcome (Grimsley et al., 2007). Fourth, this model focused on supply-side value creation based on the provider service logic, not on demand-side value creation based on logic for usage.

To make up for the above four shortcomings, based on extant research (Sections 2.2 and 2.3), we develop a research model (Fig. 1) to examine the relationship between citizen AI voice robot usage and value creation in the public sector. We define AI voice robot usage as the extent to which a citizen believes that this technology can facilitate communication between the government and him (or her). As Fig. 1 shows, citizens' effective use of AI voice robots shapes their perceptions of private value (perceived usefulness and perceived enjoyment) and public value (procedural justice and trust in government), which in turn affects citizen perception of public service value. The model also emphasizes that gender and experience moderate the relationship between the effective use of AI voice robots with public value and private value.

Several aspects differ from public value theory analyzing public value (e.g., Grimsley & Meehan, 2007). First, we regard public value creation as a process, and there is a sequential causal relationship between different elements. Second, we refined the meaning of services and outcomes. Services specifically refer to citizens' effective use of AI voice robots, and outcomes refer to public value and private value. Third, to avoid overlapping of classifications, we regard trust as a dimension of public value because public trust is central for determining public action and cooperation (Thomas, 1998), and the restoration of trust stands as one of the top priorities in the development of IT for governments (Parent, Vandebeek, & Gemino, 2005). Moreover, extant literature has often identified trust as one of the crucial enablers of e-government (Carter & Bélanger, 2005; Teo, Srivastava, & Jiang,

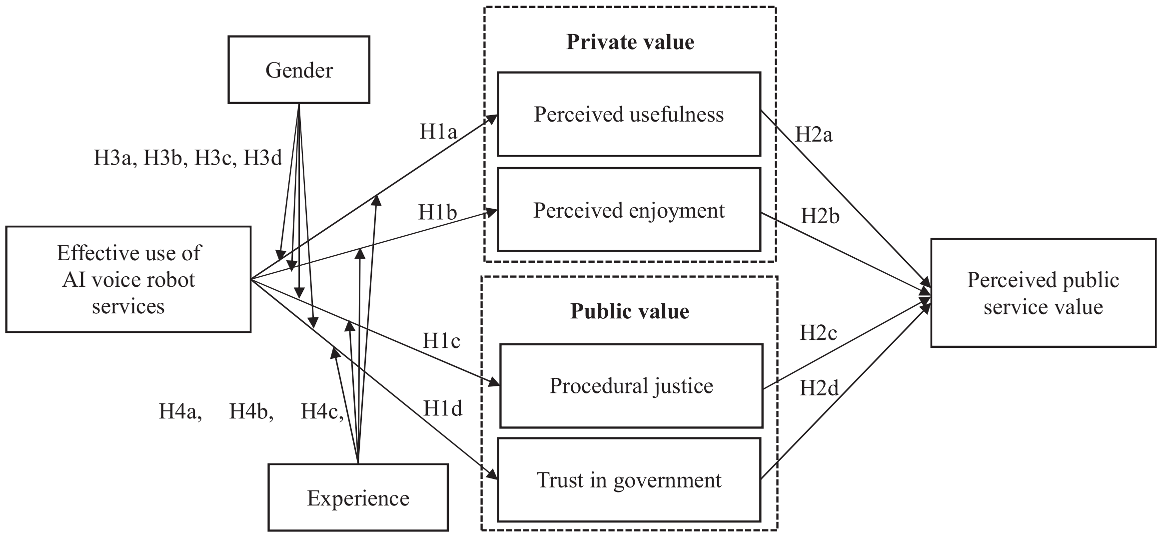

Fig. 1. Research model.

2008). Fourth, to further enrich the theory of public value creation, our model focused on demand-side value creation based on logic for usage.

3.1. *AI voice robot use and private value*

Private value is consumed individually by citizens and satisfies their personal needs (Bryson et al., 2014; Ju et al., 2019; Petrescu, 2019). In the context of AI robot use, private value (based on personal needs) reflects the motivation of citizens to use AI to a certain extent because people's various behaviors are mainly driven by needs-based motivations based on motivation theory (Deci & Ryan, 1985). Extant studies widely accepted that extrinsic and intrinsic motivation can be represented by perceived usefulness and perceived enjoyment, respectively (e.g., Teo, Lim, & Lai, 1999; Li et al., 2019). Hence, perceived usefulness and perceived enjoyment are considered as key indicators of private value in our study.

Based on the literature (e.g., Kim, Chan, & Gupta, 2007), *perceived usefulness* of AI voice robot services refers to the degree to which a citizen believes that using AI voice robots would bring valuable extrinsic outcomes (e.g., improving service performance, saving time, and enhancing efficiency). Extant research indicated that social media use can enhance user perception of service outcomes (e.g., Ou, Pavlou, & Davison, 2014; Song & Lee, 2016). AI voice robots use natural language processing and deep learning techniques to enable them to communicate automatically with citizens and can deeply understand the meaning of citizens' spoken words and respond accordingly. Without the AI voice robot, tax staff may have to answer repetitive consultation calls daily to answer the same questions and be prone to boredom or anger at difficult or unreasonable callers. This issue is mitigated with the AI voice robot, which is not adversely affected by day-to-day repetitive tasks, unlike humans who are prone to boredom or anger. These advantages of AI voice robots may be beneficial to citizens who access public services. Therefore, we hypothesize that:

H1a. : Citizens' effective use of AI voice robot services is positively related to perceived usefulness.

