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It Is Me, Chatbot: Working to Address the COVID-19 Outbreak-Related Mental Health Issues in China. User Experience, Satisfaction, and Influencing Factors

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ABSTRACT

The global spread of COVID-19 has caused a huge number of confirmed cases and deaths, which in return leads to a plethora of mental disorders across the world. In order to address citizens' psychological problems, government agencies in many countries have employed AI-based chatbots to provide mental health services. However, there is a limited understanding of the determinants affecting citizens' user experience and user satisfaction when mental health services supported by chatbots are provided. Thus, based on the Theory of Consumption Values (TCV), this study proposes an analytical framework to investigate the factors that are important to citizens' user experience and user satisfaction when they interact with mental health chatbots. Analysis of data collected from 295 chatbot users in Wuhan and Chongqing reveals that personalization, enjoyment, learning, and condition are positively related to user experience and user satisfaction. However, voice interaction fails to devote to citizens' user experience and user satisfaction. Thus, government agencies and their AI service contractors should enhance the functions and systems of mental health chatbots to ensure citizens' user experience and user satisfaction. Also, they should more positively promote the use of mental health chatbots during the public health emergency.

1. Introduction

Chatbots are automated programs that use artificial intelligence (AI) features like natural language processing (NLP) to communicate with humans (Aoki, 2020; Valtolina et al., 2019). It is believed that chatbots have a number of advantages, including accessibility, flexibility, low cost, etc. (Przegalinska et al., 2019). Due to these advantages, AI-based chatbots have been widely adopted to support and strengthen the quality of services in business industries, such as tourism and insurance (Androutsopoulou et al., 2019; Lokot & Diakopoulos, 2016; Muthugala & Jayasekara, 2019). Recently, government has also employed chatbots to provide public services at an accelerating rate (Aoki, 2020).

The coronavirus disease 2019 (COVID-19) pandemic has caused a plethora of mental disorders across the world (Ransing et al., 2020). At the start of 2020, the COVID-19 outbreak has led to thousands of deaths and infected hundreds of thousands more in China (Liu et al., 2020). As a result, the public have experienced serious psychological issues like anxiety, depression and stress (Ransing et al., 2020). In order to address these mental health issues, Chinese government has cooperated with the private sectors to launch a number of AI-based chatbots. These chatbots have offered a series of mental health services to help users solve psychological problems.

Like China, government agencies in many countries have launched chatbots to provide psychological assistance during the COVID-19 outbreak (Smith et al., 2020). With the wide use of mental health chatbots, many studies have conducted to understand different aspects of mental health chatbots, such as effectiveness (Ahuja et al., 2020; Ransing et al., 2020) and acceptability (Ail et al., 2020). For instance, Ransing et al. (2020) found that mental health chatbots can help to manage the mental health interventions for quarantined people and vulnerable population in India during the COVID-19 pandemic. The research by Ahuja et al. (2020) found that chatbots devote to easing the stress placed on the overtaxed mental health hotlines in United States during the lockdown. Smith et al. (2020) believed that mental health chatbots can enable remote triaging of care in Singapore during the COVID-19 pandemic. Although numerous studies have concentrated on the use of mental health chatbots during the pandemic, we know little about what influences citizens' user experience and user satisfaction when they use chatbots. Such a knowledge gap can significantly prevent quality improvement of AI-based mental health services.

This study therefore focuses on two objectives: (1) Investigating driving factors that influence citizens' user experience with mental health chatbots. (2) Exploring factors that can significantly influence citizens' user satisfaction with mental health chatbots. These purposes are worthwhile for several reasons. Practically speaking, the public do not adopt information system (IS) if they have bad experience or they feel dissatisfied, as numerous literature on IS acceptance has

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suggested (Deng et al., 2010; Zhang & Zhu, 2021). Thus, a better understanding on the determinants of user experience and user satisfaction can promote quality improvement of mental health chatbots, and ultimately devote to stimulating stronger user intention. As for research, although chatbots have been studied chiefly in the field of computer science, there is a lack of research in the public health emergency context, especially the hypothesis-testing research guided by theory (Aoki, 2020). This research gap should be fulfilled to support inform policy making by government agencies, who may become the chief users of AI-based technologies (e.g., chatbots) (Engin & Treleaven, 2019).

From February to March 2020, Chinese government implemented a national lockdown. This background offers an opportunity to investigate user experience and user satisfaction with mental health chatbots. Based on the Theory of Consumption Values (TCV), this paper constructed a research model to empirically test the use of a mental health chatbot in China during the COVID-19 outbreak. Through the empirical study, we revealed the determinant factors behind user experience as well as user satisfaction.

2. Theoretical background

2.1. AI-based mental health chatbots

With the development of chatbots, government agencies have experimented with chatbots to respond to citizen enquires in some fields of public services (Aoki, 2020). Recently, an increasing number of chatbots have been developed for providing mental health services, they converse and interact with human users using spoken, written, and visual languages (Abd-alrazaq et al., 2019). In most cases, mental health chatbots are used for therapeutic and training purposes. They deliver cognitive behavioral therapy for those who are depressed and anxious (Fitzpatrick et al., 2017). Furthermore, patients with autism are trained by mental health chatbots to improve social skills (Ail et al., 2020).

It is believed that the adoption of chatbots can greatly support the existing mental health care system during a public health emergency. For example, because the mental health hotline is usually overtaxed during a pandemic, many people are unable receive mental health services (Ransing et al., 2020). Chatbots can simultaneously offer psychological assistance to many more people than a manned call center. This advantage helps ease the stress placed on mental health hotlines and improves the effectiveness of mental health service delivery, particularly during a public health emergency like the COVID-19 pandemic (Ahuja et al., 2020). In addition, chatbots can enable remote triaging of care in some places with adequate facilities (Smith et al., 2020), which in turn helps solve the shortages of mental health professionals during a public health emergency (Ransing et al., 2020).

Previous studies have been conducted to understand different aspects of mental health chatbots, such as effectiveness (Cheng & Jiang, 2020; Fitzpatrick et al., 2017), usability (Cameron et al., 2019), and acceptability (Ail et al., 2020). For instance, Fitzpatrick et al. (2017) found that a chatbot called “Woebot” could reduce symptoms of depression in college students more significantly than conventional therapies. Cameron et al. (2019) assessed the usability of a chatbot named “iHelpr.” Through the questionnaire survey, they identified some shortages of “iHelpr” and provided suggestions to make it easier to use. Although many studies have explored the usage of mental health chatbots, empirical research on the determinant factors of citizens’ user experience and user satisfaction is limited, especially in the context of public health emergencies. As mentioned above, chatbots have the potential to support the mental health system during a public health emergency. Thus, a better understanding of the determinants of user experience and user satisfaction is necessary. Such deeper knowledge can help policy makers and AI engineers improve different aspects of mental health chatbots, including functions, capabilities, and images. As a result, chatbots can offer greater services to support the mental health system during a public health emergency.

During the COVID-19 pandemic, chatbots are being widely used by government agencies worldwide to provide mental health services. For instance, the Singapore government has launched chatbots to deliver therapy for people with depression and insomnia (Smith et al., 2020). In India, government agencies have launched chatbots to organize mental health interventions for millions of patients (Ransing et al., 2020). In China, chatbots have been employed to offer free 24-hour psychological assistance to both medical staff and the public (Liu et al., 2020). Thus, the extensive adoption of mental health chatbots during the COVID-19 pandemic provides a great opportunity to explore the determinants of user experience and user satisfaction.

2.2. User experience and user satisfaction

User experience refers to the feelings that emerge from the process of interacting with and experiencing a product or service (Hassenzahl & Tractinsky, 2006; International Organization for Standardization, 2010). According to Lallemand et al. (2015), user experience is concerned with all aspects of the users’ feelings (functional, emotional, hedonic, social, experiential, etc.) during the process of human-product interaction. Each aspect of feelings leads to a specific evaluation on that product or service (Yu et al., 2020).

It is common to see research on user experience in the context of brand and product design (Gentile et al., 2007; Sheng & Teo, 2012) because this notion is the antecedent of brand equity and frequency to use (Sheng & Teo, 2012). Over the last several decades, the integration of IS and public services has emerged in the public field. Thus, many studies have focused on the user experience of IS in the context of public service. To list a few, Kumar et al. (2017) investigated citizens’ user experience with e-government services. Madariaga et al. (2019) developed a monitoring framework to interpret the user experience of government documents from different dimensions, such as interaction goals and information volume. Foth and Schroeter (2010) explored how a public transportation system could construct a core platform to improve user experience.

