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What influences patients' continuance intention to use AI-powered service robots at hospitals? The role of individual characteristics[☆]

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ABSTRACT

AI-powered service robots have gradually developed into popular self-service agents in the health care industry. Though prior research has investigated what affects individuals' adoption of AI-powered service robots in the service industry, few have considered patients' continuance intention for AI-powered service robots at hospitals from the perspective of patients' characteristics. Drawing on the Technology Adoption Model and individual characteristics (i.e., trust in technology and independent personality), we develop a framework testing the factors influencing patients' continuance intention (CI) for AI-powered service robots at hospitals with Intelligent Guide Robots as an example. The model is validated using PLS-SEM analysis and data from 543 patients of a 3-A hospital in Eastern China. The study finds that patients' trust in AI techniques and independent personality positively influence their perception of usefulness (PU), ease-of-use (PEOU), and enjoyment (PE), respectively. Moreover, PU, PEOU, and PE are significant predictors of CI toward AI-powered service robots. PEOU and PE partially mediate the relationship between trust/independent personality and CI. The findings imply that organizations in the healthcare could try their best to increase users' trustworthiness toward AI techniques. In addition, developers could continuously upgrade AI-powered service robots to improve patients' PE and PEOU.

Author statement

Xiaohui Liu: Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Writing - original draft. **Mengmeng Wang:** Conceptualization; Investigation; Writing - original draft. **Xiaoyu He:** Writing - original draft; Writing - review & editing. **Huizhang Shen:** Supervision; Funding acquisition; Validation.

1. Introduction

The healthcare industry has widely adopted applications powered by Artificial Intelligence (abbr. AI) techniques in recent years, which not only facilitates physicians to diagnose and treat, make decisions, and do research [1–5] but also help patients to gain information they want to know efficiently. According to the report from Sage Growth Partners, 90% of hospitals in the US have an AI/automation strategy in place in 2020, compared with 53% in Q3 2019.[1] The healthcare industry would benefit from implementing AI techniques in increasing efficiency and reducing costs [6,7]. As a commonly used application of AI techniques, AI-powered service robots (hereafter refer to *service robots*), characterized by anthropomorphic human-computer interface and self-renewal ability of the knowledge base through deep learning algorithms, have provided to be convenient, fast, and precise patient service in healthcare organizations, which is an essential component of "smart hospitals" [8]. Specifically, the implementation of service robots can benefit both patients and hospitals in terms of reducing patients' waiting time, improving patients' satisfaction, increasing service efficiency, lowering the burden of nurses, and saving costs at the stage of outpatient service [5]. Therefore, healthcare executives are increasingly prioritizing service robots in hospitals.

However, despite the increasing attention paid to service robots, their implementation and scaling remain significant challenges for hospitals. For example, the report from Sage Growth Partners shows that 93% of cited hospitals' AI strategies are not fully operational, which

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[1] https://www.prnewswire.com/news-releases/new-report-finds-90-percent-of-hospitals-have-an-ai-strategy-up-37-percent-from-2019-301242756.html.

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implies that only a small group of early adopters intend to continuously use the service robots [9]. This low rate of continuing use service robots might put these benefits aside, wasting money as well as hindering the development of innovative hospitals. Consequently, exploring factors and mechanism influencing patients' adoption and continued usage of service robots at the outpatient stage would be crucial of solving such questions in healthcare industry.

Though prior studies about technology adoption in the healthcare industry have explored technological innovations in the likes of hospital information systems [10,11] or the decision support systems [4], few research focus on the adoption of service robots in such field. Thus, managers may need some guidance on successfully attracting potential new users and retaining existing users of the service robots in the healthcare sector. In order to shed some light on this underdeveloped research field, we propose a research framework to help managers better understand patients' decisions to use AI service robots at hospitals continuously.

This study focuses on the determinants of patients' continuance intention to use AI service robots in outpatient-service settings and proposes a research framework based on the Technology Adoption Model (TAM). Due to its ability to easily explain and greatly extent users' adoption behaviour, TAM has been regarded as one of the best frameworks to study users' reactions toward technological innovations [12]. Prior literature has verified the explanation power of TAM in various contexts, such as in finance settings [12,13] and food services [14] in terms of service robots [13]. also claim that TAM is applicable regardless of time, settings, populations, and the technologies. Consequently, we believe that TAM is suitable for explaining users' continuous intentions of AI service robots in the healthcare settings.

Particularly, we integrate characteristics of human into the TAM model to study patients' continuance intention of service robots. Both [7,15] proposed that customer characteristics are determinants of their acceptance behaviour. Additionally, previous study has emphasized the need to investigate the role of individual characteristics on users' decisions to adopt new technologies [7,16], which inspires us to conduct this study by integrating individual characteristics with TAM.

Regarding to the first characteristic - the trust in AI techniques, we posit that patients' continuous usage intention of service robots may vary across patients' different levels of trust in AI techniques. Previous studies on human-robot interaction have verified the determinant role of individual trust in AI techniques [1,2]. In the healthcare context, during the interaction with new technology, patients may feel uncertain about the risk of delegating tasks to service robots since they may think that such human programs may not be flexible while taking the responsibility compared with humans [17,18]. However, with trust in AI techniques, patients may perceive lower levels of uncertainty and risks for using this new AI related technology [19]. Therefore, it is reasonable to assume that trust in AI techniques is essential in continuously using service robots at hospitals. This study highlights the need to understand the function of trust in AI techniques in patients' continuance intention of service robots within the healthcare field.

Moreover, we consider a new personality due to the specialty of the outpatient services in China, that is, the independence which has not been explored in previous literature. Previous study has shown that personality traits may be crucial for users' attitudes toward service robots [20–22], such as the extroverted, openness, and conscientiousness personality traits [21,22]. In the stage of outpatient service in China, both nurses and service robots are available for patients, and they are free to choose either with meagre hassle costs. Patients with independent personality might prefer to reach out to robots instead of human-to-human interaction services since they do not like asking for help [23]. In addition, concerns about AI techniques have existed inevitably since it was born, such as the safety of AI robots [2]. People with the independent trait may be apt more to answer for the consequences of their actions, take risks and form new habits [23], making them more willing to accept new technologies. Therefore, the independent personality may be a vital factor impacting patients' continuance intention of using service robots. Previous studies on personality have mainly elucidated the role of the Big Five personalities in affecting continuance intention, for example, openness to experience [24] and concentration [25]. However, few researchers have paid attention to the role of independence played in the continuous usage of AI techniques.