Based on the literature (e.g., Agarwal & Karahanna, 2000), *perceived enjoyment* of AI voice robot refers to the degree to which a citizen believes that using AI voice robot is fun in its own right, apart from any outcomes that can be anticipated. Existing research has demonstrated that new technologies can enhance user perception of enjoyment (e.g., Kim et al., 2007; Wu & Lu, 2013). As an emerging IT technology, AI might have a strong appeal to citizens because humanity has a universal desire to satisfy their curiosity, and using AI voice robots can satisfy their curiosity (Lowry, Gaskin, Twyman, Hammer, & Roberts, 2013). For example, when customers are tired or bored, they can also call the AI voice robot to tell a story and laugh, which undoubtedly adds to their interest. Moreover, AI voice robots can follow complex and subtle conversations, and satisfy citizen requirements in a deep, sympathetic and even humorous way (Wilson, Daugherty, & Bianzino, 2017), thereby enhancing citizen perceived enjoyment. Consequently, the following hypothesis is proposed:

H1b. : Citizens' effective use of AI voice robot services is positively related to perceived enjoyment.

3.2. *AI voice robot use and public value*

Public value is acquired collectively by all citizens, either directly or indirectly (e.g., Wang, 2012; Petrescu, 2019; Ju et al., 2019). In the context of AI chatbot use, public value can represent the social goal of the government to some extent because the public sector is more focused on the achievement of social goals than the private sector (Grimsley et al., 2007). The public sector value makes significantly more contribution to society than the private sector (Lyons et al., 2006). In the social goals of the government, advancing public trust and social justice (equity) are the most important goals (Bryson et al., 2014; Lim et al., 2012). Although AI voice robot use includes information and transaction, our study focuses on the former because AI voice robot use in the public sector is in its infancy stage, and its main function is to provide information services. Chen, Vogel, and Wang (2016) argued that the three key elements of procedural fairness for mobile government information services are transparency, information accuracy and voice opportunity. Transparency relates to timely delivery of current information, information accuracy relates to understandability, correctness and reliable information, and voice opportunity relates to giving citizens an opportunity to express their opinions. For accessing public services, AI voice robots can provide timely responses to citizen queries, tax appointments and online tax processing functions, which enhances the transparency of services. The information provided is also accurate as AI robots are able to give consistent and accurate answers to specific queries. Citizens can also input their feedback on the feedback screen of the AI voice robot.

We can consider the AI voice robot to be similar to chatbots (but with voice function). Research has forecasted that 85% of customer interaction will be handled without human agents by 2021, and that chatbots are able to answer 80% of the standard questions (Jovic, 2020). Hence, chatbots and AI voice robots need to be able to convey procedural fairness and trust among citizens. While the interaction ability of the AI voice robot is somewhat inferior to an actual human, the AI voice robots do satisfy at least partially the three elements for procedural fairness suggested by Chen et al. (2016), which would help to facilitate procedural justice and build trust in government. Therefore, procedural justice and trust in government are regarded as the key indicators of public value in our study.

Based on the literature (e.g., Turel, Yuan, & Connelly, 2008), *procedural justice* can be defined as the extent to which citizens perceived fairness about processes, procedures, and policies during the process of AI voice robot service offerings. Prior studies suggested that IT is a suitable tool to build a culture of transparency and mitigate corruption in the public sector (Bertot, Jaeger, & Grimes, 2010; Srivastava, Teo, & Devaraj, 2016). When citizens use AI voice robots to access public services, AI voice robots can provide timely responses to citizen queries , tax appointments and online tax processing functions, which enhances the transparency of services. Further, an AI voice robot cannot accept bribes compared to a human tax advisor. Consequently, avoiding direct contact with government staff can reduce misconduct (kickbacks, corruption, and unfair decisions) in face-to-face services (Chen et al., 2016), which will enhance citizens' perception of fairness of government decisions and services. Therefore, we put forward the following hypothesis:

H1c. : Citizens' effective use of AI voice robot services is positively related to procedural justice.

Based on the literature (e.g., Citrin & Muste, 1999), *trust in government* (also known as public trust) can be defined as the extent to which citizens are confident that the government will observe established rules and serve the general interest during the process of AI voice robot service offerings. Extant research indicated that government use of IT (e.g., ICTs, e-government, and social media) can effectively increase public trust (Bertot et al., 2010; Klein & Robison, 2020; Welch, Hinnant, & Moon, 2005). In the formation of trust in government, the information that citizens receive is the most important variable for citizens to predict whether the government will act in their best interests (Song & Lee, 2016). The AI voice robot can automatically provide citizens with timely information and services without prejudice, which may help increase citizens' perception of government transparency and trust in government. Further, the AI voice robot is humanoid in appearance. Past research has suggested that service robots with human-like features are likely to increase trust, intention to use and enjoyment (e.g., Van Pinxteren, Wetzels, Ruger, Pluymaekers, & Wetzels, 2019). Consequently, the following hypothesis is proposed:

H1d. : Citizens' effective use of AI voice robot services is positively related to trust in government.

3.3. Private value and public service value

Extant studies have suggested that perceived usefulness and perceived enjoyment positively affected perceived value in m-commerce (Ko, Kim, & Lee, 2009), e-government (Lean, Zailani, Ramayah, & Fernando, 2009), and e-learning (Shyu & Huang, 2011). AI voice robot services have the following important advantages. First, due to 24/7 availability, citizens can access the services at any time. Second, because AI voice robots can provide fast, automated answers to most questions raised by citizens, they can save time. Finally, through deep learning, AI voice robots can update the knowledge base (questions, answers) in a timely manner to provide citizens with accurate and personalized services. Hence, we infer that usefulness is positively associated with perceived value. Consequently, we propose the following hypothesis.