According to many previous studies on user experience of IS in the context of public service, people are more likely to use IS to obtain public services if they have good user experience (Deng et al., 2010; Zhang & Zhu, 2021). In this sense, a deeper understanding of the determinants of user experience is worthwhile. With the development of AI, a growing number of AI projects have been implemented by government agencies to promote public interest and provide public values (Chen et al., 2021). However, empirical studies on user experience with AI-based services are still rare. Regarding chatbots, it is currently difficult to find a research that focuses on citizens' user experience with mental health chatbots during a public health emergency.

For nearly three decades, user satisfaction has played a central role in behavioral research in IS (Ashfaq et al., 2020; Melone, 1990). Typically, user satisfaction is defined as a pleasurable fulfillment response resulting from an evaluation with respective to how well the consumption of a product or service meets a demand or goal (Deng et al., 2010; Oliver, 1997). Before using a product or service, a user has an expectation that reflects the pre-experience belief about that product or service (Olson & Dover, 1979). After experiencing the product or service, the user forms a sense of disconfirmation, which manifests in three ways: (1) the product or service is better than expectation; (2) the product or service is the same as expectation; and (3) the product or service is worse than expectation. Such a sense of disconfirmation thereby determines user satisfaction (Oliver & Wayne, 1988). Thus, user satisfaction is correlated to user experience (Borsci et al., 2015), as it can be considered as a post-experience evaluation (Deng et al., 2010). In this research, user experience as a concept focuses on the different aspects of users' feelings about human-chabot interaction, and user satisfaction as a construct more concentrates on users' judgment that how well the use of mental health chatbots can meet their needs.

As many previous studies have concluded, user satisfaction has long been recognized as a significant factor that positively affects IS acceptance intention (Jung & Lee, 1995; Li & Fang, 2019). To list a few, Zheng et al. (2013) suggested that a person's continuance intention to consume in a virtual community is influenced by user satisfaction. Nascimento et al. (2018) found that users have a stronger intention to use a smartwatch when they derive satisfaction from the smartwatch. Li and Fang (2019) argued that user satisfaction has a significant impact on the intention to adopt smartphone apps. Due to the causal relationship between user satisfaction and acceptance intention, it is not surprising that numerous studies have made efforts to explore the antecedents of satisfaction in IS (M. Kim et al., 2015; Y. Kim et al., 2021).

With the integration of AI and public service, AI technologies are increasingly being used in the public field. Thus, a few studies that focus on the determinants of user satisfaction with AI-based applications have emerged. For instance, Ashfaq et al. (2020) investigated the determinants of people's user satisfaction when they use chatbots. They found that information quality and service quality have a significant impact on user satisfaction. Overall, there is still a lack of research on user satisfaction regarding AI-based service. Given that AI-based chatbots are an effective tool to support the mental health system during a public health emergency, it is necessary to understand which factors significantly influence citizens' user satisfaction when they use these chatbots.

2.3. The theory of consumption values

The theory of consumption values (TCV) was introduced by Sheth et al. in (1991). Since then, this theory has been extensively used to explain how consumers evaluate and adopt a full range of products or services, both tangible and intangible (Yeo et al., 2016). Generally, consumption refers to the use of products or services by consumers (Sheth et al., 1991). From an economic perspective, consumption is related to expenditure, which is the purchase of products or services for use by consumers (Lee et al., 2018). TCV believes that a person chooses to use or not use (buy or not buy) a specific product or service after assessing multiple consumption values, including functional, emotional, epistemic, social, and conditional values (Sweeney & Soutar, 2001). In essence, TCV posits that (1) consumption values significantly influence consumer decision making, (2) the relative significance of consumption values may vary with the changing context, and (3) consumption values are independent of each other (Sheth et al., 1991).

The original TCV presents a narrow view in which consumption values influence only choice decisions. However, recently, an increasing number of studies have proved that consumption value as a cognitive concept can affect many other behavioral outcomes, such as user experience and user satisfaction (Hwnag & Kim, 2007; Yeo et al., 2016). According to Sweeney and Soutar (2001), consumption values are created before or during the purchase process, while customer experience and satisfaction are formed at the post-purchase stage. The perception of values is the preceding factor of experience and satisfaction levels, whereas experience and satisfaction levels act as resulting factors (Yeo et al., 2016). In other words, consumption values, such as functional, emotional, and social values, are the determinants of user experience and user satisfaction.

The New Public Management approach tends to define citizens as customers of government agencies. The purpose of government reform is to improve administration efficiency and provide services that meet consumer demands (Aberbach & Christensen, 2005). From the perspective of New Public Management, mental health chatbots and citizens can be regarded as products and customers, respectively. Also, the use of mental health chatbots can be considered as the consumption of products by citizens (customers). Citizens' (customers) user experience and user satisfaction with mental health chatbots (products) can be affected by multiple consumption values. Thus, it is appropriate to use TCV to analyze the determinants of user experience and user satisfaction with mental health chatbots.

Previous studies on the use of mental health chatbots have predominantly depended on technology acceptance theories (Ashfaq et al., 2020; Luo et al., 2019), such as Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology Model (UTAUT). Because TAM and UTAUT mainly focus on the relationship between the function and quality of a technology-powered product and user behavior, they cannot fully explain the use of mental health chatbots in a wide range of human-robot interaction contexts, especially during the COVID-19-related lockdown. Compared to many technology acceptance theories, TCV is more comprehensive as it explains user behavior through various value-oriented elements, including function, emotion, social influence, and environment. Thus, TCV can construct a theoretical framework to deeper understand the determinants of user experience and user satisfaction with mental health chatbots during the COVID-19 pandemic.

As mentioned above, TCV argues that the relative importance of consumption values may vary from context to context (Sheth et al., 1991). Therefore, we contextualize the value components to fit the features and characteristics of mental health chatbots. Specifically, functional value relates to functional and utilitarian performance (Teng, 2018). As for mental health chatbots, their functional value comes from a series of facts, including voice interaction and personalization. Voice interaction can lead to human-like friendly interactions between chatbots and users. Personalization can accurately identify user's issues and provide appropriate therapies according to the user's needs. Thus, we contextualize the functional value of mental health chatbots as voice interaction and personalization. Emotional value refers to the perceived utility in improving feelings (Sheth et al., 1991). Enjoyment is a key element of chatbots (Ashfaq et al., 2020). An effective human–robot interaction can induce a pleasant feeling and significantly reduce depressive symptoms and anxiety in people (Cheng & Jiang, 2020). Thus, we employ enjoyment to represent the emotional value of mental health chatbots. Epistemic value is defined as the perceived utility acquired from an alternative's capability to offer novelty and satisfy a desire for knowledge (Sheth et al., 1991). Therefore, learning is the epistemic value of mental health chatbots. Conditional value refers to the perceived utility received as a result of the situation or condition in which a product or service is used (Lee et al., 2018). This value should be displayed in a specific event (Teng, 2018). During a pandemic, the traditional mental health system is overtaxed, and many people are unable obtain mental health services. In such a situation, the significance of mental health chatbots can be seen. This study excludes social value as it does not show a direct relationship with the use of mental health chatbots. Moreover, people are not related to other groups when they use mental health chatbots.

3. Research model and hypotheses

Personalization refers to the provision of personally relevant products and services according to the user's unique characteristics and demands (Xiao & Benbasat, 2007). With the development of machine learning and data mining technology, personalization has become an important function of AI-based applications (Chen et al., 2021). Based on the analysis of historical data, personalization allows AI-based applications to provide products and services that customers might be interested in and thus improve customers' user experience and user satisfaction (Shi et al., 2020). According to Bhalla (2014), personalization is a significant variable that affects user experience in a digital retail environment. Chen et al. (2021) argued that user experience with AI-based self-service can be greatly influenced by personalization. Through a systematic review, Kocaballi et al. (2019) found that the personalization of mental health chatbots can lead to a higher level of user satisfaction. Commonly, personalized services provided by mental health chatbots include feedback, health reports, alerts, and recommendations (Kocaballi et al., 2019). During the COVID-19 pandemic, different people have experienced different mental health problems (Liu et al., 2020). Thus, personalization of chatbots may improve user experience and user satisfaction by mitigating users' cognitive load and offering personalized services or treatments that align with users' mental health issues. Based on the above arguments, the following hypotheses are formulated:

H1. Personalization has a positive impact on user experience of mental health chatbots during the COVID-19 pandemic.