Consequently, we propose an integrated model based on TAM to examine whether patients' characteristics as the antecedents to patients' perception can affect their continuance intention of service robots at hospitals in healthcare systems. This study posits that patients' continuance intention of the service robots is dependent on their perceived usefulness (PU), perceived ease-of-use (PEOU), and perceived enjoyment (PE). Besides, patients' trust in AI techniques and personality of independence positively affect their PU, PEOU, and PE. We develop a research model to confirm the above belief and validate the determinant role of trust in AI techniques and personality of independence on PU, PEOU, and PE, which affect users' intention to use the service products powered by novel technology. In addition, a questionnaire survey was conducted among patients in a representative hospital in Eastern China to provide a sample for estimation.

The contribution of this research to previous IS literature on continued usage intention of service robots is twofold. First, we extend TAM in the adoption of service robots in healthcare industry by integrating characteristics of patients with TAM (i.e., trust in AI techniques and independent personality), which identifies new important determinants of patients' continuance intention of service robots in the healthcare industry. The results demonstrate that patients' trust in AI techniques and personality of independence positively affect their PU, PEOU, and PE, respectively. Besides, patients' continuance intention of the service robots remains dependent on their PU, PEOU, and PE. Second, this study enriches technology adoption literature by undermining the mediation role of PE and PEOU between patients' characteristics and their continuance intention toward service robots. Our finding shows PE and PEOU partially mediated the relationship between two individual factors and patients' intention on adopting service robots continuingly. The mediation effect helps to explain such behavioural intention from a broader scope.

In practice, our findings may benefit both hospitals and the general public in terms of reducing human costs and the burden of outpatient traffic for hospitals, enhancing patients experience, and improving service quality of patient care as well as the efficiency at all levels of hospital service. Importantly, this research identifies the determinants of patients' continuance intention of service robots, which can help managers and practitioners improve the understanding of patients' perception of AI service robots, thus guiding the successful implementation of AI service robots in the healthcare sector.

2. Theoretical background and literature review

2.1. AI-powered service robots

The usage of AI-powered service robots is an emerging phenomenon at present among the growing frontline of AI-based technologies [6,7,26,27]. AI-powered service robots (i.e., service robots) have multiple definitions [28–30]. Combining with the service encounter in this study, we adopt [30]'s definition, namely, "*system-based autonomous and adaptable interfaces that interact, communicate, and deliver services to an organization's customers*" (p.909). Service robots have significantly impact on end-user engagement [16]. They are capable of providing basic services and basic information about the focal service encounter, thus providing a convenient, efficacy, and efficient experience for end users [7]. The growing application of service robots has promoted an emerging subject of research about factors affecting their adoption among end-users [15]. In line with the three-part framework of service robots proposed by Ref. [7], past studies have been conducted on the antecedents of users' adoption behaviour from the perspective of individual features [31,32], characteristics of AI devices [33], and service encounter characteristics [34] within various contexts in the likes of tourism [35], hospitality [36], and store-based retailing [37], and healthcare [38].

However, a relatively limited number of studies have investigated the antecedents of users' continued usage intention of service robots in the context of the healthcare industry, though the growing number of service robots has been implemented in this industry [1,39,40]. For instance, Ref. [39] have shown that the feature of a service robot, the polite speech it used, may increase users' satisfaction with healthcare service. Ref. [40] identified key features of service robots through a literature review which could refer to the successful factors of users' adoption of service robots in the healthcare field. While considerable knowledge is available to understand the antecedents of adopting service robots in the healthcare industry, there is a paucity of studies that theoretically explore users' continuance usage in the healthcare encounter.

Moreover, the characteristics of the healthcare industry in China spur us to do this study. Generally speaking, Chinese patients cannot access healthcare services with a referral from a family doctor, and they have to consult with nurses or doctors if they want to know what specialty they need to visit. Therefore, outpatient service has been an integral part of Chinese hospitals. Clinics and medical care providers usually face numerous outpatients every day. However, there is relatively few nursing personnel to triage outpatients upon arrival. This conflict in supply and demand and the high-level repetitive make the healthcare industry need more patients to actively adopt and use the service robot so that the managers can improve operational efficiencies of hospital management and provide satisfactory services for patients [41]. Implementing service robots is a good way for medical healthcare organizations to realize the transformation from high-level outpatients' medical service to organizational patient-centred management efficiencies [8].

Therefore, by investigating the factors underlying characteristics of patients and their interaction with service robots, researchers potentially induce patients to engender successfully continued usage of service robots and enable the further application of such AI-powered products in the healthcare industry. This study attempts to integrate individual characteristics with TAM for investigating patients' adoption of service robots in healthcare industry, which can be considered as a kind of context-specific theorizing.

2.2. Technology Acceptance Model (TAM)

Several existing studies about the continued usage of services or products through variables like perceived usefulness (PU), perceived ease-of-use (PEOU), and perceived enjoyment (PE) based on AI techniques have utilized the traditional Technology Acceptance Model (TAM) and extended TAM [42,43]. For example, [44] investigated teachers' attitudes toward using AI applications in high education by drawing on TAM [45]'s study utilized the tenets of the extended unified theory of acceptance and use of technology (UTAUT2) and explored factors influencing consumer adoption intention of an AI-Powered Chatbot for health management. TAM has been regarded as one of the best frameworks to understand users' response toward technological products or services. However, some researchers argued that the original technology theories were developed for studying non-intelligence technology products [31] insomuch that some predictors reflecting AI-powered technology products should be involved based on traditional acceptance theories [46]. For example, [29] examined how structural differences between experience and credence attributes in different service encounters affect consumers' adoption intention of service robots by drawing on TAM and two additional antecedents (privacy concerns and trust) [30]. proposed that users' acceptance of service robots can be affected by three elements, functional element (e.g., PE, PEOU, and PE), relational elements (e.g., trust in services), and social-emotional elements (e.g., embarrass).

Though these studies combined factors with the important common constructs that present in TAM or extended TAM to bring some new theoretical views, few studies have integrated individual-related factors influencing patients' continuous intention of using service robots in the healthcare industry. Therefore, this study tries to go into the research gap by employing variables in TAM and integrating individual characteristics related to patients' attitudes toward service robots at hospitals to understand patients' adoption of service robots in healthcare fields.

2.3. Trust in AI techniques and continuance intention

In a broad sense, trust is defined as a "confident relationship with the unknown or unfamiliarity" [47]. Most Information System (IS) scholars have agreed that trust is a critical reason that users enjoy using technology-powered services or products, perceiving the focal service or product as applicable, depending on it, and continuously using it [48]. In this vein, prior studies have revealed that trust serves as a crucial antecedent for the continuance intention of technological products or services [49] and conceptualized it from three perspectives to explore its relationship between humans and technology, namely trust in venders [50], trust in products/services [51], trust in technology [25,52].

