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Patient acceptance of medical service robots in the medical intelligence era: an empirical study based on an extended AI device use acceptance model

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In the era of medical intelligence, there are still few studies focusing on medical service robots from a user experience perspective. Guided by the model of artificial intelligence (AI) device use acceptance (AIDUA), this article develops a theoretical model to explain patients' intention to use medical service robots at hospitals. The proposed model specifically distinguished the dimensions of anthropomorphic attributes of service robots and further introduces two variables, perceived empathy and interaction experience, as a way to construct a three-stage psychological mechanism for patient acceptance of robots. 400 questionnaires from Chinese patients were collected offline and analyzed using structural equation modeling (SEM). The results revealed that the four attributes of anthropomorphism play a differential influence in performance expectations and effort expectations, but all positively contribute to empathy, which in turn positively affects interaction quality. Interaction quality, performance expectations, and effort expectations all influence patients' emotions, thus having an impact on patients' intentions to accept service robots. The findings from this study will assist the healthcare sector in upgrading medical service robots, which will improve patient acceptance of these robots.

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Introduction

Advances in artificial intelligence (AI) and robotics are driving intelligent robots into the service industry, accelerating the digitalization, personalization, and intelligence of the service industry (Jung et al. 2023). Faced with an aging population with growing health needs, many healthcare organizations have adopted AI strategies to improve diagnosis and treatment (Eldakak et al. 2024). Medical robotic systems provide conveniences to the healthcare field when performing certain functions like monitoring and supporting patients and healthcare professionals (González-González et al. 2021). The International Federation of Robotics (IFR) categorizes medical robots into four distinct groups based on their application scenarios: surgical robots, rehabilitation robots, assistive robots, and service robots (Wang et al. 2008). In contrast to the previous three types of medical robots, which are primarily designed for healthcare professionals, medical service robots are specifically tailored for public service scenarios, such as patient consultation and guidance. This enables patients to navigate the consultation stage more efficiently. Medical service robots characterized by an anthropomorphic human-computer interface and the self-renewal ability of the knowledge base through deep learning algorithms are designed to provide targeted healthcare services in medical institutions (Liu et al. 2022). Specific applications of medical service robots include providing intelligent guidance to patients at the outpatient stage, as well as offering public services such as entertainment and companionship. This has enabled hospitals to provide convenient and accurate patient services.

Despite the growing interest in medical service robots, there are still many problems with their practical application in the healthcare field. The Chinese hospital industry adopted several medical service robots to assist healthcare workers and reduce patient-doctor contact during the COVID-19 pandemic, but patient acceptance of the robots has not been high. Prior studies in this area have generally concentrated on the development, design, and management of medical robots. Given that medical service robots are still in their infancy, healthcare workers are not unanimous in their views on service robots, with most being optimistic that their implementation will boost operational flexibility without having a negative effect on hospital strategy (Mettler et al. 2017). Higher-mannered robots are more inclined to be successful in convincing patients to follow their advice in the setting of healthcare delivery (Lee et al. 2017). The mediatory role of trust in patients' acceptance of using AI service robots was emphasized by Liu et al. (2022). However, little is currently understood about the psychological processes through which patients accept medical care robots, especially the role of patients' emotions.

In the human-robot interaction field, determining which factors affect users to accept service robots has been a concern (Alaiad et al. 2014). The psychology of people using service robots is complex. Previous research has extensively utilized the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) models to explore users' behavioral intentions toward service robots. For instance, in the restaurant industry, Abdelhakim et al. (2023) employed the UTAUT model to examine the acceptance intentions of fast food employees towards service robots across two cultural contexts: Egyptian and Malaysian. Service robots have been most extensively studied in the hospitality industry. Scholar employed the TAM model to investigate consumers' perceptions of the importance of using robots for 12 services (Alma Çallı et al. 2022). The findings revealed that consumers' perceived ease of use and perceived usefulness of robots varied across different hospitality contexts. In the context of home healthcare, scholars investigated the potential factors influencing Malaysians' willingness to adopt emerging technologies like home healthcare robots using the UTAUT model (Yeoh and Chin, 2022). These two classical models have extensively influenced the examination of user behavior regarding the adoption of new technologies. However, these frameworks overlook the distinct intelligent attributes of robotic systems and the emotional factors of users. Moreover, they fail to concurrently consider the behaviors of user acceptance and rejection in relation to artificial intelligence devices.