H2. Personalization has a positive impact on user satisfaction with mental health chatbots during the COVID-19 pandemic.

As a kind of natural human–computer interaction, voice interaction has been increasingly applied to AI-based robots in recent years (Chen et al., 2021). This function allows robots to make human-like communication with users. Normally, the voice interaction cycle of an AI-based robot can be divided into five parts: wake up, response, input, analysis, and feedback (Kiseleva et al., 2016). Since humans prefer to use voice to interact with each other, voice interaction makes communication between robots and users more natural (Muthugala & Jayasekara, 2019). According to Mavridis (2015), voice interaction can strengthen the overall human–robot interaction quality, including user experience and user satisfaction. This argument is supported by many studies. For instance, Ni and Wang (2019) argued that the use of voice interaction can positively improve people's user experience of AI-based toys. Kiseleva et al. (2016) considered voice interaction to be an important variable that influences user satisfaction with AI-based search assistants. In this research, voice interaction leads to a more natural interaction between chatbots and citizens. As a result, citizens' user experiences and user satisfaction might be improved. Thus, we hypothesize the following:

H3. Voice interaction has a positive impact on user experience of mental health chatbots during the COVID-19 pandemic.

H4. Voice interaction has a positive impact on user satisfaction with mental health chatbots during the COVID-19 pandemic.

In the context of IS, enjoyment refers to the extent to which using an IS product or service is perceived as enjoyable, fun, and pleasurable (Lee et al., 2018). Recently, enjoyment has been believed to have a direct effect on the user experience of chatbots. For example, Rese et al. (2020) believed that customers tended to consider their user experience as a delight when they enjoyed the interaction with chatbots. According to Kasilingam (2020), a feeling of enjoyment leads to pleasure experience and thus stimulates citizens' intention to adopt smartphone chatbots for shopping. In addition, several lines of evidence suggest that enjoyment is a significant predictor of user satisfaction with chatbots, especially mental health chatbots (Fitzpatrick et al., 2017). When users interact with a mental health chatbot, a feeling of enjoyment can help relieve depression, anxiety, and stress more effectively, which in return will devote to overall satisfaction (Abd-alrazaq et al., 2019). In this study, we expect that when users consider the services and treatments provided by chatbots as enjoyable, they will have better user experience and user satisfaction. Thus, the following hypotheses are formulated:

H5. Enjoyment has a positive impact on user experience of mental health chatbots during the COVID-19 pandemic.

H6. Enjoyment has a positive impact on user satisfaction with mental health chatbots during the COVID-19 pandemic.

The TCV has been contextualized to identify learning as a key value component (Chen & Sharma, 2013). According to Teng (2018), learning satisfies users' desire to acquire new knowledge. When people see an innovation, they usually feel novelty and thus desire to know more about it (Nelson & Consoli, 2010). Such a desire for knowledge might be satisfied by using this innovation (Qaoumi et al., 2018). Commonly, if people perceive that using an innovation enriches their understanding, they tend to consider their user experience as worthwhile (Sheth et al., 1991). Similarly, if the users acquire greater knowledge via the adoption of the innovation, they will be more likely to feel satisfied (Qaoumi et al., 2018). As a new technological innovation, mental health chatbots provide citizens with a feeling of novelty. Such feeling stimulates citizens' desire to learn. Ultimately, the learning process and achievement may affect their user experience and user satisfaction. Thus, we hypothesize the following:

H7. Learning has a positive impact on user experience of mental health chatbots during the COVID-19 pandemic.

H8. Learning has a positive impact on user satisfaction with mental health chatbots during the COVID-19 pandemic.

In this research, conditional value is the perceived utility received from using chatbots to meet the mental health demands of the current condition a person faces. According to Hung and Hsieh (2010), a condition can promote or restrain a decision. The condition and situation in which mental health chatbots are used drives conditional value. This includes time, place, technological context, and people's mental state (Omigie et al., 2017; Pihlström & Brush, 2008). During the COVID-19 pandemic, a person may feel satisfied with mental health chatbots because they are available for use in most cases. In addition, a citizen may consider the use of chatbots as positive on the condition that chatbots make mental health services faster and more available and reduce the risks associated with touching. Thus, we hypothesize the following:

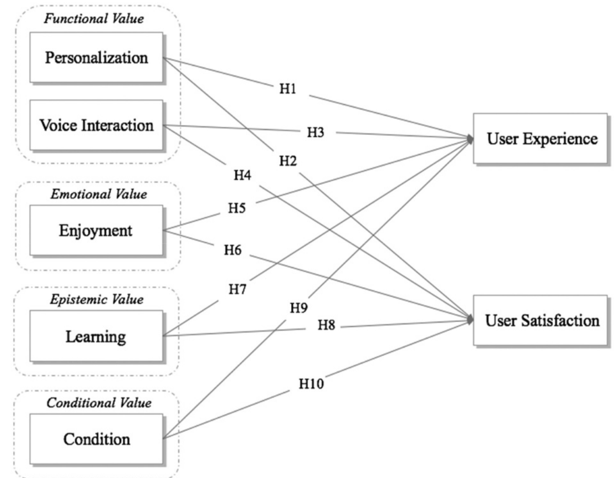

Figure 1. Research model and hypotheses in this research.

H9. Condition has a positive impact on user experience of mental health chatbots during the COVID-19 pandemic.

H10. Condition has a positive impact on user satisfaction with mental health chatbots during the COVID-19 pandemic.

Figure 1 depicts the conceptual research model and research hypotheses.

4. Method

4.1. Data

This is a cross-sectional study conducted using data collected from two cities: Wuhan (the epicenter) and Chongqing (the neighboring city), during the COVID-19 pandemic in China. COVID-19 was first reported in Wuhan and spread rapidly throughout China and the world. From January to April 2020, Wuhan became the epicenter of the COVID-19 spread in China (Liu et al., 2020). To control the epidemic, the Chinese government implemented a complete lockdown in Wuhan from January 23, 2020 (Yuan et al., 2020). Consequently, many severe restrictions were implemented in Wuhan, such as traffic restrictions, home quarantine policies, and school lockdowns.

Major migration from Wuhan to Chongqing during the Spring Festival, as the two cities are close to each other, made Chongqing one of the hardest-hit areas (He et al., 2021). To reduce the spread of the infection, Chongqing initiated a level one response on January 24, 2020. This means that Chongqing also implemented the same restrictions as Wuhan did. The lockdown and stringent restrictions in Wuhan and Chongqing caused a major and sudden change in the residents' lives. People experienced a sudden separation from their loved ones, encountered a shortage of living supplies, and/or experienced financial distress (Chen et al., 2020). Under these circumstances, many people experienced psychological distress; including depression, anxiety, and sleep disorders/deprivation.

To offer psychological assistance to those with mental disorders, the local government has cooperated with the private sector to launch a mental health chatbot named Xiaolv. Table 1 shows basic information of Xiaolv. Residents could chat with this virtual agent through WeChat – a popular messaging and social media application (app) in China (Zhu & Kou, 2019). Xiaolv can sense mental health issues from the conversation's context. Based on the analysis of the users' problems, Xiaolv provides a series of services; such as encouragement, gaming, recommendations, and guidance. Figure 2 shows an image of the chatbot interface and a use case during the COVID-19 pandemic.

During the lockdown, the local governments in Wuhan and Chongqing mobilized urban and rural communities to implement community-based control and prevention measures. The precise community gridded management highlighted the epidemic's monitoring and healthcare for all residents. The community workers were advised to deliver public health services and information to residents (He et al., 2021). Each community worker shouldered the

Table 1. Basic information of Xiaolv.

Category	Content
Bot name	Xiaolv
Programming languages/Apps/Integration	iOS SDK/Java SDK/Python SDK
Languages	Chinese
Channels	Wechat/Web
Clients/Fields	• Mental healthcare • Psychological assistance
Features	• Live chat • Multiple channels • Data storage • 24/7 user support • Natural language processing • Service recommendation • Free

responsibility of serving at least 10 families. Due to the lack of community workers, many Chinese undergraduate students became community volunteers. Community health service centers randomly assigned several families to each student volunteer. The students then offered community health services to the designated families. To practice social distancing, the student volunteers usually contacted the designated families through WeChat groups.