As for AI-based technology, an emerging novel technology being developed at a rapid pace, products or services developed by such technology are more likely to face individuals' trust attitudes toward AI because trust is especially critical in the early stage of developing a novel technology [53]. Therefore, trust in technology is the most critical variable influencing users' intention to continue using AI-powered services or products [54]. In addition, people are aware of the ethical implications of AI techniques, such as the ethical concerns over its unintended impacts, the acceptance of machines, and the lack of massive experiential data, which has hindered individuals' engagement with AI-powered services or products [2]. Prior literature has investigated factors increasing individual's trust in AI techniques in e-commerce, hospitality, etc. [32]. However, on the antecedents' side, the role of trust in AI techniques in affecting individuals' attitudes and continued usage of AI-based techniques is also worthy of research [55], especially for service robots which implemented widely at present. Therefore, this study investigates the impact of patients' trust in AI techniques on their continued intention to use service robots in the healthcare industry.

2.4. Personality and continuance intention in the context of the healthcare industry

Personality is a common psychological construct that reflects a stable set of human characteristics, defines human essence, and reflects human thoughts and behaviour. Therefore, it is reasonable to expect that personality will predict human cognition and behaviour in IS-related processes and outcomes [56]. Several past studies on technology adoption have already investigated the relationship between personality traits and human's adoption behaviour from the perspective of the Five-Factor or "Big Five" model of personality (i.e., neuroticism or emotional stability, extraversion, openness, agreeableness, and conscientiousness) [57–60]. As for the adoption of technological products developed by AI, Scholars have conceded that individual personality traits are crucial for affecting human attitudes and behaviour intentions toward AI-powered service agents [7,20]. For example, [21] showed that extroverted people are inclined to satisfy the AI-powered service when interacting with the same automated agents in the focal service encounter.

However, several researchers have explored other personality traits, especially independence, a kind of personality trait that plays a critical role in continuing use service robots in the healthcare industry. Specifically, independence is a kind of personality trait in which "a person consistently prefers to act on his or her thoughts and feelings than taking in the views of others" [23]. Hospitals disposed of service robots for guiding patients would keep artificial service windows if some patients are not suitable for leveraging service robots. However, hospital managers still hope patients can complete routine work with the help of service robots while seeing a doctor. Their goal in disposing service robots in hospitals is to improve service and work efficiency and use human resources sparingly. In this sense, patients enabled to complete work without relying on others are willing to continue to use service robots. Conceivably, the independence trait is crucial in individuals' continued behaviour in the health care industry. Therefore, this study attempts to probe the impact of patients' personality independence on their PU, PEOU, PE, and CI of service robots in the hospital.

3. Research model and hypotheses

The research model was developed by incorporating trust in AI techniques, independent personality, and TAM to investigate the influence of two individual characteristics on service robots' continued use in the healthcare field. Hypotheses in this study were derived as shown in Fig. 1.

3.1. PU, PEOU, PE, and continuance intention

PU is defined by Ref. [42] as "the degree to which a person believes that using a particular system would enhance his or her job performance." Many studies find that PU positively impacts users' continuous intention to use the new technology [42,60,61]. It is asserted that PU is one of the extrinsic motivations to use the technology [13] continuously. In the case of service robots at a hospital, performance refers to patients' benefits from using the service robots, such as providing instant service support to solve problems or offering real-time information to save time [5]. Once they have perceived the value of service robots, based on the literature, we posit that patients will have a solid intention to continue using this technology [43,62,63].

PEOU refers to "the degree to which a person believes that using a particular system would be free of effort" [42]. Prior literature has also found that it is also a pivotal determinant in technology continuous intention use of new technology [13,43,50,64]. In the context of healthcare, service robots with a straightforward operation interface and efficient communication may allow patients to complete their tasks with less effort. Furthermore, if patients perceive the ease of use of the service robots, they are more prone to perceive low hassle costs of understanding the instructions and continue to use the new technology [65,66]. Therefore, we argue that if service robots are easy to use, patients will be more likely to use them continuously.

It shows that the more manageable the technology is to use, the less effort is needed for patients to operate it, and the more effort they can allocate to other tasks [67]. For easy-to-use service robots, patients may have high performance and perceive a high level of usefulness of the service robots [42]. Thus, we assert PEOU has a positive impact on the PU of service robots. Besides PU and PEOU, PE relates to the perceptions of pleasure and satisfaction when adopting the technology [68], which directs to the intrinsic motivation for patients' continuous usage of new technology [13,43]. If patients have a fun and enjoyable experience when using service robots, they may positively think about the product [69]. Thus, we argue that patients may be more prone to continue using them. Accordingly, we have the following hypotheses:

Hypothesis 1a. PU positively affects patients' continuance intention of AI-powered service robots at hospitals in the healthcare field.

Hypothesis 1b. PEOU positively affects patients' continuance intention of AI-powered service robots at hospitals in the healthcare field.

Hypothesis 1c. PEOU positively affects PU.

Hypothesis 1d. PE positively affects patients' continuance intention of AI-powered service robots at hospitals in the healthcare field.

3.2. Trust in AI techniques

Generally speaking, individuals' trust in technology refers to specific beliefs about how technology operates in a work environment [25]. Researchers also consider it as a critical factor influencing individuals' cognitive effect and approach behaviour on continued usage of information technology artifacts [1,2,70], such as information systems, e-commerce, and e-government. In terms of AI techniques, this study draws upon [71]'s research and refers trust in AI techniques as individuals' judgment or expectation of AI technology's helpfulness, reliability, and functionality within service robots in the healthcare industry [71].

First, patients' expectation of the helpfulness of AI techniques enables them to believe that service robots can provide valuable guiding services and expected information, which enhances their perception of the usefulness of service robots [72]. Suppose patients cannot trust AI techniques to perform effective information-seeking tasks, return accurate information, or provide influential registration services [29]. In that case, they will be more likely to suffer an efficiency loss from using service robots. As a result, there is no reason for patients to perceive the usefulness (PU) of service robots.

Second, patients' expectations toward the functionality of AI techniques will enable patients to comprehend the process using service robots without much effort [29]. When patients trust AI techniques, service robots provide them with a variety of convenience in processing their tasks due to their belief in the functionality of AI techniques. For instance, perceptions of functionality would enable patients easily handle the task-processing, promote learnability of seeking desired

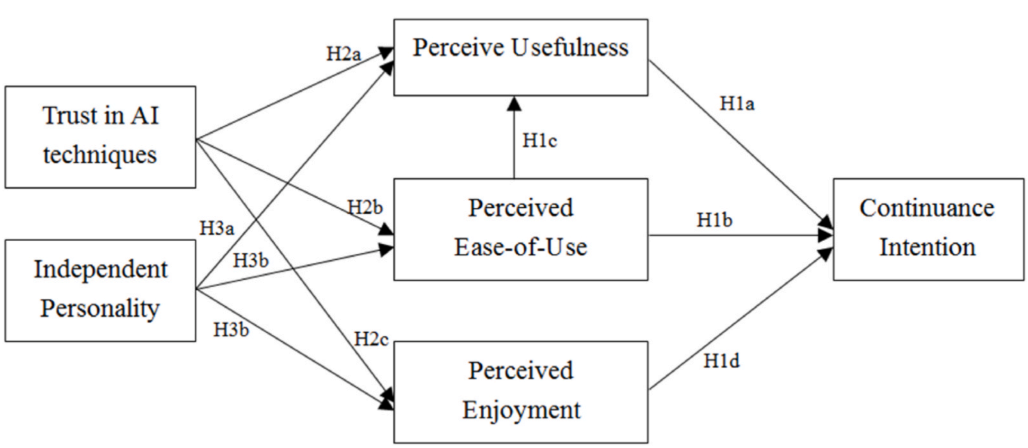

Fig. 1. Research model.

information, and require little mental effort [7]. It would reduce the need for patients to understand, monitor, and control the information-seeking or transaction circumstance, thereby attenuating time and effort [8]. It is reasonable to assume that a patient who trusts in AI techniques will perceive a high likelihood that using service robots will minimize their efforts to deal with the focal products. As a result, increasing trust in AI techniques improves the PEOU towards service robots.