H2a. : Perceived usefulness is positively related to *perceived public service value.*

Interestingly, AI voice robots can also answer questions in a friendly and even humorous way, based on citizen characteristics. For example, when it encounters a question that cannot be answered, it will say, "I am studying." This humor engenders enjoyment and fun, which significantly affects perceived value beyond usefulness (Davis, Bagozzi, & Warshaw, 1989; Sohn & Kwon, 2020). In addition, AI voice robot also has the function of telling stories when customers are waiting in a long queue for tax business. This function can effectively reduce customer boredom and anxiety, and bring a certain amount of distraction and entertainment to customers, thereby increasing the user-perceived value. In short, the extant study indicated that perceived enjoyment which is represented as an intrinsic motivation plays an important role in producing positive value perceptions toward the technology (Lee, Chung, & Lee, 2013). Hence, we infer that enjoyment is positively associated with perceived value. Consequently, we propose the following hypothesis:

H2b. : Perceived enjoyment is positively related to *perceived public service value.*

3.4. Public value and public service value

Public service value is defined as the total value perceived by users in using AI voice robot services in this study. Procedural justice and trust in government are regarded as the two most important aspects of government social objectives, and they are also important components of the public service value in our study (Grimsley et al., 2007; Scott et al., 2016). In this sense, increasing procedural justice is conducive to increasing the total value of public services. In addition, according to justice theory, the fairness of the process is conducive to achieving distributive justice, which focuses on outcomes (Zhao, Lu, Zhang, & Chau, 2012), and increasing user perception of outcomes is conducive to increasing user perception of the service value of AI voice robot (Kelly, Mulgan, & Muers, 2002). When citizens perceive procedural justice from using AI voice robot services, it will increase their chances of obtaining expected outcomes and increase their perception of the public service value. Therefore, we put forward the following hypothesis:

H2c. : Procedural justice is positively related to *perceived public service value.*

In addition, from a benefits perspective, trust in government reflects an outcome that is relevant to the direct experience of citizen use of AI voice robot in our study. Extant studies indicated that improved trust and confidence in government might increase citizen participation and enhance public service value (Scott et al., 2016; Twizeyimana & Andersson, 2019). In the AI voice robot environment, the stronger public trust means that citizens are likely to believe that AI services can respond to their concerns, act in their best interests, and fulfill government obligations (Thiebes, Lins, & Sunyaev, 2020; Vimalkumar, Sharma, Singh, & Dwivedi, 2021). Consequently, it is easier for citizens to accept the new technical services provided by the government, thereby increasing citizen participation and interaction with the government (Hu, Lu, Pan, Gong, & Yang, 2021; Janssen et al., 2020), as well as enhancing citizen perception of the public service value. Therefore, we put forward the following hypothesis:

H2d. : Trust in government is positively related to *perceived public service value.*

3.5. The role of gender

Social structural theory argues that a gender-based division in a society results in all other gender differences (Eagly & Wood, 1991). For example, the size and strength of men are greater than women, making them more prone to engage in activities such as war, which makes them have greater status and wealth, as well as the power to rule over women (Hyde, 2014). Similarly, men have more power, status, and resources than women in modern American society, which may make men and women act in different social roles and affect their social behaviors (Lin, Featherman, & Sarker, 2017).

Based on the social structural theory, extant studies indicated that men are result-oriented (or task-oriented) and pay more attention to achieving expected outcomes (such as being individualistic, favoring utilitarian value, and achieving task performance) (Shao, Zhang, Li, & Guo, 2019; Venkatesh, Morris, & Ackerman, 2000). Specific to our study, perceived usefulness can be regarded as a result-oriented variable because it helps to meet citizens' utilitarian value of AI voice robot use (Wu & Lu, 2013). Hence, we propose the following hypothesis:

H3a. : The relationship between the effective use of AI voice robot services and perceived usefulness is stronger for men than for women.

Based on the social structural theory, women are process-oriented and focus more on enjoying the process (such as enjoyment, curiosity, and control) (Kaino, 2008; Lin et al., 2017). Therefore, women are more likely to get pleasure in using technology, while men pay more attention to the results of using technology; they get relatively less pleasure in using technology (Shao et al., 2019). Specific to our study, perceived enjoyment can be considered as a process-oriented variable, because these variables are mainly to satisfy citizen hedonic value of AI voice robot use (Lowry et al., 2013). Based on the above discussion, men derive less enjoyment in the effective use of AI compared to women. Hence, we propose the following hypothesis:

H3b. : The relationship between the effective use of AI voice robot services and perceived enjoyment is weaker for men than for women.

Similar to the logic of H3b and based on social structural theory, procedural justice can be regarded as a process-oriented variable. Procedural justice refers to the perceived fairness of the procedures involved in decision-making (McFarlin & Sweeney, 1992). Specific to our study, procedural justice suggests that citizens feel that they are treated fairly while enjoying AI services, and women are much more concerned about the experience (e.g., enjoyment) of using AI services. Based on the above discussion, women are more likely to perceive that there is *procedural justice*, when they enjoy interacting with the AI voice robot since responses are standardized and everyone is treated fairly (as there is no explicit demonstration of bias) (Shao et al., 2019). In contrast, men tend to pay more attention to the results of using AI services rather than the enjoyment of using such services (Zhou, Jin, & Fang, 2014). Consequently, they may perceive relatively little *procedural justice* in the process of effective use of AI (Olowookere et al., 2020). Hence, we propose the following hypothesis:

H3c. : The relationship between the effective use of AI voice robot services and procedural justice is weaker for men than for women.

Similar to the logic of H3a, trust in government can be regarded as a result-oriented construct because it mainly explains the benefits of citizens using AI from the perspective of utility value (Eagly & Wood, 1991). Specific to our study, men are more result-oriented (or task-oriented) and are expected to pay more attention to achieving expected trust in government (Deaux & Lewis, 1984; Wu & Lu, 2013). Compared with men, women are more inclined to pay attention to the pleasure gained from use (San Martín & Jiménez, 2011). Therefore, in the process of effectively using AI services, men have stronger trust in the government than women. Hence, we propose the following hypothesis:

H3d. : The relationship between the effective use of AI voice robot and trust in government is stronger for men than for women.