In this study, we cooperated with the student volunteers in Wuhan and Chongqing to collect research data. We contacted 34 volunteer students. The students were unfamiliar with the designated families prior to being assigned to them by the community health service centers. They helped us to send the Xiaolv chatbot's link through a WeChat group to 136 families in 28 communities. People could choose whether to use the chatbot or not. After a week, the student volunteers submitted another online questionnaire via the WeChat group and requested the families to complete the survey. Due to the complete lockdown, the student volunteers' cooperation ensured the survey's feasibility and accessibility.

The questionnaire was created using the Qualtrics platform. Before circulating the questionnaire, we invited IS experts to provide suggestions. We also conducted a pilot test with 23 students and collected revision advice from them. After the modifications, the questionnaire comprised three parts. First, we identified those people who had used the chatbot by asking: "Have you already used the chatbot?" "what is the name of the chatbot?," and "can it speak to you?" Thereafter, we collected their demographic information, such as age, education, gender, and income. The third section included a set of items measuring the consumption values, the user experience, and user satisfaction.

The data were collected from January to March 2020. In total, we collected 314 responses from 136 families. This included 49 families within vulnerable populations, such as the elderly, children, disabled people, and pregnant women. After deleting responses with missing data and eliminating those who indicated that they had not interacted with Xiaolv, a sample of 295 valid responses were collected. Table 2 shows the respondents' and volunteers' demographic information in this study. As shown,

Figure 2. An image of the chatbot interface. The chatbot Xiaolv will analyze users' issues through the human-like conversation and provide appropriate services accordingly.

Table 2. Demographic information.

Category		Number	Percentage (%)
Gender	Male	158	53.6
	Female	137	46.4
Age	18–30	51	17.3
	31–40	154	52.2
	41–50	47	15.9
	Over 50	43	14.6
Education	Under high school	54	18.3
	High school	78	26.4
	Bachelor degree	152	51.4
	Master's degree and above	11	3.7
Annual income	\$0 – \$4500	83	28.1
	\$4501 – \$15,000	140	47.5
	\$15,001 – \$45,000	61	20.7
	Over \$45,001	11	3.7
Communities	In Wuhan	16	57.1
	In Chongqing	12	42.9
Families	Within vulnerable populations	49	36
	Without vulnerable populations	87	64
Volunteers	Male	29	85.3
	Female	5	14.7

158 respondents were male (53.6%), more than half of the respondents held a bachelor's degree (51.4%) or higher (3.7%), 154 respondents (52.2%) were between 31 and 40 years old, and 90 (30.5%) were over 40 years old. According to previous studies (Doong & Ho, 2012; Van Dijk, 2006), educational background has a positive impact on intention to use IS. Since many of the respondents in our study held a bachelor's degree, they may be more willing to use mental health chatbots compared with the general population.

4.2. Measurement

In this study, each item was scored on a seven-point Likert scale, ranging from one (highly disagree) to seven (highly agree). All the measurement items were adapted from existing literature. The personalization was measured using four items adapted from Roy et al. (2017) and Chen et al. (2021). Measurement items for voice interaction were adapted from Ni and Wang (2019). To measure enjoyment, we used three items following Lee et al. (2018). Items measuring learning were modified from Teng (2018). Measurement items for the condition were adapted from Omigie et al. (2017). The scale developed by Gentile et al. (2007) was used to measure the chatbot's user experience. Finally, user satisfaction was assessed based on three items from Li and Fang (2019) and M. Kim et al. (2015). All the measurement items are listed in Appendix A.

4.3. Analysis methods

Partial least squares structural equation modeling (PLS-SEM) was used to test the measurement model and the corresponding hypotheses. PLS-SEM is suitable for establishing constructs and verifying relationships between paths by factoring observed variables (Y. Kim et al., 2021). It is also slightly unrestricted for the sample size (Venturini & Mehmetoglu, 2019). According to Kasilingam (2020), PLS-SEM is flexible regarding its data requirements, model complexity, and relationship specifications. Moreover, PLS-SEM can compare several groups by specifying a permutation-based analysis of the variance approach (Kasilingam, 2020).

Thus, we attempted to verify the research model through PLS-SEM. Before hypotheses testing, we confirmed the fitness by assessing the reliability, convergent validity, cross-factor loading, and discriminant validity of the research model. When there were no problems with either validity or reliability, we then tested the hypotheses between constructs in the research model.

5. Results

5.1. Measurement model analysis

First, we tested the reliability and convergent validity of the measurement instruments. According to Table 3, the Cronbach's alpha values for all the items were above 0.70, indicating that the measurement was reliable (M. Kim et al., 2015). In addition, the composite reliability (CR) for each construct was above the recommended level 0.60 (Lee et al., 2018). The average variance extracted (AVE) for each construct exceeded the desirable value of 0.50 (Zhang & Zhu, 2021). In addition, all the factor loadings were above the recommended value of 0.60 (Teng, 2018). Therefore, the conditions for reliability and convergent validity were met by the measurement model.

The discriminant validity was then examined. Table 4 shows the cross-factor loadings of all the items, indicating that they scored the highest on their respective constructs (Zhang & Zhu, 2021). Table 5 shows that the square root of the AVE for each construct exceeded the correlation values between any two constructs. This demonstrates that

Table 3. The reliability and validity of the measurement.

Constructs/items	Factor loading	Mean	Cronbach's alphas	CR	AVE	VIF
Personalization (P)			0.859	0.904	0.703	
P1	0.871	4.36				2.416
P2	0.846	4.31				2.258
P3	0.827	4.24				2.131
P4	0.809	4.56				2.009
Voice interaction (VI)			0.813	0.889	0.728	
VI1	0.874	4.50				1.913
VI2	0.864	4.72				1.918
VI3	0.821	4.66				1.627
Enjoyment (E)			0.785	0.875	0.700	
E1	0.846	4.14				1.765
E2	0.807	4.32				1.492
E3	0.856	4.39				1.765
Learning (L)			0.812	0.889	0.727	
L1	0.863	4.47				1.888
L2	0.849	4.52				1.677
L3	0.845	4.63				1.819
Condition (C)			0.838	0.903	0.756	
C1	0.896	4.43				2.321
C2	0.830	4.59				1.695
C3	0.881	4.50				2.187
User experience (EP)			0.872	0.912	0.722	
EP1	0.841	4.41				2.098
EP2	0.838	4.35				2.232
EP3	0.854	4.36				2.224
EP4	0.865	4.43				2.407
User satisfaction (SA)			0.795	0.880	0.710	
SA1	0.847	4.49				1.704
SA2	0.835	4.48				1.637
SA3	0.845	4.39				1.729

Table 4. Cross-factor loadings.

	P	VI	E	L	C	EP	SA
P1	**0.871**	0.389	0.713	0.720	0.717	0.740	0.737
P2	**0.846**	0.353	0.630	0.686	0.669	0.660	0.651
P3	**0.827**	0.416	0.620	0.639	0.639	0.649	0.620
P4	**0.809**	0.388	0.621	0.638	0.643	0.623	0.601
VI1	0.414	**0.874**	0.359	0.416	0.424	0.389	0.381
VI2	0.367	**0.864**	0.357	0.363	0.413	0.358	0.354
VI3	0.397	**0.821**	0.352	0.362	0.393	0.354	0.327
E1	0.613	0.288	**0.846**	0.655	0.673	0.672	0.614
E2	0.631	0.361	**0.807**	0.676	0.682	0.680	0.622
E3	0.692	0.394	**0.856**	0.701	0.709	0.707	0.668
L1	0.697	0.359	0.667	**0.863**	0.692	0.707	0.676
L2	0.707	0.313	0.733	**0.849**	0.728	0.770	0.691
L3	0.641	0.482	0.667	**0.845**	0.680	0.690	0.606
C1	0.707	0.429	0.742	0.730	**0.896**	0.743	0.713
C2	0.657	0.405	0.644	0.705	**0.830**	0.696	0.649
C3	0.714	0.420	0.755	0.710	**0.881**	0.727	0.685
EP1	0.692	0.424	0.688	0.771	0.704	**0.841**	0.732
EP2	0.627	0.343	0.658	0.667	0.685	**0.838**	0.711
EP3	0.696	0.342	0.702	0.717	0.708	**0.854**	0.716
EP4	0.698	0.352	0.738	0.727	0.725	**0.865**	0.727
SA1	0.687	0.370	0.616	0.651	0.677	0.723	**0.847**
SA2	0.624	0.359	0.678	0.688	0.655	0.699	**0.835**
SA3	0.662	0.321	0.623	0.616	0.653	0.724	**0.845**

Table 5. Discriminant validity.