Third, patients' expectations of the reliability of AI techniques will help them obtain entertainment from reducing their perceived risk in using service robots [55]. Perceived risk toward service robots is a pivotal factor resulting from individuals' perception of the trustworthiness of technology, as perceived reliability overcomes the doubtfulness perceived in continued usage of AI-powered products [2]. In this vein, patients' trust in AI techniques will promote them to regard service robots as reliable products and decrease the subjective probability of adverse outcomes during the usage process. Thus, they are more willing to explore various functions of service robots. As long as they concentrate on user experiences, they will probably enjoy using such service robots.

Thus, it can be hypothesized that:

Hypothesis 2. Patients' trust in AI techniques positively affects their (a) perceived usefulness; (b) perceived ease of use, and (c) perceived enjoyment of AI-powered service robots at hospitals in the healthcare field.

3.3. *Independent personality and continuance intention*

Individuals characterized with an independent personality prefer to act on their thoughts and feelings, learn new technologies free from all inhibitions, and complete tasks without any help [23]. In this sense, patients with independent personality would be inclined to operate service robots, a novel self-service product compared with conventional hospital staff service. Notably, patients with higher independent traits are more confident in comprehending the functionalities of service robots, which enables them to carry out various tasks (e.g., registration and consultation) efficiently on their own [55]. Moreover, it would facilitate them digging out the helpfulness of service robots, promoting them perceiving high-performance in achieving their task goal.

In addition, individuals with independent personalities tend to explore technological products deeply due to their inclination to complete works autonomously [73]. With such exploration, they would master service features of such novel service speedy [22]. Conceivably, patients with high-level independence are more likely to possess smooth experience in using service robots. It would facilitate patients to carry out their tasks with less effort and time, which is easier to induce the perception of ease of use.

Furthermore, influenced by their willingness to learn new technologies, patients with high-level independence are more likely to enjoy activities about exploring novel products or services [22] and have fun when using service robots. Moreover, with the novelty of AI techniques, service robots usually are configured in attractive interaction interfaces. Therefore, patients' interaction with the service robots promotes them to obtain entertainment. As long as they feel the fun and are engaged in enjoyable mental conditions, they will perceive enjoyment in using service robots.

Building upon these findings, we hypothesize:

Hypothesis 3. Patients' independent personality positively affects their (a) perceived usefulness; (b) perceived ease of use, and (c) perceived enjoyment of AI-powered service robots at hospitals in the healthcare field.

4. Methodology

We conducted a questionnaire survey to test our research model on Chinese patients at an exemplary hospital named APH in East China, a 3-A hospital representing one of China's best hospitals. The hospital successfully implied Intelligent Guidance Robots (IGRs) named Xiaoyi, developed by iFlytek,[2] which is a leading AI company in China since 2017, a typical example of AI-powered service robots in the medical healthcare encounter [8]. Xiaoyi was designed to improve outpatients' self-serving utility and reduce human-to-human interactions at hospitals [8]. The cloud language library has been put into Xiaoyi to answer various hospital-related and disease-related information, and deep learning algorithms have been developed to achieve self-learning in order to understand patients' needs better. Specifically, Xiaoyi can use voice interaction to provide consultation services in the likes of directions and navigation functions, connect with the hospital scheduling system in real-time to capture, analyse patient information, make initial diagnostics, and direct patients to related departments. Due to the characteristics of the medical healthcare system in China, it is unique that hospital practice in China needs to triage patients (especially for outpatients) at the hospitals' lobbies. Specifically, outpatients need guidance and triaging upon arrival, then be directed to the appropriate departments. Therefore, hospitals require a specialized workforce to perform these highly repeated, mobility, and low-risk tasks. Therefore, Xiaoyi plays an important role in releasing the burden of employers and reducing patients' waiting time in high-demand periods [5], which eases the burden of traditional human-to-human interactions and improves the outpatients' satisfaction [8]. However, many patients still prefer human workers in the outpatient service, around 89%, according to a survey in2017.[3] Even with highly efficient and more accurate IGRs, this reality makes our research that explores factors of influencing the continued usage intention of service robots more meaningful in practice.

In the questionnaire survey, each participant was asked to confirm that they had an actual interaction with IGRs at APH. Only experienced patients can continue to answer questions about their perception on trust in AI techniques, independent personality, usefulness, ease of use, enjoyment, and continued usage intention of IGRs. The collected data was analysed by partial least squares structural equation modelling (PLS-SEM) to confirm hypotheses.

4.1. *Measurement*

The measurements for most variables were adapted from previous studies. Six constructs are used in this study: trust in AI techniques (TRAI), independent personality (IND), perceived usefulness (PU), perceived ease-of-use (PEOU), perceived enjoyment (PE), and continuance intention (CI). The items were measured with a seven-point Likert scale, ranging from 1 (strongly disagree) to 7 (strongly agree). Trust in AI techniques was measured based on the items from Ref. [54]. The measurement of personality independence was adapted from Ref. [74]. The measurements of PU, PEOU, PE, and CI were based on prior research about TAM [62,75–77]. Measurement items in the research model are shown in Table 1.

4.2. *Sample and data collection*

An offline survey design was employed to collect data on all constructs by utilizing a multistage iterative process. In the offline survey, we obtained informed consent from all participants at first. Specifically, the questionnaire in the survey was drafted and circulated among 50 respondents with IGRs experience to pre-test the survey. Respondents' feedback helped us modify any awkward wording, ambiguous expressions, and distortions of the original meanings in the questionnaire. After that, with the help of nurses, we collected data from outpatients who had an actual interaction with IGRs at the focal hospital. Nurses

[2] https://en.wikipedia.org/wiki/Xiaoyi_(robot).
[3] http://www.buzhibushi.com/info/UtE4P2gks0k=.

Table 1
Means, standard deviations, factor loadings of constructs.