3.6. The role of experience

Experience refers to the opportunity to use the target IT (e.g., IS, e-commerce, m-government), which is typically measured as the passage of time from the initial use of technology by an individual (Balakrishnan & Dwivedi, 2021a, 2021b; Venkatesh, Thong, & Xu, 2012). In our study, we define experience as AI services usage times in the past half-year. Existing studies often use experience as a moderating variable, and the results of the research indicate that users with different experiences of using IT have differences in usage behavior (Dwivedi et al., 2019; Weerakkody, El-Haddadeh, Al-Sobhi, Shareef, & Dwivedi, 2013; Zuiderwijk, Janssen, & Dwivedi, 2015).

We expect the effect of the effective use of AI voice robots on private and public value to be moderated by experience due to differences in citizens' innovativeness, novelty-seeking, and perceptions of the novelty of the AI voice robot. When citizens start to use AI public service, they may strive to use it for its novelty (Holbrook & Hirschman, 1982). As the experience increases, citizens will focus more on functionality, such as gains in efficiency or effectiveness. Hence, we propose the following hypothesis:

H4a. : The relationship between the effective use of AI voice robot services and perceived usefulness is stronger for citizens with more experience than citizens with less experience.

In contrast, as the experience increases, citizens' entertainment will gradually decrease or even disappear (Chau & Hui, 1998) as the novelty effect wears off. Thus, the effective use of AI voice robot services will play a less important role in perceived enjoyment with increasing experience. Hence, we propose the following hypothesis:

H4b. : The relationship between the effective use of AI voice robot services and perceived enjoyment is weaker for citizens with more experience than citizens with less experience.

Similar to the logic of H4b, with experience increases, citizens mainly use AI services to carry out procedural work to obtain high efficiency and effectiveness when the novelty of AI public services is diminishing (Chau & Hui, 1998, 1998). This suggests that citizens will pay more attention to the results of AI services rather than to the process. Consequently, the effective use of AI voice robots will play a less important role in determining procedural justice with increasing experience. Hence, we propose the following hypothesis:

H4c. : The relationship between the effective use of AI voice robot services and procedural justice is weaker for citizens with more experience than citizens with less experience.

In contrast, as the experience increases, citizens pay more attention to the results of AI services rather than the process (Holbrook & Hirschman, 1982). Consequently, the effective use of AI voice robot will play a more important role in determining trust in government with increasing experience. Hence, we propose the following hypothesis:

H4d. : The relationship between the effective use of AI voice robot services and trust in government is stronger for citizens with more experience than citizens with less experience.

4. Research method

4.1. Measures

We used the validated scales from the existing literature to measure all variables in our model. A seven-point Likert scale ("1-strongly disagree" and "7-strongly agree") was employed to measure all items. To ensure content validity, we made some revisions (e.g., e-government was replaced by AI voice robot) to adapt items to our AI voice robot use context. Please refer to Appendix A for our measurement items and sources.

Considering that our survey was conducted in China, we adopted the conventional back-translation method to design our questionnaire. First, we translated the English questionnaire into the Chinese version. Second, we invited a translator who did not understand the research background to translate the Chinese questionnaire back into English. Finally, we compared the two English versions of the questionnaire and did not find significant differences between them. In addition, we asked two faculty members to review and comment on our questionnaire before it was finalized. We launched a pilot test with 60 Tax Baby (an AI voice robot) users (not included in the main survey) and the results indicated that the scales were reliable and valid. The final survey items are included in Appendix A. To account for the possible differences among participants, the control variables included age, education, and income.

4.2. Data collection

In August 2017, China's first tax AI voice robot, named "Tax Baby" (Shui Bao), was born in Beijing city. Tax Baby is humanoid in appearance with an input touch screen at its chest, where users can select the type of information needed as well as input questions as well as feedback to the tax authorities. The AI voice robot was specifically designed to provide tax-related services. While its services may not be as comprehensive as those provided by humans, it does have some advantages over a human tax advisor in terms of quick access to information, timely reply to queries, and a stable temperament.

The most important functions offered by this robot are inquiries about tax regulations, taxation consultation, invoice verification, tax video learning, voice conversation, tax appointment and online tax processing functions. Taxpayers can use bank cards to pay taxes via Tax baby. The Tax Baby will suggest that the taxpayer will go to the counter for consultation when it is unable to solve the problem. Hence, the aim of Tax Baby is to work alongside human tax advisors, where humans can handle the more complex tasks (e.g., the government's temporary tax cuts and subsidies for enterprises; changes to taxpayer accounts, which are not clearly stipulated by the law for the time being) and the AI voice robots can handle the more standard tasks (e.g., print the tax certificate, report the loss and reissue of the electronic key for online tax payment, tax matters clearly stipulated by the law).

Currently, "Tax Baby" has been used in "Smart Tax Service Halls" (self-service tax zone) of many provinces (municipalities) such as Henan province, Beijing city, Shanghai city, and Jiangsu province. Tax Baby can provide online services (such as the dialog between humans and machines, handling voice queries, and answering questions) and offline services (such as guiding taxpayers to handle tax services in the tax hall). For example,

Taxpayer: Hello, what is your name?"
Tax Baby: "Hello, my name is Tax Baby."
Taxpayer: "Tax baby, I want to use the self-service tax terminal."
Tax Baby: "Please follow me. I am sorry if I walk a little slow. Here is the tax self-service area."
Taxpayer: "Thanks."
Tax Baby: "Please enjoy yourself."

Compared with other government sectors, the informatization construction of the Chinese taxation sector is the most mature, which is regarded as an outstanding representation of China's e-government (Wang, 2014). Data was collected from citizens who had used "Tax Baby." The survey was conducted via a professional service company whose customers are located all over China. The service company randomly invited 1000 users to fill out the questionnaire from March 2018 to April 2018. There were 550 respondents, of which 492 valid questionnaires (age: Mean = 37.8 years, SD = 6.24; gender: 56.7% female; education (0 - below college; 1 - college and above): Mean = 0.59, SD = 0.26; experience, Mean = 6.58, SD = 2.43) were used to test our model because 58 questionnaires were incomplete. The characteristics of the valid survey participants are summarized in Table 1.