	P	VI	E	L	C	EP	SA
Personalization	0.839						
Voice interaction	0.460	0.853					
Enjoyment	0.773	0.417	0.837				
Learning	0.801	0.447	0.810	0.852			
Condition	0.797	0.481	0.822	0.822	0.869		
Experience	0.799	0.431	0.821	0.849	0.831	0.850	
Satisfaction	0.781	0.416	0.759	0.774	0.786	0.839	0.842

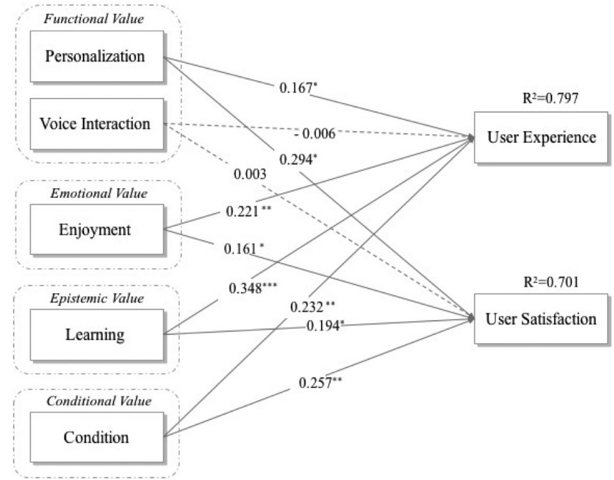

Figure 3. Path coefficients for hypotheses testing. Path significance: *p < .05, **p < .01, ***p < .001.

Table 6. Results of hypotheses testing.

Hypothesis	Path	T statistics	Result
H1	P → EP	2.100	Supported
H2	P → SA	2.304	Supported
H3	VI → EP	0.197	Not supported
H4	VI → SA	0.056	Not supported
H5	E → EP	3.220	Supported
H6	E → SA	2.205	Supported
H7	L → EP	5.775	Supported
H8	L → SA	2.456	Supported
H9	C → EP	3.249	Supported
H10	C → SA	3.363	Supported

all the values met the recommendations for discriminant validity (Kasilingam, 2020). Additionally, the SRMR in this study was found to be 0.058. This was less than the threshold of 0.08, indicating an excellent model fit (Ashfaq et al., 2020).

5.2. Multicollinearity

Before testing the hypotheses, we further tested the variance inflation factor (VIF) to check for multicollinearity. According to Ashfaq et al. (2020), a VIF of over 5.0 for multicollinearity is problematic. Table 3 shows all VIF values in this study, the highest being 2.416. Thus, the model is free from multicollinearity.

5.3. Hypotheses testing

The research hypotheses were tested using a bootstrapping procedure with 5000 subsamples and a two-tailed test. This test had a significance of 0.05 measured by Smart PLS 3.0. The path coefficients are shown in Figure 3. Personalization is positively related to the user experience (β = 0.167, t = 2.100, p < .05) and user satisfaction (β = 0.294, t = 2.304, p < .05). This offers support to H1 and H2. However, voice interaction has an insignificant effect on the user experience and user satisfaction. Thus, H3 and H4 are rejected. Enjoyment has a positive impact on user experience (β = 0.221, t = 3.220, p < .01) and user satisfaction (β = 0.161, t = 2.205, p < .05). Thus, H5 and H6 were supported. Learning has a strong and positive influence on user experience (β = 0.348, t = 5.775, p < .001) and user satisfaction (β = 0.194, t = 2.456, p < .05). This supported H7 and H8. Similarly, condition is positively related to user experience (β = 0.232, t = 3.249, p < .01) and user satisfaction (β = 0.257, t = 3.363, p < .01). Therefore, H9 and H10 are supported. Table 6 shows the results of the hypotheses testing, and Figure 4 shows the barchart of descriptive statistics.

6. Discussion and implications

The development of AI technologies helps government agencies create self-reform to meet the growing demands of its citizens. This study focuses on a new AI application in the public service context, namely, a mental health chatbot. It is empowered by the NLP, machine learning, and other technologies. These technologies enable chatbots to accurately identify the users' mental health issues, communicate with them like humans, and provide them with personalized therapies. In addition, as compared with the traditional manned call center, AI-based chatbots can maintain their efficiency much longer. Due to these advantages, chatbots have been widely used by government agencies around the world to support mental health systems during the COVID-19 pandemic.

To achieve the expected benefits of mental health chatbots during public health emergencies, it is necessary to ensure that people experience enjoyment and are satisfied when they use

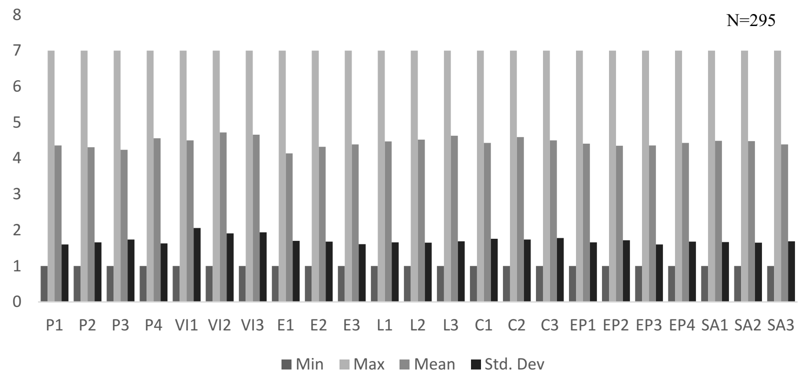

Figure 4. The barchart of descriptive statistics.

these chatbots. However, our knowledge of the determinants of user experience and user satisfaction is limited. Therefore, this study seeks to investigate the factors that significantly influence user experience and user satisfaction, by focusing on people who used a mental health chatbot in China during the COVID-19 pandemic. A theoretical framework based on TCV was constructed to conduct the empirical analysis.

The findings highlight the importance of personalization, enjoyment, learning, and condition. The results show that mental health chatbot's personalized therapies can greatly improve user experience and satisfaction. This result emphasizes that the most important task of mental health chatbots is to offer accurate, appropriate, and effective therapies. Additionally, if people feel enjoyable when they interact with the chatbot, they will consider it a positive experience and feel satisfied.

Moreover, this research also brought out a novelty that learning is positively related to user experience and user satisfaction. Previous studies on human-computer interaction often focused on those factors of computers to explain user experience and user satisfaction, such as perceived ease of use, information quality, and system quality (Ashfaq et al., 2020; Chen et al., 2021; Luo et al., 2019; Zhang & Zhu, 2021). However, few studies empirically revealed how humanity can influence human-computer interaction. The findings of this research showed that curiosity and desire to gain knowledge are important to user experience and user satisfaction. If people can acquire knowledge and satisfy their need for novelty by using the chatbot, their user experience and user satisfaction will be improved. This result may devote to filling a research gap in the field of human-computer interaction.

Meanwhile, the unique circumstances of the COVID-19 pandemic make citizens value the use of the chatbot and thus they are more likely to feel enjoyable and satisfied when they use it. Since the data in this research were collected from Wuhan (the epicenter of the COVID-19 spread in China) and Chongqing (one of the hardest-hit areas in China), the respondents may be more influenced by conditional values compared with the general population. However, voice interaction fails in giving users' positive experiences and feelings. This may be because the chatbot's voice system of the chatbot is not advanced, and people therefore feel unnatural when they communicate with the it.

6.1. Theoretical implications

Despite the rapid implementation of mental health chatbots, there has been little focus on the citizens' experiences and satisfaction when using these chatbots. This is especially regarding during public health emergencies. This paper is devoted to the advancement of the theory regarding the use of mental health chatbots in several ways. First, to the best of our knowledge, this study is one of the earliest attempts to explore user experience and user satisfaction with mental health chatbots through the lens of TCV. Many previous studies on mental health chatbots have depended on technology acceptance theories (Ashfaq et al., 2020; Luo et al., 2019), such as TAM and UTAUT. This research offers a new perspective to understand the determinants of user experience and user satisfaction with mental health chatbots. Thus, the study's findings strengthen the theoretical framework regarding the use of mental health chatbots.