Construct	Item ID	Items	Mean	Std.	Loadings
Trust in AI techniques (TRAI)	TRAI 01	AI products bring considerable benefits to humans, and I believe in the power of technology.	6.126	1.037	0.751
	TRAI 02	I believe that AI products will protect my privacy.	5.508	1.323	0.737
	TRAI 03	I believe that AI products will not abuse my personal information.	5.585	1.299	0.730
	TRAI 04	I believe that AI products will provide me with more high-qualified information and services.	5.754	1.151	0.856
Independent Personality (IND)	IND01	My reaction to things in normal life is quite resolute.	5.517	1.249	0.823
	IND02	I am an independent person in life and work.	5.377	1.394	0.798
	IND03	I do not prefer relying on other people.	5.418	1.388	0.741
Perceived Usefulness (PU)	PU01	I think IGRs enables me to get healthcare service faster.	6.039	1.116	0.812
	PU02	I think IGRs increases my productivity during health service process.	5.967	1.132	0.811
	PU03	I think IGRs are useful for searching and obtaining the information I need.	5.952	1.069	0.842
	PU04	I think IGRs improve my performance.	5.868	1.165	0.823
Perceived Ease-of-Use (PEOU)	PEOU01	I feel it is easy to learn and use IGRs.	5.693	1.256	0.829
	PEOU02	I feel the operation interface of IGRs is clear and understandable.	5.797	1.173	0.860
	PEOU03	I feel IGRs is very easy to use.	5.580	1.277	0.821
Perceived Enjoyment (PE)	PE01	The process in using IGRs is enjoyable.	5.647	1.221	0.877
	PE02	The process in using IGRs is exciting.	5.359	1.357	0.855
	PE03	To use IGRs makes me pleasant.	5.555	1.266	0.876
Continuance Intention (CI)	CI01	I prefer continuing using IGRs to stop using it.	5.608	1.214	0.858
	CI02	I will continue using IGRs rather than using traditional manual methods.	5.580	1.241	0.763
	CI03	I am not going to use IGRs any more (Reverse code).	5.589	1.271	0.811

took students we recruited to meet participants who were randomly sampled based on their treatment ID, and then students would explain the purpose of this study to them in detail and wait for them to return the questionnaire as soon as they finished. To encourage their responses, we provided gifts like a towel and toothpaste to them for taking up their time.

Consequently, with full support from APH, all participants filled the questionnaire carefully. Among the 600 returned completing a questionnaire, we discarded 57 questionnaires completed within 10 min. This study tossed those samples because more than 90% of participants in the pre-test needed more than 10 min to finish the questionnaire. Therefore, we believed that patients who completed the questionnaire within 10 min were likely to provide poor-quality responses. Besides, we discarded the responses with the same values for most items. The final sample comprised 543 complete responses, excluding the pre-test data. Table 2 shows the descriptive statistics of the patients' demographic information.

4.3. Data analysis

Smart PLS 3.0 was used to evaluate measurement quality and estimate the research model [78]. Generally, Partial least squares structural equation modelling (PLS-SEM) was used to validate hypotheses by simultaneously evaluating the measurement quality and constructing interrelationships, i.e., measurement and structural models. Considering that this study explores determinants of patients' continuance intention of using service robots, PLS-SEM, a powerful data analysis technique for theory building, is suitable to validate our research model. Moreover, the sample number of this study passed the minimum requirements of sample size when using PLS-SEM.

5. Results

Since all data were perceptual and simultaneously collected from a single source, standard method variance posed a threat to the validity of this study. To test this bias, we conducted Harman's single test and compared the fit between the one-factor model and measurement model to check for potential standard method bias [79]. Exploratory factor analysis (EFA) performed Harman's single test [80]. The results (see Table 1 in Appendix A) showed that six distinct factors with eigenvalues of more than 1.0 explained 60.72% of the total variance. The first factor explained not the majority of the total variance (30.71% of variance), which indicates that the standard method variance was not likely to be a severe problem [81,82] (see Table 2 in Appendix A). The results of both methods indicated that common method bias was not a severe issue in the current dataset.

To ensure that no risk of multicollinearity existed in this study, we tested the data and found that none of the inter-construct correlations was above 0.900 [83]. Besides, the test results indicated that the variance inflation factor (VIF) of all constructs varied between 1.297 and 3.142, which was well below the commonly accepted benchmark value of 3.3 [84]. Therefore, it suggests that multicollinearity was not severe in our dataset.

5.1. Assessment of global model fit

According to Ref. [85]'s recommendation, the evaluation of the overall fit of the saturated model should be the first stage of PLS model assessment, which tests whether or not the model fits the data. Therefore, we used smart PLS 3.0 to perform a complete bootstrap-based test

Table 2
Demographic statistics [N = 543].

Category		Number	Percentage (%)
Gender	Male	284	52.3%
	Female	259	47.7%
Age	<18 years	6	1.1%
	18–28 years	143	26.3%
	28–48 years	173	31.9%
	48–60 years	109	20.1%
	>60 years	112	20.6%
Educational background	Elementary school	64	11.8%
	Middle school	168	30.9%
	High school	133	24.5%
	College	161	29.7%
	Graduate school	17	3.1%

of model fit [86] to get three measures, namely, the standardized root mean squared residual (SRMR), the unweighted least squares discrepancy (dULS), and the geodesic discrepancy (dG). Then we compared these three values with bootstrap-based 95% (HI95) or 99% (HI99) percentiles. It can be validated that the research model is accurate only when all values are less than HI95 or HI99 [85]. Table 3 shows that the three measures of the saturated model fit are below HI99, implying that our research model cannot be rejected. Additionally, following [85]'s recommendation, SRMR was used as the approximate model fit criterion to evaluate the discrepancy of the empirical correlation matrix with the model-implied correlation matrix, in which an SRMR value is suggested to be less than 0.080, an adequate fit threshold for PLS-SEM path models. Our model's SRMR value of 0.046 demonstrated a relatively adequate model fit.

5.2. Measurement model

The measurement model was evaluated for convergent validity by assessing item loadings, composite reliability (CR), Cronbach's alpha, Dijkstra–Henseler's indicator (Rho_A), and average variance extracted (AVE) [87]. First, the reliability of each construct was assessed by evaluating CR, Cronbach's alpha, rho_A, and AVE. Table 1 shows that all standardized item loadings exceed the suggested value of 0.700 [88], and the values of rho_A are greater than 0.700 [88]. In addition, AVE values for all constructs were higher than 0.500 [89]. Similarly, CR and Cronbach's alpha for each construct were well above the minimum threshold of 0.700 [88], indicating satisfactory internal consistency.