A T-tests was conducted to compare respondents with non-respondents. The income suggests no significant differences in terms of age, education, income, and experience between the two groups. A limitation of self-reported data is that it may be affected by common method variance (CMV). Harman's one-factor test was used to evaluate the CMV. The results indicated that no single factor accounted for the majority of variance (e.g., the most covariance explained by one factor is 36.35%) (Harman, 1976), which suggested that CMV was not a threat in this study. Further, the marker variable method was used to test CMV. The average substantive variance of the indicators is 0.608, while the average method-based variance is 0.05. Hence, the result also suggests that CMV would not pose a threat because the method variance is insignificant with a small magnitude (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003).

Table 1
Demographics of the two group samples ($N = 492$).

Characteristics		Frequency	Percentage
Gender (GEN)	Male (0)	213	43.29
	Female (1)	279	56.71
Age (year)	20–29	182	36.99
	30–39	156	31.71
	40–49	104	21.14
	≥ 50	050	10.16
Education (EDU)	Below college	201	40.85
	College	234	47.56
	Bachelor or above	057	11.59
Experience (Usage times in the past half year)	1–2	061	12.40
	2–4	185	37.60
	5–9	167	33.94
	≥ 10	079	16.06
Income	Under RMB 36,000	054	10.98
	RMB 36,001–60,000	217	44.11
	RMB 60,001–96,000	155	31.50
	RMB 96,001 or above	066	13.41

5. Results

We tested our model by following the two-step Structural Equation Modeling (SEM) approach recommended by Anderson and Gerbing (1988). First, we examined the measurement model using confirmatory factor analysis (CFA) to assess the construct reliability and validity. Second, we used AMOS18.0 (covariance-based SEM) to test the structural model.

5.1. Measurement model

We tested the measurement model in two steps. First, we measured reliability using Cronbach's α (with a threshold value of 0.70). Next, we used composite reliability (CR) and average variance extracted (AVE), with threshold values of 0.7 and 0.5 respectively, together with factor analysis to evaluate convergent validity (Fornell & Larcker, 1981). Table 2 shows the measurement model results, which include information about reliability, validity, and factor loadings. In Table 2, Cronbach's alphas are between 0.75 and 0.89, and CR values are between 0.73 and 0.90, which are well above the 0.70 criterion for internal consistency reliability. All items had high factor loadings (ranging from 0.75 to 0.89) onto their corresponding constructs, which satisfied convergent validity. The average variance extracted (AVE) (between 0.75 and 0.87) was greater than 0.7 in all cases (i.e., above the recommended value of 0.5) and greater than the square of the correlations, suggesting discriminant validity (Barclay, Higgins, & Thompson, 1995). For testing discriminant validity, we first compared the square roots of AVEs with the correlations among the constructs and found that more variance was shared between the construct and its indicators than with other constructs (Fornell & Larcker, 1981). The results show that all square roots of AVEs (in bold along the diagonal in Table 2) are greater than the correlations among constructs, indicating that all the constructs

Table 2
Descriptive statistics, reliability and validity, and correlations.

	Mean	SD	AVE	C.R	α	Factor loadings	1	2	3	4	5	6
1. EU	4.76	1.03	0.87	0.79	0.86	0.86/0.78/0.75/0.85	**0.93**					
2. PU	4.24	1.17	0.75	0.76	0.75	0.86/0.79/0.84/0.83	0.61	**0.87**				
3. PE	5.17	1.24	0.82	0.83	0.82	0.78/0.83/0.86	0.67	0.52	**0.91**			
4. PJ	4.68	1.15	0.76	0.90	0.89	0.86/0.87/0.76	0.62	0.56	0.49	**0.87**		
5. TG	4.45	1.09	0.85	0.73	0.79	0.85/0.76/0.88/0.82	0.65	0.39	0.53	0.59	**0.92**	
6. PV	4.87	1.26	0.79	0.85	0.83	0.89/0.82/0.86/0.83	0.63	0.48	0.48	0.43	0.45	**0.89**

Note: (1) AVE > 0.50 ; CR > 0.70 ; Cronbach's α > 0.70; (2) All correlations are significant at the 0.01 level; (3) The diagonal elements (in bold) are square roots of AVE.

had good discriminant validity.

Second, to evaluate the overall measurement model, we followed the suggestion by Hu and Bentler (1999) and reported the multiple fitness indices, including the goodness of fit (GFI), adjusted goodness of fit index (AGFI), comparative fit index (CFI), and standardized root-mean square residual (SRMR). The measurement model fit results ($\chi 2/df = 2.65$, GFI = 0.97, AGFI = 0.92, CFI = 0.95, and SRMR = 0.042) indicated good fit to the data.

5.2. Structural model

After confirming the reliability and validity of the measurement model with the help of CFA, we tested the hypotheses by examining the path coefficients of the structural model (Fig. 2). The results showed a good model fit: $\chi 2/df = 2.83$, $p < 0.001$, GFI = 0.98, NFI = 0.98, CFI = 0.98 and RMSEA = 0.038. Our model accounted for 38% (R^2 *0.38*) of the variance in perceived public service value.

All hypotheses were supported in our model with the exception of H1d (*b = 0.11, p > 0.05) and* H4c. The relationship between the effective use of AI voice robots and trust in government is not significant. Effective use of AI voice robot had significant positive relationship with perceived usefulness (*b = 0.27, p < 0.01*), perceived enjoyment (*b = 0.34, p < 0.001*), and procedural justice (*b = 0.23, p < 0.01*), which supported H1a *and* H1b, *and* H1c, respectively. Perceived usefulness (*b = 0.21, p < 0.0 p < 0.001*), perceived enjoyment (*b = 0.30, p < 0.001*), procedural justice (*b = 0.15, p < 0.01*), and trust in government (*b = 0.08, p < 0.01*) were positively associated with perceived public service value. Hence, H2a, H2b, H2c, and H2d were supported. We also tested the research model when all the control variables were excluded, and the results showed no differences. In addition, to test the gender differences, we adopted a multiple-group approach, in which the groups were divided into men (*N1 = 213*) and women (*N2 = 279*) groups (Baron & Kenny, 1986). Table 3 showed the results of our multiple-group test. The results indicated that gender affects the use of AI voice robot services. Hence, H3a, H3b, H3c, and H3d were supported.