Second, this study extends the existing literature on the use of mental health chatbots during public health emergencies. Although chatbots have been widely used to provide mental health services during the COVID-19 outbreak, it is difficult to find research that investigates user experiences and user satisfaction levels when using mental health chatbots during this pandemic. This study fills this gap. Third, this research contributes to our knowledge of TCV. Generally, TCV is used in a business context. In this study, TCV was employed to explore the use of mental health chatbots in the public service context. We contextualized the value components (personalization, voice interaction, enjoyment, learning, and condition) to fit the features and characteristics of mental health chatbots. Thereafter, we established that the functional value (personalization), emotional value (enjoyment), epistemic value (learning), and conditional value (condition) are positively related to user experience and user satisfaction.

6.2. Practical implications

The recommendations based on the study's results can be offered to public managers and AI engineers. First, the study highlights the importance of personalization in user experience and user satisfaction. Therefore, government agencies and their AI service contractors need to collaborate to enhance the personalized functions of mental health chatbots.

For instance, it is necessary to build a bigger database to train the chatbots, to improve their ability to provide accurate, effective, and appropriate therapies for different people. In addition, value co-creation (VCC) strategies are commonly used in today's service delivery as users are looking for personalized experiences rather than "one-sizes-fits-all" offerings (Lim et al., 2021). However, the implications of VCC in the area of mental health chatbots are still rare. Thus, it is important to invite stakeholders to offer suggestions to mental health chatbots. By promoting VCC, government agencies and their AI service contractors can maximize people's persuasion and appeal to their specific needs.

Second, the impact of voice interaction is insignificant. This may be because the voice system is not advanced. Thus, it is necessary to upgrade the voice interaction systems used in chatbots. AI engineers may create a flexible system that allows users to upload their favorite voices. This study's findings also outline the significance of enjoyment. Thus, government agencies and their AI service contractors should ensure that the interaction between the users and chatbots is pleasant. For instance, they can upgrade the chatbots to be more humorous. Also, AI engineers may also add more gamified features to mental health chatbots to increase hedonic experiences.

In addition, learning contributes to user experience and satisfaction. Therefore, the AI engineers may embed subject-related information into the chatbots, such as history, content, and news, so that the users can enrich their knowledge in their areas of interest. Finally, condition has a significant impact on user experience and user satisfaction. This result establishes that mental health chatbots can strongly assist citizens during public health emergencies. Thus, government agencies need to continue to promote the benefits of mental health chatbots during public health emergencies.

7. Conclusion and limitations

The COVID-19 pandemic has caused a plethora of mental disorders across the world (Ransing et al., 2020). As a response, government agencies have used AI-based chatbots to offer mental health services. Based on TCV, this study investigated the determinants behind citizens' user experience and user satisfaction when they used mental health chatbot in China. The findings show that personalization, enjoyment, learning, and condition contribute to both user experience and user satisfaction. On the other hand, voice interaction exerts insignificant impact on user experience and user satisfaction. This study enhances the theoretical framework regarding the use of chatbots. It also has significant managerial implications for policy makers and AI services contractors. The findings of this study can serve as the launching pad for future exploration of AI-based chatbots in public sectors.

This study is not without limitations. First, due to the lockdown during the COVID-19 pandemic in China, the research data was only collected from Wuhan and Chongqing, and thus it is unclear that the findings of this research can be generalized to other groups, regions or countries. Future studies could conduct wider investigation to examine the generalizability and validity of the model in this study. Second, this study selected only one chatbot as research target. The shortages of this chatbot might influence the research results. In the future, it would be beneficial to choose more mental health chatbots as research targets. Third, the research model only consists of five constructs in this research. In addition to these constructs, some other factors, such as items from the System Usability Scale (SUS) can also assess and explain user satisfaction (Borsci et al., 2015, 2009). Thus, future studies should explore more value components that fit the features and characteristics of mental health chatbots. Forth, there were many research hypotheses for a small dataset in this study, it may need bonferroni correction to counteract the problem of multiple comparisons. Finally, the potential moderating effect of demographic factors has not been analyzed in this study. This research gap should be fulfilled in the future.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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References

Abd-alrazaq, A. A., Alajlani, M., Alalwan, A. A., Bewick, B. M., Gardner, P., & Househ, M. (2019). An overview of the features of chatbots in mental health: A scoping review. *International Journal of Medical Informatics*, *132*, 103978. https://doi.org/10.1016/j.ijmedinf.2019.103978

Aberbach, J. D., & Christensen, T. (2005). Citizens and consumers: An NPM dilemma. *Public Management Review*, *7*(2), 225–246. https://doi.org/10.1080/14719030500091319

Ahuja, A. S., Reddy, V. P., & Marques, O. (2020). Artificial intelligence and COVID-19: A multidisciplinary approach. *Integrative Medicine Research*, *9*(3), 100434. https://doi.org/10.1016/j.imr.2020.100434

Ail, M. R., Rasazi, Z., Mamun, A. A., Langevin, R., Rawassizadeh, R., Schubert, L., & Hoque, M. E. (2020, October). A virtual conversational agent for teens with autism: Experimental results and design lessons. In *Proceedings of the 20th ACM International Conference on Intelligent Virtual Agents (IVA '20)*, Scotland, UK. (pp. 1–8). New York, NY: ACM. https://doi.org/10.1145/3383652.3423900

Androutsopoulou, A., Karacapilidis, N., Loukis, E., & Charalabidis, Y. (2019). Transforming the communication between citizens and government through AI-guided chatbots. *Government Information Quarterly*, *36*(2), 358–367. https://doi.org/10.1016/j.giq.2018.10.001

Aoki, N. (2020). An experimental study of public trust in AI chatbots in the public sector. *Government Information Quarterly*, *37*(4), 101490. https://doi.org/10.1016/j.giq.2020.101490

Ashfaq, M., Yun, J., Yu, S., & Loureiro, S. M. C. (2020). I, Chatbot: Modeling the determinants of users' satisfaction and continuance intention of AI-powered service agents. *Telematics and Informatics*, *54*, 101473. https://doi.org/10.1016/j.tele.2020.101473

Bhalla, R. (2014). The omni-channel customer experience: Driving engagement through digitization. *Journal of Digital & Social Media Marketing*, *1*(4), 365–372. https://www.ingentaconnect.com/content/hsp/jdsmm/2014/00000001/00000004/art00008

Borsci, S., Federici, S., Bacci, S., Gnaldi, M., & Bartolucci, F. (2015). Assessing user satisfaction in the era of user experience: Comparison of the SUS, UMUX, and UMUX-LITE as a function of product experience. *International Journal of Human-Computer Interaction*, *31*(8), 484–495. https://doi.org/10.1080/10447318.2015.1064648

Borsci, S., Federici, S., & Lauriola, M. (2009). On the dimensionality of the System Usability Scale (SUS): A test of alternative measurement models. *Cognitive Processing*, *10*(3), 193–197. https://doi.org/10.1007/s10339-009-0268-9

Cameron, G., Cameron, D., Megaw, G., Bond, R., Mulvenna, M., O'Neill, S., Armour, C., & McTear, M. (2019, April). Assessing the usability of a chatbot for mental health care. In *International Workshop on Internet Science*, St. Petersburg, Russia. (pp. 121–132). Cham: Springer.