Second, we tested for discriminant validity by three methods. For one thing, according to the recommendation of [90]; we estimated whether the AVE score on each construct is higher than the squared correlation shared with all other constructs. The results in Table 4 confirmed discriminant validity. We also assessed discriminant validity by the cross-loadings [85]. As displayed in Table 5, the loading coefficients of each construct are higher than other coefficient loadings. Additionally, we assessed discriminant validity by Heterotrait-Monotrait Ratio (HTMT), and the results in Table 6 show that the HTMT ratio of all latent variables are below 0.90 [85], indicating sufficient discriminant validity between the two constructs.

5.3. Structural model

This study employed the structural model through PLS-SEM analysis which adopted a bootstrapping procedure with 2000 iterations to determine the statistical significance of the path coefficients. The parameter estimated in the structural model demonstrates the direct effects of one construct on the other. Moreover, a significant coefficient at a certain level reveals a meaningful relationship between the latent variables. Fig. 2 and Table 7 present the results regarding testing the direct hypotheses, which support most hypotheses.

Specifically, H1a, H1b, H1c, and H1d were developed for estimating TAM in the context of service robots in healthcare industries. Specifically, H1a, which hypothesized a positive relationship between PU and patients' CI of using service robots, was supported (path coefficient = 0.371, p = 0.000). H1b hypothesized a positive relationship between PEOU and patients' CI was supported (path coefficient = 0.387, p = 0.000). H1c, which hypothesized the positive impact of PEOU on PU, was supported (path coefficient = 0.390, p = 0.001). The significant positive effect of PE on CI of using service robots (path coefficient = 0.179, p = 0.000) showed that H1d was supported. Patients' trust in AI techniques has positive and significant effects on PU (path coefficient = 0.651, p = 0.000), PEOU (path coefficient = 0.548, p = 0.000), and PE (path coefficient = 0.501, p = 0.000), supporting H2a, H2b, and H2c, respectively. As predicted by H3a, H3b, and H3c, confirmation of independent personality significantly influenced patient PU, PEOU, and PE with path coefficients of 0.178 (p =0.042), 0.229 (p =0.000), and 0.226 (p =0.000), respectively. Patients' PU, PEOU, PE, trust in AI techniques, and independent personality explained 50.70% of the variance in the CI of using AI-powered service robots. All these indicators showed that the model fits the data well.

Table 3
Assessment of global model fit.

Measures	Value	HI95	HI99
SRMR	0.046	0.049	0.051
dULS	0.580	0.667	0.711
dG	0.268	0.315	0.333

Notes.
SRMR = standardized root mean squared residual; dULS = unweighted least squares discrepancy; dG = geodesic discrepancy; HI95 = bootstrap-based 95% percentile; HI99 = bootstrap-based 99% percentile.

The values examined the structural model evaluation for the variance explained (R^2), beta value, and identical t values, as well as the effect size (f^2) [91]. The R^2 value of 50.70% for our model's dependent variables is considered moderate and strong [92]. For evaluating the predictive relevance, we used Stone-Geisser's blindfolding test by testing whether or not the values for predictive relevance are more significant than zero [93]. The Q^2 value of 0.294 (CI) implied that the proposed conceptual model has high predictive validity. In order to evaluate how much an exogenous latent variable contributes to an endogenous latent variable's R^2 value, we adopted effect sizes which are evaluated to measure the size of the relationship between latent variables. In line with the guidance of [94]; the effect sizes of all significant paths were estimated and presented in Table 7.

5.4. Post-hoc analysis

To test whether or not the influence of trust in AI techniques or an independent personality on CI is mediated by PU, PEOU, and PE, we followed the steps for testing the mediation effect recommended by Ref. [95]. The findings were extracted from PLS-SEM by conducting bootstrapping procedure with 5000 recommended by Ref. [96]. Following the suggestion of [95]; we first confirmed whether or not the significance of the direct effect without the inclusion of the mediator and the indirect effect due to the inclusion of the mediator are apparent. All direct and indirect effects were significant in this study, with a 95% confidence interval excluding zero. Furthermore, we assessed Variance Accounted For (VAF) values to evaluate the strength of mediation, which can be calculated by dividing the coefficient of the indirect effect over the total effect [95]. According to studies by Ref. [95]; one can interpret VAF value in the following way: complete mediation occurs when the value is above 80%, partial mediation occurs when the value is between 20% and 80%, no mediation occurs when the value is below 20%. Table 8 summarizes the paths, direct and indirect effects, and any significant mediation effects. Regarding the mediating effect of trust in AI techniques on CI, there is a partial mediation by PEOU and PE, respectively, which means PEOU or PE counts for some but not all of the relationships between AI techniques and CI. Similarly, the mediation effect of independent personality on CI is partially mediated by PEOU and PE, respectively, which means that PEOU and PE count for some but not all the relationship between independent personalities on CI.

6. Conclusions

6.1. Discussion of findings

Patients' continued usage of service robots play a significant role in improving hospitals' operational efficiency and patients experience during a hospital visit [8]. Therefore, this research explored factors influencing patients' continuance intention towards service robots in the healthcare industry. These findings suggest the following four

Table 4
Measurement Model: reliability and convergent validity.

Constructs	AVE	Composite Reliability	Crombach's Alpha	Rho_A	TRAI	IDP	PU	PEOU	PE	CI
TRAI	0.567	0.839	0.746	0.760	0.725*					
IND	0.623	0.832	0.705	0.727	0.430	0.789*				
PU	0.676	0.840	0.840	0.840	0.582	0.472	0.774*			
PEOU	0.701	0.875	0.787	0.743	0.631	0.498	0.674	0.756*		
PE	0.756	0.808	0.839	0.771	0.664	0.498	0.658	0.723	0.822*	
CI	0.658	0.728	0.743	0.707	0.607	0.491	0.612	0.660	0.738	0.753*

Notes.
1. TRAI = Trust in AI techniques; IND = Independent Personality; PU = Perceived Usefulness; PEOU = Perceived Ease-of-Use; PE = Perceived Enjoyment; CI = Continuance Intention.
2. AVE stands for average variance extract.
3. * the bold number is the square root of AVE.

Table 5
Discriminant validity: Cross-loadings for the Measurement Model.

	TRAI	IND	PU	PEOU	PE	CI
TR01	0.751	0.382	0.686	0.556	0.532	0.526
TR04	0.737	0.355	0.469	0.449	0.445	0.353
TR05	0.730	0.312	0.438	0.412	0.423	0.356
TR06	0.856	0.411	0.625	0.554	0.562	0.455
IND01	0.456	0.823	0.467	0.491	0.521	0.424
IND02	0.305	0.798	0.368	0.374	0.337	0.266
IND03	0.342	0.741	0.313	0.323	0.311	0.26
PU01	0.572	0.354	0.812	0.587	0.575	0.524
PU02	0.582	0.429	0.811	0.604	0.615	0.547
PU03	0.642	0.403	0.842	0.648	0.575	0.476
PU04	0.629	0.454	0.823	0.600	0.551	0.473
PEOU01	0.49	0.433	0.581	0.829	0.605	0.534
PEOU03	0.642	0.413	0.725	0.860	0.682	0.568
PEOU04	0.482	0.461	0.537	0.821	0.561	0.461
PE01	0.598	0.482	0.647	0.673	0.877	0.579
PE02	0.507	0.436	0.569	0.581	0.855	0.496
PE03	0.572	0.422	0.619	0.673	0.877	0.489
CI01	0.547	0.373	0.575	0.594	0.594	0.858
CI02	0.424	0.325	0.475	0.473	0.444	0.763
CI03	0.365	0.313	0.424	0.433	0.397	0.811

Notes.
TRAI = Trust in AI techniques; IND = Independent Personality; PU = Perceived Usefulness; PEOU = Perceived Ease-of-Use; PE = Perceived Enjoyment; CI = Continuance Intention.