Table 3
Comparison of paths for women and men.

Paths coefficients	Full sample (*N = 492*)	Women group (*N = 279*)	Men group (*N = 213*)	*t* statistics (*Women vs Men*)
Effective use of AI voice robot → Perceived usefulness	0.27***	0.24**	0.38***	27.83***
Effective use of AI voice robot → Perceived enjoyment	0.34**	0.45***	0.32**	31.65***
Effective use of AI voice robot → rocedural justice	0.23**	0.28**	0.14*	22.37**
Effective use of AI voice robot → Trust in government	0.11^{ns}	0.08^{ns}	0.17**	19.53**

Note: **p* < .05, ***p* < .01, ****p* < .001 (one-tailed test for the hypothesized interaction effects).

We define the group that has used AI services less than 5 times in the past 6 months as the group with less experience (*N3 = 246*); those with more than or equal to 5 times as the group with more experience (*N4 = 246*). Table 4 showed the results of our multiple-group test. The results indicated that citizens with different levels of experience use AI voice robots in different ways. Hence, H4a, H4b, and H4d were supported, but H4c *was not supported.*

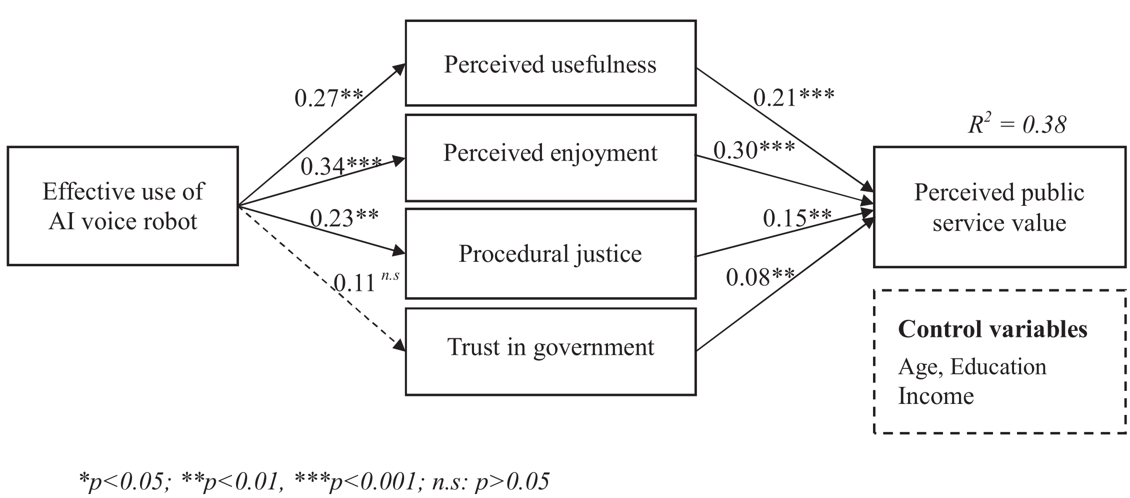

Fig. 2. Results of the model.

Table 4
Comparison of paths for more and less experience group.

Paths coefficients	Full sample *(N = 492)*	More experience group *(N = 246)*	Less Experience group *(N = 246)*	*t* statistics *(More vs Less)*
Effective use of AI voice robot → Perceived usefulness	0.27***	0.31**	0.22***	24.36***
Effective use of AI voice robot → Perceived enjoyment	0.34**	0.28***	0.41**	30.53***
Effective use of AI voice robot → Procedural justice	0.23**	0.29**	0.08^{ns}	6.42^{ns}
Effective use of AI voice robot → Trust in government	0.11^{ns}	0.06*	0.19^{ns}	18.47**

Note: **p* < .05, ***p* < .01, ****p* < .001 (one-tailed test for the hypothesized interaction effects).

6. Discussion

The objective of this study is to understand value creation when citizens use AI voice robots in the public sector. Value creation is a complicated and conceptualized concept of both private and public value. It pertains to the economic goals (meeting the needs of citizens for efficiency and effectiveness) and social goals (maintaining social fairness and gaining citizen trust) corresponding to the government's application of AI to provide public services to citizens. Grounded in elements of public value management and the extant literature on value creation, we propose that citizens' AI voice robot use affects public service value through both private value and public value. The empirical results provided support to fourteen of the sixteen hypotheses and showed that private value and public value provided a considerable amount of explanatory power (38%) on public service value. We found that the effective use of AI by citizens has a positive effect on value creation in the public services, but citizen effective use of AI voice robot had a greater impact on private value than on public value. This suggests that individuals found direct value for themselves more important than the more general value for society. Our result is similar to previous research that suggests that private value has a stronger influence on continuous e-participation intentions (Ju et al., 2019). We also found that gender differences did exist in the relationship between AI voice robot use and value creation in the public sector. This result is in line with previous findings (e.g., Shao et al., 2019; Hyde, 2014), which suggest that men and women have different effects on trust-building mechanisms. Similarly, our results also indicated that experience differences did exist in the relationship between AI voice robot use and value creation in the public sector.