Chen, R., & Sharma, S. K. (2013). Understanding member use of social networking sites: A value analysis. *Communications of the Association for Information Systems*, *33*(1), 97–114. https://doi.org/10.17705/1CAIS.03306

Chen, S., Cheng, Z., & Wu, J. (2020). Risk factors for adolescents' mental health during the COVID-19 pandemic: A comparison between Wuhan and other urban areas in China. *Globalization and Health*, *16*(1), 96. https://doi.org/10.1186/s12992-020-00627-7

Chen, T., Guo, W., Gao, X., & Liang, Z. (2021). AI-based self-service technology in public service delivery: User experience and influencing factors. *Government Information Quarterly*, *38(4)*, 101520. https://doi.org/10.1016/j.giq.2020.101520

Cheng, Y., & Jiang, H. (2020). AI-powered mental health chatbots: Examining users' motivations, active communicative action and engagement after mass-shooting disasters. *Journal of Contingencies and Crisis Management*, *28*(3), 339–354. https://doi.org/10.1111/1468-5973.12319

Deng, L., Turner, D. E., Gehling, R., & Prince, B. (2010). User experience, satisfaction, and continual usage intention of IT. *European Journal of Information Systems*, *19*(1), 60–75. https://doi.org/10.1057/ejis.2009.50

Doong, S. H., & Ho, S. C. (2012). The impact of ICT development on the global digital divide. *Electronic Commerce Research and Applications*, *1*(5), 518–533. https://doi.org/10.1016/j.elerap.2012.02.002

Engin, Z., & Treleaven, P. (2019). Algorithmic government: Automating public services and supporting civil servants in using data science technologies. *The Computer Journal*, *62*(*3*), 448–460.

Fitzpatrick, K. K., Darcy, A., & Vierhile, M. (2017). Delivering cognitive behavior therapy to young adults with symptoms of depression and anxiety using a fully automated conversational agent (Woebot): A randomized controlled trial. *JMIR Mental Health*, *4*(2), e19. https://doi.org/10.2196/mental.7785

Foth, M., & Schroeter, R. (2010, October). Enhancing the experience of public transport users with urban screens and mobile applications. In *Proceedings of the 14th international academic mindtrek conference: Envisioning future media environment*, Finland. (pp. 33–40). New York, NY: ACM.

Gentile, C., Noci, G., & Spiller, N. (2007). How to sustain the customer experience: An overview of experience components that co-create value with the customer. *European Management Journal*, *25*(5), 395–410. https://doi.org/10.1016/j.emj.2007.08.005

Hassenzahl, M., & Tractinsky, N. (2006). User experience a research agenda. *Behaviour & Information Technology*, *25*(2), 91–97. https://doi.org/10.1080/01449290500330331

He, S., Chen, S., Kong, L., & Liu, W. (2021). Analysis of risk perceptions and related factors concerning COVID-19 epidemic in Chongqing, China. *Journal of Community Health*, *46*(2), 278–285. https://doi.org/10.1007/s10900-020-00870-4

Hung, C. L., & Hsieh, C. Y. (2010). Searching the fit pattern between cultural dimensions and consumption values of mobile commerce in Taiwan. *Asia Pacific Management Review*, *15*(2), 147–165. https://www.proquest.com/docview/1115696143?pq-origsite=summon

Hwnag, Y. C., & Kim, C. (2007). A study on the antecedents and consequence of perceived value in the retail environment. *Journal of Korean Marketing Association*, *12*(2), 77–103.

International Organization for Standardization. (2010). *ISO 9241-210:2010, ergonomics of human-system interaction-part 210: Human-central design for interactive systems.*

Jung, K. E., & Lee, D. M. (1995). Reciprocal effect of the factors influencing the satisfaction of is users. *Asia Pacific Journal of Information Systems*, *5*(2), 199–226.

Kasilingam, D. L. (2020). Understanding the attitude and intention to use smartphone chatbots for shopping. *Technology in Society*, *62*, 101280. https://doi.org/10.1016/j.techsoc.2020.101280

Kim, M., Chang, Y., Park, M., & Lee, J. (2015). The effects of service interactivity on the satisfaction and the loyalty of smartphone users. *Telematics and Informatics*, *32*(4), 949–960. https://doi.org/10.1016/j.tele.2015.05.003

Kim, Y., Wang, Q., & Roh, T. (2021). Do information and service quality affect perceived privacy protection, satisfaction, and loyalty? Evidence from a Chinese O2O-based mobile shopping application. *Telematics and Informatics*, *56*, 101483. https://doi.org/10.1016/j.tele.2020.101483

Kiseleva, J., Williams, K., Awadallah, A. H., Crook, A. C., Zitouni, I., & Anastasakos, T. (2016, July). Predicting user satisfaction with intelligent assistants. In *Proceedings of the 39th International ACM SIGIR conference on Research and Development in Information Retrieval*, Pisa, Italy. (pp. 45–54). ACM.

Kocaballi, A. B., Berkovsky, S., Quiroz, J. C., Laranjo, L., Tong, H. L., Rezazadegan, D., Briatore, A., & Coiera, E. (2019). The personalization of conversational agents in health care: Systematic review. *Journal of Medical Internet Research*, *21*(11), e15360. https://doi.org/10.2196/15360

Kumar, R., Sachan, A., & Mukherjee, A. (2017). Qualitative approach to determine user experience of e-government services. *Computers in Human Behavior*, *71*, 299–306. https://doi.org/10.1016/j.chb.2017.02.023

Lallemand, C., Gronier, G., & Koenig, V. (2015). User experience: A concept without consensus? Exploring practitioners' perspectives through an international survey. *Computers in Human Behavior*, *43*, 35–48. https://doi.org/10.1016/j.chb.2014.10.048

Lee, S., Lee, J., & Kim, H. (2018). A customer value theory approach to the engagement with a brand: The case of KaoKao Talk plus in Korea. *Asia Pacific Journal of Information Systems*, *28*(1), 36–60. https://doi.org/10.14329/apjis.2018.28.1.36

Li, C., & Fang, Y. (2019). Predicting continuance intention toward mobile branded apps through satisfaction and attachment. *Telematics and Informatics*, *43*, 101248. https://doi.org/10.1016/j.tele.2019.101248

Lim, X. J., Cheah, J. H., Ng, S. I., Basha, N. K., & Liu, Y. (2021). Are men from Mars, women from Venus? Examining gender differences towards continuous use intention of branded apps. *Journal of Retailing and Consumer Service*, *60*, 102422. https://doi.org/10.1016/j.jretconser.2020.102422

Liu, S., Yang, L., Zhang, C., Xiang, Y., Liu, Z., Hu, S., & Zhang, B. (2020). Online mental health services in China during the COVID-19 outbreak. *The Lancet Psychiatry*, *7*(4), 30077–30078. https://doi.org/10.1016/S2215-0366(20)30077-8

Lokot, T., & Diakopoulos, N. (2016). News bots: Automating news and information dissemination on Twitter. *Digital Journalism*, *4*(6), 682–699. https://doi.org/10.1080/21670811.2015.1081822

Luo, X., Tong, S., Fang, Z., & Qu, Z. (2019). Frontiers: Machines vs. humans: The impact of artificial intelligence chatbot disclosure on customer purchase. *Marketing Science*, *38*(6), 937–947. https://doi.org/10.1287/mksc.2019.1192

Madariaga, L., Nussbaum, M., Marañón, F., Alarcón, C., & Naranjo, M. A. (2019). User experience of government documents: A framework for informing design decisions. *Government Information Quarterly*, *36*(2), 179–195. https://doi.org/10.1016/j.giq.2018.12.005

Mavridis, N. (2015). A review of verbal and non-verbal human-robot interactive communication. *Robotics & Autonomous Systems*, *63(1)*, 22–35. https://doi.org/10.1016/j.robot.2014.09.031

Melone, N. P. (1990). A theoretical assessment of the user satisfaction construct in information systems research. *Management Science*, *36*(1), 76–91. https://doi.org/10.1287/mnsc.36.1.76

Muthugala, V., & Jayasekara, B. (2019). Enhancing interpretation of uncertain information in navigational commands for service robots using neuro-fuzzy approach. *Journal of Ambient Intelligence and Smart Environments*, *11*(2), 195–197. https://doi.org/10.3233/AIS-190513

Nascimento, B., Oliveira, T., & Tam, C. (2018). Wearable technology: What explains continuance intention in smartwathces? *Journal of Retailing & Consumer Services*, *43*, 157–169. https://doi.org/10.1016/j.jretconser.2018.03.017

Nelson, R. R., & Consoli, D. (2010). An evolutionary theory of household consumption behavior. *Journal of Evolutionary Economics*, *20*(5), 665–687. https://doi.org/10.1007/s00191-010-0171-7

Ni, Y., & Wang, Y. (2019, November). Design of a smart storytelling toy based on voice interaction. In *Proceedings of the 2019 2nd World Conference on Mechanical Engineering and Intelligent Manufacturing*, Shanghai, China. (pp. 229–233). IEEE.