Table 6
Discriminant validity: Heterotrait-Monotrait Ratio (HTMT).

	TRAI	IND	PU	PEOU	PE
IND	0.658				
PU	0.609	0.627			
PEOU	0.890	0.712	0.734		
PE	0.821	0.641	0.752	0.841	
CI	0.837	0.642	0.818	0.778	0.771

Notes: TRAI = Trust in AI techniques; IND = Independent Personality; PU = Perceived Usefulness; PEOU = Perceived Ease-of-Use; PE = Perceived Enjoyment; CI = Continuance Intention.

significant outcomes.

First, if patients find a service robot useful, easy to use, and enjoyable, they are eager to continue using it. The significant path between PU/PEOU and CI revealed that PU and PEOU are crucial predictors for continuance intention. Moreover, the positive and significant path from PEOU to PU demonstrated that when service robots is deemed to be easy to use, patients can identify the robots' high-performance and perceive a high level of usefulness of the service robots. Findings mentioned above is in conformity with the original TAM theory [5,43]. Besides, the significant positive path between PE and CI demonstrated that PE is a necessary antecedent for patients' continuance intention, which is consistent with the results of [97]'s study.

Second, in the context of self-service at hospitals, if a patient believes AI techniques provide reliable information, prompt responses, and offer effective service, there is a positive influence on users' PU, PEOU, and PE toward service robots [1,7,98]. It, in turn, affects their continued intention of using such self-service robots. This study provides valuable insight into why individuals' trust in AI techniques is a crucial predictor of their perception towards service robots from a functional view, which ultimately positively affect users' continuance intention toward service robots [98].

Third, the independent trait of patients has a significantly positive effect on their perception of service robots' usefulness, ease-of-use, and enjoyment, which in turn influence their continuance intention towards such AI-based technological products. This finding shows the critical role of independent traits in determining and predicting patients' continued usage of service robots [7,20].

Lastly, the post-hoc analysis results show that both PEOU and PE play mediating roles between individual characteristics and patients' continuance intention, whereas PU has an insignificant mediating effect on the relationship above. Here we may claim that patients' trust in AI techniques and their personality trait of independence affect the activity of continuing usage of service robots only mediated by their PEOU and PE toward such self-service products [2,56]. Specifically, the novelty of service robots may influence this compared with other self-services, which implies that patients would perceive ease and enjoy when using the innovative products firstly and then much more tend to explore innovative products [31,55]. Consequently, PEOU and PE stimulated from patients generally help patients who are independent and trust AI techniques to perform more tasks by service robots continuingly.

6.2. Theoretical contribution and practical implication

The contribution of this research to previous literature on AI-powered service robots' continued usage intention is twofold. First, based on the TAM, we identify key elements in deciding users' continuous usage intention of service robots by integrating individual characteristics with TAM. In the context of patient service in China, patients' trust in AI techniques and their independent trait are two important individual-related factors, which may vary patients' perceptions of service robots. Although previous studies have focused on the adoption of new technologies in the healthcare sector using TAM [6,31], few has focused on the service robots in the healthcare field. Considering the importance of service robots in developing intellectualization of Chinese healthcare organizations, this study is promoted to explore factors influencing patients' continuance behaviour toward service robots. Therefore, this research sheds new light on the role of individual characteristics in the continuance intention of new technology from the perspective of TAM models in the healthcare sector.

In practice, our findings provide managers with advice about the introduction of service robots to patients. Especially, our results on the impact of individual characteristics on continuance intention suggest that managers or practitioners can target some groups of users to

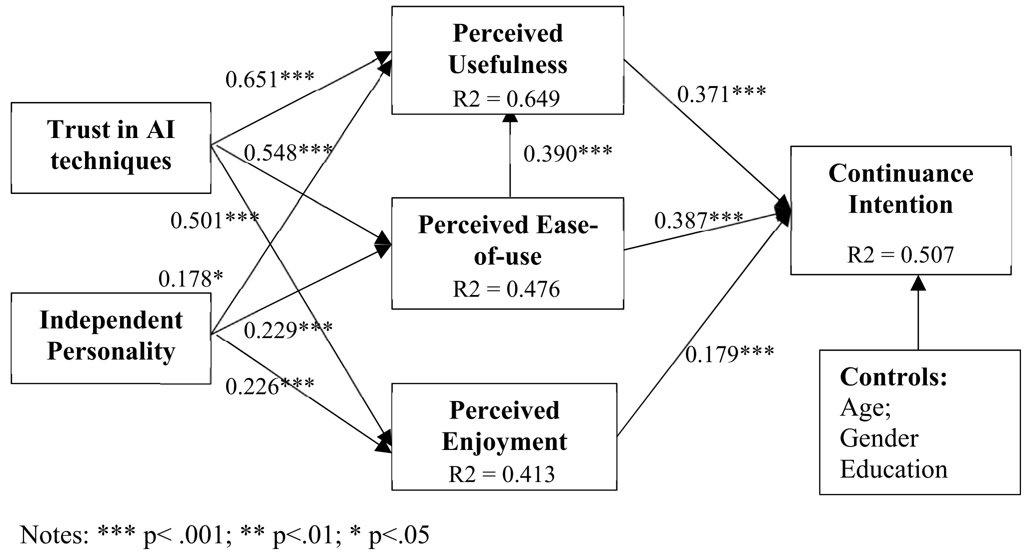

Fig. 2. The results of PLS-SEM analysis.

Table 7
Hypothesis testing results of the structural model.