Consistent with the extant public service value research (e.g., Wang, 2012; Petrescu, 2019; Ju et al., 2019), value from the perspective of citizens can be divided into private value and public value. We highlight that citizens can gain both public and private value at the same time when acquiring public services. More importantly, we propose a more nuanced public value and private value. We use procedural justice and trust in government as indicators of public value, and perceived usefulness and perceived enjoyment as indicators of private value, which makes our research different from existing research that has the two kinds of value as a single dimension (e.g., Ju et al., 2019). Contrary to our expectation, the relationship between the effective use of AI voice robot and trust in government is not found to be significant. This suggests that there is a certain difference in value orientation between governments and citizens' behavior (Thacher & Rein, 2004). For example, the government promotes a certain technology sometimes to cater to the preference of superiors and may not effectively meet the needs of citizens (Wu & Zhang, 2018). When citizens discover that the government's purpose of promoting IT is inconsistent with the goal of personal use of IT, it may damage their trust in the government.

Our result is also different from past studies, which found that the use of IT by the government can improve service quality (Chen et al., 2016; Shareef, Kumar, Dwivedi, & Kumar, 2016; Tan, Benbasat, & Cenfetelli, 2013) and increase government transparency (Bertot et al., 2010; Song & Lee, 2016; Venkatesh, Thong, Chan, & Hu, 2016), thus winning the trust of citizens (Lim et al., 2012; Welch et al., 2005). According to stakeholder theory (Donaldson & Preston, 1995), the purpose of the government's use of IT to provide public services may not be consistent with the purpose of citizens using IT to obtain public services. For example, in terms of intelligent communication, AI intelligent robots can realize real-person voice interaction and predict intelligent question and answer, but they can only solve some procedural taxation problems and are insufficient for some non-procedural problems such as tax planning. Hence, one possible reason is that the services provided by the government are not the services that citizens need, or they do not meet the expectations of citizens. In addition, the ease of operation may also need to be further improved. For example, AI robots always ask citizens questions systematically, and citizens may be curious when they use them for the first time. However, after repeated use, there may be a certain degree of boredom, because the robot will not automatically skip some familiar steps and directly enter the result you want.

The other inconsistency with our expectations is that H4c has not been supported. We speculate that this may be related to the government management model. The staff of government departments in some key positions have relatively large discretion in the identification and handling of improper business (Chen, Pan, Zhang, Huang, & Zhu, 2009), which may lead to some black-box operations and unfairness. As citizens use AI more often, they increasingly feel that using IT is beneficial to increase the transparency of information and reduce contact with government workers, thereby reducing human intervention (Bullock, 2020; Young et al., 2019).

6.1. Contributions to research

Our study makes three contributions to research. First, we extend elements of the public value framework by taking a citizen perspective, which is different from most prior studies (e.g., Moore, 1995; Spano, 2009; Cabral et al., 2019). Although there are a few studies on the breakdown of public service value with private and public value from the perspective of citizens, there is a need to refine further the dimensions of public value and private value (e.g., Bozeman, 2019; Ju et al., 2019). Consequently, we categorize public service value into public value and private value from the citizens' perspective. The emphasis on public service value from citizens' perspective is needed because citizen-centric public service is regarded as the ideal way to supply public services (Chen, 2010). Moreover, we use procedural justice and trust in government to measure public value based on the social objectives and use perceived usefulness and enjoyment to measure private value originating from motivation theory. By dividing government service value into public value and private value, we examine the dual focus of the government in improving government service value based on citizens' needs to increase public satisfaction (Dudley, Lin, Mancini, & Ng, 2015). Our results suggest that private value has a greater effect on value creation than public value, which is different from the common idea that value creation from the government perspective indicates that social objectives (similar to the public value in the citizen perspective of value creation) is more important to citizens (Grimsley et al., 2007). This may be because private value is the most effective value for the individual decision-maker (Fukumoto & Bozeman, 2019).

Second, we extend value creation into the AI technology context in the public sector by providing empirical evidence for the relationship between emerging AI voice robot use and government service value. Extant research on government service value creation under IT-context focuses primarily on general IT (e.g., Bertot et al., 2010; Srivastava et al., 2016), e-government (Grimsley et al., 2007; Wang et al., 2016), and m-government (Shareef et al., 2016; Wang, 2014; Yang et al., 2018). Past research described the process of public value generation, but often did not validate it with a survey study (e.g., Wirtz & Müller, 2019; Sun & Medaglia, 2019). To fill this gap, we conducted a survey study, and our data revealed that AI voice robot use was positively related to private value and public value (except trust in government). More importantly, we tested our research model with the data of citizen use of mechanical voice robots, which is different from using virtual AI chatbots in most existing studies in the business sector (e.g., Riikkinen et al., 2018; Son & Oh, 2018). We extended the research on AI usage from virtual (online) to real-world (offline) scenarios, which further revealed the relationship between AI use and value creation, and provided empirical support for the widely adopted online-to-offline (O2O) service model in the public sector.

Third, we found that gender is an important moderator in value formation under the AI technology context. Gender difference in IT usage behavior is not new (Venkatesh et al., 2000) and has been examined in several contexts such as general IS (Ahuja & Thatcher, 2005), e-government (Dwivedi & Williams, 2008), mobile SI use (Shao et al., 2019; Sun, Shen, & Wang, 2016). However, there are opportunities to further expand the issue of gender differences into the new IT context involving AI technologies. For example, some studies have shown that men are more likely to use new technologies than women (Shao et al., 2019; Zhou et al., 2014), while other studies have shown that men and women (especially for young people) had no significant differences in attitudes toward new technologies (Morris, Venkatesh, & Ackerman, 2005; Wajcman, 2007). These contradictory results indicate that examining gender differences in user IT behavior is needed. Our study provided empirical evidence that gender differences indeed existed in AI voice robot use by citizens.

6.2. Contributions to practice

Our study makes three contributions to practice. First, we recommend that the public sector to adopt a citizen-centric strategy to deliver public services. Our results indicate that private value has a greater effect on the perception of public service value than public value, which is consistent with prior research (e.g., Ju et al., 2019). Therefore, it is imperative for governments to understand what drives the public service value variables, how they are linked, and how they contribute to public service value. According to our empirical results, we suggest that governments should pay more attention to enhance enjoyment (adding gamification elements such as expression and action elements) and usefulness (such as enriching conversation content, increasing service items), rather than procedural justice and trust in government. For the developers of AI voice robots, it is also necessary to continuously improve service quality and continuously enhance the usefulness and enjoyment of the products.