Oliver, R. L., & Wayne, S. D. (1988). Response determinants in satisfaction judgments. *Journal of Consumer Research*, *14*(4), 495–507. https://doi.org/10.1086/209131

Oliver, R. L. (1997). *Satisfaction: A behavioral perspective on the consumer*. McGraw-Hill.

Olson, J. C., & Dover, P. A. (1979). Disconfirmation of consumer expectations through product trial. *Journal of Applied Psychology*, *64*(2), 179–189. https://doi.org/10.1037/0021-9010.64.2.179

Omigie, N. O., Zo, H., Rho, J. J., & Ciganek, A. P. (2017). Customer pre-adoption choice behavior for M-PESA mobile financial services. Extending the theory of consumption values. *Industrial Management & Data Systems*, *117*(5), 910–926. https://doi.org/10.1108/IMDS-06-2016-0228

Pihlström, M., & Brush, G. J. (2008). Comparing the perceived value of information and entertainment mobile services. *Psychology & Marketing*, *25*(8), 732–755. https://doi.org/10.1002/mar.20236

Przegalinska, A., Ciechanowski, L., Stroz, A., Gloor, P., & Mazurek, G. (2019). In bot we trust: A new methodology of chatbot performance measures. *Business Horizons*, *62*(6), 785–797. https://doi.org/10.1016/j.bushor.2019.08.005

Qaoumi, K. E., Masson, P. L., Weil, B., & ün, A. (2018). Testing evolutionary theory of household consumption behavior in the case of novelty – A product characteristics approach. *Journal of Evolutionary Economics*, *28*(2), 437–460. https://doi.org/10.1007/s00191-017-0521-9

Ransing, R., Nagendrappa, S., Patil, A., Shoib, S., & Sarkar, D. (2020). Potential role of artificial intelligence to address the COVID-19 outbreak-related mental health issues in India. *Psychiatry Research*, *290*, 113176. https://doi.org/10.1016/j.psychres.2020.113176

Rese, A., Ganster, L., & Baier, D. (2020). Chatbots in retailers' customer communication: How to measure their acceptance? *Journal of Retailing and Consumer Services*, *56*, 102176. https://doi.org/10.1016/j.jretconser.2020.102176

Roy, S. K., Balaji, M. S., Sadeque, S., Nguyen, B., & Melewar, T. C. (2017). Constituents and consequences of smart customer experience in retailing. *Technological Forecasting and Social Change*, *124*, 257–270. https://doi.org/10.1016/j.techfore.2016.09.022

Sheng, M. L., & Teo, T. S. H. (2012). Product attributes and brand equity in the mobile domain: The mediating role of customer experience. *International Journal of Information Management*, *32*(2), 139–146. https://doi.org/10.1016/j.ijinfomgt.2011.11.017

Sheth, J. N., Newman, B. I., & Gross, B. L. (1991). Why we buy and what we buy: A theory of consumption values. *Journal of Business Research*, *22*(2), 159–170. https://doi.org/10.1016/0148-2963(91)90050-8

Shi, S., Wang, Y., Chen, X., & Zhang, Q. (2020). Conceptualization of omnichannel customer experience and its impact on shopping intention: A mixed-method approach. *International Journal of Information Management*, *50*, 325–336. https://doi.org/10.1016/j.ijinfomgt.2019.09.001

Smith, A. C., Thomas, E., Snoswell, C. L., Haydon, H., Mehrotra, A., Clemensen, J., & Caffery, L. J. (2020). Telehealth for global emergencies: Implications for coronavirus disease 2019 (COVID-19). *Journal of Telemedicine and Telecare*, *26*(5), 309–313. https://doi.org/10.1177/1357633X20916567

Sweeney, J. C., & Soutar, G. N. (2001). Consumer perceived value: The development of a multiple item scale. *Journal of Retailing*, *77*(2), 203–220. https://doi.org/10.1016/S0022-4359(01)00041-0

Teng, C. (2018). Look to the future: Enhancing online gamer loyalty from the perspective of the theory of consumption values. *Decision Support Systems*, *114*, 49–60. https://doi.org/10.1016/j.dss.2018.08.007

Valtolina, S., Barricelli, B. R., & Gaetano, S. D. (2019). Communicability of traditional interfaces VS chatbots in healthcare and smart home domains. *Behaviour & Information Technology*, *39*(1), 108–132. https://doi.org/10.1080/0144929X.2019.1637025

Van Dijk, J. A. (2006). Digital divide research, achievements and shortcoming. *Poetics*, *34*(4–5), 221–235. https://doi.org/10.1016/j.poetic.2006.05.004

Venturini, S., & Mehmetoglu, M. (2019). Plssem: A stata package for structural equation modeling with partial least squares. *Journal of Statistical Software*, *88(8)*, 1–35. https://doi.org/10.18637/jss.v088.i08

Xiao, X., & Benbasat, B. (2007). E-commerce product recommendation agents: Use, characteristics, and impact. *MIS Quarterly*, *31*(1), 137–209. https://doi.org/10.2307/25148784

Yeo, B. L., Mohamed, R. N., & Muda, M. (2016). A study of Malaysian customers purchase motivation of halal cosmetics retail products: Examining theory of consumption value and customer satisfaction. *Procedia Economics and Finance*, *37*, 176–182. https://doi.org/10.1016/S2212-5671(16)30110-1

Yu, M., Zhou, R., Cai, Z., Tan, C. W., & Wang, H. (2020). Unravelling the relationship between response time and user experience in mobile applications. *Internet Research*, *30*(5), 1353–1382. https://doi.org/10.1108/INTR-05-2019-0223

Yuan, Z., Xiao, Y., Dai, Z., Huang, J., Zhang, Z., & Chen, Y. (2020). Modeling the effects of Wuhan's lockdown during COVID-19, China. *Bulletin of the World Health Organization*, *98*(7), 484–494. https://doi.org/10.2471/BLT.20.254045

Zhang, B., & Zhu, Y. (2021). Comparing attitudes towards adoption of e-government between urban users and rural users: An empirical study in Chongqing municipality, China. *Behaviour & Information Technology*, *40(11)* , 1154–1168. https://doi.org/10.1080/0144929X.2020.1743361

Zheng, Y., Zhao, K., & Stylianou, A. (2013). The impacts of information quality and system quality on users' continuance intention in information-exchange virtual communities: An empirical investigation. *Decision Support Systems*, *56*(1), 513–524. https://doi.org/10.1016/j.dss.2012.11.008

Zhu, Y., & Kou, G. (2019). Linking smart governance to future generation: A study on the use of local e-government service among undergraduate students in a Chinese municipality. *Informatics*, *6*(4), 45. https://doi.org/10.3390/informatics6040045

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Appendix A. Measures of variables

Constructs	Items	Source
Personalization	P1. The chatbot can understand my specific moods and demands. P2. The chatbot can offer recommendations that match my demands and the situation. P3. The services provided by the chatbot are customized to my needs. P4. Through the interaction with the chatbot, I can get personalized therapies that are tailored to my mental issues.	Roy et al. (2017); Chen et al. (2021)
Voice interaction	VI1. The chatbot can talk to me like a human. VI2. The chatbot's voice sounds natural. VI3. The chatbot can fluently talk to me.	Ni and Wang (2019)
Enjoyment	E1. The interaction with the chatbot makes me feel pleasure. E2. I feel relaxed when I interact with the chatbot. E3. The interaction with the chatbot is enjoyable.	Lee et al. (2018)
Learning	L1. By interacting with the chatbot, I can enrich my understanding about AI. L2. I can acquire more knowledge about AI by using the chatbot. L3. The use of the chatbot can satisfy my desire for knowledge.	Teng (2018)
Condition	C1. I value the use of chatbot because the mental health hotline is not available. C2. I value the use of chatbot because I cannot go outside to receive therapy. C3. I value the use of chatbot because I cannot find any professionals to help me.	Omigie et al. (2017)
User experience	EP1. This chatbot tries to be emotional. EP2. This chatbot tries to be professional. EP3. This chatbot makes me feel better. EP4. The overall user experience of this chatbot is great.	Gentile et al. (2007)
User satisfaction	SA1. My choice to use this chatbot is a wise one. SA2. This chatbot never make me disappointed. SA3. Overall, my feeling to this chatbot is satisfactory.	Li and Fang (2019); M. Kim et al. (2015)