Hypothesize	Path			coeffi.	p-value	Results
H1a	PU	– >	CI	0.371	0.000 ***	Supported
H1b	PEOU	– >	CI	0.387	0.000 ***	Supported
H1c	PE	– >	CI	0.179	0.001 **	Supported
H1d	PEOU	– >	PU	0.390	0.000 ***	Supported
H2a	TRAI	– >	PU	0.651	0.000 ***	Supported
H2b	TRAI	– >	PEOU	0.548	0.000 ***	Supported
H2c	TRAI	– >	PE	0.501	0.000 ***	Supported
H3a	IND	– >	PU	0.178	0.042 *	Supported
H3b	IND	– >	PEOU	0.229	0.000 ***	Supported
H3c	IND	– >	PE	0.226	0.000 ***	Supported

Notes.
1.TRAI = Trust in AI techniques; IND = Independent Personality; PU = Perceived Usefulness; PEOU = Perceived Ease-of-Use; PE = Perceived Enjoyment; CI = Continuance Intention.
2. ***p < .001; **p < .01; *p < .05; n.s. Represents that correlation is not significant at 0.05.

implement the use of new technology. Given the differences in individuals' independent trait and their trust belief on AI techniques, some segments of users may be prone to pay a higher price for human interactions and human services, while others may prefer to interact with autonomous systems [15,45]. Thus, managers of the outpatient services may try to attract and retain the patients with higher level of trust in AI techniques and independent personality if they want to successfully implement the service robots.

Besides, the positive effect of trust in AI techniques on patients' continued behaviour suggests that managers or robot designers can influence patients' adoption or usage intentions of new technologies by affecting the level of patients' trust in AI techniques. For instance, designers can enhance patients' trust in AI through enhancing human appearance of the robots [35]. Also, female robots may evoke greater trust for contact than male robots [7]. Furthermore, regarding to independent personality, to attract the high level of independent patients, robot designers may involve more proactive attributes of these robots, such as allowing the service robots to initiate the communication or seek out opportunities to help patients, rather than responding to patients [7].

6.3. *Future research and limitations*

This research has several limitations that suggest lines for future research. First, the data sample is limited to Chinese patients, inducing that the results might not be generalized to countries with totally different medical healthcare environments. Prior literature conceded that culture would influence users' attitudes toward service robots, and they may feel a closer connection to service robots that belong to the same cultural group [7]. Besides, the context in this research may vary across different cultures, such as the different situations of outpatient services in the U.S. between that in China. Specifically, as the benefits from the use of the IGRs may decrease for patients in the U.S. due to the existence of the family doctors and the appointment systems in the outpatient services, patients' perception in terms of the IGRs may vary

Table 8
Post-hoc analysis results (Mediation analysis).

Relationship	Direct effect without mediator		Indirect effect with mediator		Mediation	
	Coeff.	p-value	Coeff.	p-value	VAF	Interpretation
IND - > PU - > CI	.180	0.000***	0.019	0.072	10.56%	None
IND - > PEOU - > CI			0.073	0.000***	40.56%	Partial
IND - > PE - > CI			0.058	0.002**	32.22%	Partial
TRAI- > PU - > CI	0.422	0.000***	0.081	0.005**	19.19%	None
TRAI- > PEOU - > CI			0.142	0.000***	33.65%	Partial
TRAI - > PE - > CI			0.113	0.001**	26.78%	Partial

Notes.
1.TRAI = Trust in AI techniques; IND = Independent Personality; PU = Perceived Usefulness; PEOU = Perceived Ease-of-Use; PE = Perceived Enjoyment; CI = Continuance Intention.
2. ***p < .001; **p < .01; *p < .05; n.s. Represents that correlation is not significant at 0.05.

dramatically which may lead to different results. We thus expect to find more across-cultural analysis in the future to study the determinants of users' continuance intention of new technologies, which may bring new theoretical and practical insights.

Second, we study a novel technological product in the healthcare industry, service robots at hospitals. Many new AI-based service products are used in a medical environment and may be quite different from the AI-based service/products we have studied in this research. These new AI-based service products might even have different adapters, such as nurses or doctors. Therefore, our findings may not be appropriate to support the promotion of those AI-based service products. Therefore, we recommend future studies to focus on other new service products developed by AI techniques in the healthcare industry and study the continuance intention from the perspective of nurses or doctors.

Third, though hospital managers want to save patients' time and improve their service experience in hospital services, patients might not suppose the service robots help them. Therefore, it may be interesting to analyse how and to what extent patients' intention to use service robots could vary depending on their perception toward time-saving and the improvement of service quality within their interaction with service robots. Besides, service consumers inevitably experience embarrassment when using service robots if such robots show improper and inappropriate acts or verbal blunders [37]. Conceivably, exploring the response of patients when they encounter service embarrassment would be interesting in the future.

Appendix A. Analysis of Common Method Variance

Appendix Table 1
Harman's single-Factor Test (Extraction Method: Principal Component Analysis)

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of variance	% of Cumulative	Total	% of variance	% of Cumulative
1	9.829	30.715	30.715	9.829	30.715	30.715
2	4.908	15.338	46.053	4.908	15.338	46.053
3	1.448	5.524	51.578	1.448	5.524	51.578
4	1.233	4.853	56.431	1.233	4.853	56.431
5	1.053	4.290	60.721	1.053	4.290	60.721
6	0.917	4.09	64.811			
7	0.818	3.932	68.743			
8	0.706	3.652	72.395			
9	0.650	3.391	75.786			
10	0.618	3.09	78.876			
11	0.578	2.885	81.761			
12	0.537	2.752	84.513			
13	0.510	2.553	87.066			
14	0.451	2.379	89.445			
15	0.436	2.192	91.637			
16	0.418	1.98	93.617			
17	0.396	1.887	95.504			
18	0.357	1.781	97.285			
19	0.350	1.478	98.763			
20	0.286	1.237	100			

Appendix Table 2
Substantive Construct Loading and Method Factor Loading

Constructs	Indicator	Substantive Factor Loading (R1)	$R1^2$	Method Factor Loading (R2)	$R2^2$
Trust belief in AI techniques	TRAI01	0.718	0.516	0.084	0.007
	TRAI 04	0.755	0.570	−0.019	0.000
	TRAI 05	0.727	0.529	−0.049	0.002
	TRAI 06	0.854	0.729	−0.021	0.000
Independent personality	IND01	0.762	0.581	0.012	0.000
	IND02	0.830	0.689	0.010	0.000
	IND03	0.786	0.618	−0.024	0.001
Perceived usefulness	PU01	0.811	0.658	0.008	0.000
	PU02	0.807	0.651	0.001	0.000
	PU03	0.843	0.711	0.010	0.000
	PU04	0.827	0.684	−0.020	0.000
Perceived ease-of-use	PEOU01	0.834	0.696	−0.031	0.001
	PEOU03	0.845	0.714	0.036	0.001
	PEOU04	0.834	0.696	−0.007	0.000
Perceived enjoyment	PE01	0.867	0.752	0.012	0.000
	PE02	0.861	0.741	−0.011	0.000
	PE03	0.882	0.778	−0.001	0.000
Continuance Intention	CI01	0.840	0.706	0.027	0.001
	CI02	0.756	0.572	−0.026	0.001
	CI03	0.831	0.691	−0.006	0.000
Average		0.814	0.664	−0.001	0.001

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