Second, we suggest that the government should utilize new AI to improve public service value. Prior literature suggested that the government could improve service quality and service value by utilizing new technologies (e.g., Tan et al., 2013; Chen et al., 2016). Our results demonstrate that the effective use of AI voice robots is positively related to private value and public value (e.g., procedural justice). This suggests that to enhance public service value, government departments should innovate service mode and actively introduce and use new technologies (such as AI) to provide citizens with high-quality services (Wirtz & Müller, 2019). The government needs to actively formulate policies that encourage citizens to use new technologies to obtain public access. Agents who develop AI voice robots need to continuously upgrade their products and services according to the government's needs and the preferences of citizens to provide more value to citizens.

Finally, we suggest that the government should pay attention to gender differences in value creation in public services provision. As there are gender differences in citizen usage behavior under different IT contexts (Cai, Fan, & Du, 2017), it is essential for governments to adopt different strategies based on gender differences when their public sector introduces new technologies (e.g., AI technologies) to serve citizens. More specifically, governments should focus on increasing the enjoyment and procedural justice gained from the process of AI for women, while governments should focus on usefulness and trust for men. For public service product development agents, they especially need to consider the differences in gender needs when developing AI voice robots. In addition, we suggest that the government should pay attention to citizens with different experiences on value creation in public services provision, because their effective use of AI has different effects on public value and private value based on our results. We specifically recommend that the government needs to attract users to continue using AI services because our research results show that the longer citizens use AI services, the stronger their perception of the usefulness of AI services.

6.3. Limitations and future research

Our research has some limitations that provide avenues for future research. First, our China-based sample may not be generalizable to other countries due to cultural differences. Future research can test our research model in the western context. Second, procedural justice and trust in government were used to measure public value. However, because the government has diverse social goals, public value has diverse dimensions. Future research could examine other indicators of public value, such as transparency, participation, and accountability. Third, gender was used as a moderator in our research. Future research could use other variables (e.g., age, income, and risk) as moderators. Future research could also examine the role of moderators in the relationships between private and public value with the perceived public service value. Fourth, the data on AI voice robot use were collected from the tax department. Future research could collect data from other departments to further test our model. In addition, our study focused on the effect of effective use of AI voice robots (offline robot) on value creation. Future research could compare the effects of online and offline chatbot use on value creation in the public sector. Fifth, this study is exploratory in nature in that the AI voice robot is still relatively new. Consequently, it may not fully capture the public value of procedural justice and trust. Nevertheless, it did partially satisfy the three elements for procedural fairness suggested by Chen et al. (2016), which would help to facilitate procedural justice and build trust in government. Follow-up on this study are recommend as technology becomes more advanced and features of the AI voice robot are further improved. In addition, future research could also examine in greater detail how humans can work jointly with AI voice robots to facilitate procedural justice and build trust in government.

7. Conclusion

Drawing on Moore's public value management literature, this research examines the role of effective use of AI on value creation and illuminates how gender moderates the relationship between AI use and public service value (public value and private value). Public service value was categorized into private value and private value. Procedural justice and trust in government were used to measure public value, and usefulness and enjoyment to measure private value. The results suggest that private value has a greater effect on value creation than public value and that gender and level of experience affects the usage of AI robot. Our results suggest that citizens prioritize their own value (private value) before the more general value (public value) for society as a whole. This implies that service provisioning should focus first on the individual and then on the broader societal need. This study complements and extends value creation literature by focusing on the relationship between AI use and value creation in the public sector, which has not been empirically examined in prior research.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Measurement and sources (Likert seven-point scale,"1-strongly disagree" and "7-strongly agree")

Effective Use of AI voice robot services (EU) (Ou et al., 2014).
EU1: The AI voice robot is an effective tool to communicate with the government.
EU2: I have used the AI voice robot to verify information with the government.
EU3: The AI voice robot facilitates the direct communication between the government and me.
EU4: I have great dialogs with the government in the AI voice robot.
Perceived usefulness (PU) (Kim et al., 2007).
PU1: Using the AI voice robot enables me to perform tasks more quickly.
PU2: Using the AI voice robot saves me time and effort in performing tasks.
PU3: Using the AI voice robot improves my task performance.
PU4: The AI voice robot is useful in performing my task.
Perceived enjoyment (PE) (Agarwal & Karahanna, 2000).
PE1: Spending time using the AI voice robot is exciting.
PE2: Spending time using the AI voice robot is pleasant.
PE3: Spending time using the AI voice robot is interesting.
Procedural justice (PJ) (Turel et al., 2008).
PJ1: The AI voice robot resolves citizens' service applications in the consistent way.
PJ2: The AI voice robot resolves citizens' service applications in the right way.
PJ3: The AI voice robot handles citizens' service applications without bias.
Trust in government (TG) (Teo et al., 2008).
TG1: The AI voice robot acts in citizens' best interests.
TG2: I feel comfortable interacting with the AI voice robot since it generally fulfills its duties efficiently.
TG3: I can rely on the AI voice robot to do its part when I interact with it.
TG4: I am comfortable relying on the AI voice robot to meet its obligations.
Perceived public service value (PV) (Wang, 2008).
PV1: Compared to the effort citizens need to put in, the use of the AI voice robot is beneficial to me and other citizens.
PV2: Compared to the time citizens need to spend, the use of the AI voice robot is worthwhile to me and other citizens.
PV3: Compared to the risk citizens need to take, the use of the AI voice robot offers value for me and other citizens.
PV4: Overall, the use of AI voice robot gives good value to me and other citizens.

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