The nascent adoption and utilization of medical service robots in China's current healthcare landscape motivates us to investigate their acceptance by patients from a user experience standpoint, particularly the influence of patient emotions on this decision-making process. Considering the ambiguity of the above study, we have introduced the latest technology acceptance model (AIDUA model, discussed in the next chapter) to elucidate patients' acceptance of medical service robots. Although the AIDUA model has been applied in various scenarios, it still has certain limitations, such as an incomplete examination of the user's emotional journey. Therefore, we have introduced new variables. Empathy and interaction quality are highlighted as key factors for user acceptance (Blut et al. 2021). Empathetic robots are more successful in establishing rapport with users, who interact more fluidly with service robots that exhibit empathy, leading to higher-quality service interactions (Leite et al. 2013). In healthcare services, incorporating anthropomorphic and interactive elements into service robotics may inspire older users to feel better (Zhang et al. 2010), which emphasizes the significance of anthropomorphic features in medical service robots on patient attitudes. Meanwhile, in order to further explore the patients' emotional experiences in their interactions with the medical service robot, we subdivided the original variable of anthropomorphism. Anthropomorphism plays a crucial role in the transformation of robots from mere machines to human-like entities. When service robots are proactive in serving customers and accommodating their needs and emotions, these human-like behaviors awaken customers' perceptions of the robot's empathy (Xie et al. 2022). Users are more inclined to increase their intimacy with service robots that have a higher level of anthropomorphism (Chiang et al. 2022). Excessive anthropomorphism can also trigger the uncanny valley effect, reducing their acceptance of robots (Ho and MacDorman, 2010). When a robot is excessively anthropomorphized, humans are more inclined to perceive it as a partner rather than merely a tool. This can also lead to various emotional risks (Bao et al. 2023). Some studies have examined the different roles of anthropomorphic features in user-service robot interactions (Li and Wang, 2021). However, few studies have distinguished between the specific roles of different types of anthropomorphism in user acceptance of new technologies, particularly in the area of medical service robots.

Consequently, our research proposed a new research framework based on the AIDUA model that aims to explore the psychological mechanisms by which Chinese patients accept medical service robots. Through offline surveys of 400 patients, we verified the applicability of the AIDUA model in the context of public medical services. The study established the importance of empathy and interaction quality on patients' emotions, which will further determine their acceptance or rejection of medical service robots. Additionally, the research also found that different anthropomorphic features of medical service robots will have a differentiated impact on patients' acceptance.

The empirical findings will enhance the comprehension of hospital administrators and developers regarding patients' psychological perceptions when interacting with medical service robots during the outpatient stage, which may improve the successful application of such robots in the healthcare field. Academically, by analyzing the complex multi-stage assessment process of patients in the process of receiving robotic service at hospitals, this study identifies the determinants of patients' acceptance or rejection of service robots, which further expands the knowledge of human-computer interaction in healthcare.

Theoretical background

Artificially intelligent device use acceptance model. AI technologies are the major drivers of the expansion of the service economy and are today the main source of innovation and revolution in services (Rust and Huang, 2014). The TAM model and the UTAUT model are the prevailing theories utilized for examining the acceptance of AI. The TAM model and the UTAUT model are widely employed for investigating the acceptance of AI (Go et al. 2020; Lee et al. 2023; Mohd Rahim et al. 2022; Wang et al. 2023; Xu et al. 2022). The primary determinants in the technology acceptance model are perceived ease of use and perceived usefulness, which influence the user's inclination to adopt the technology and subsequently impact their behavioral intentions (Servidio and Cronin, 2018). Research has augmented the TAM by integrating additional variables such as trust to provide a more comprehensive analysis (Liu et al. 2022). A further extension of the TAM model, the UTAUT model demonstrates that performance expectations, social influence, effort expectations, and facilitating conditions can anticipate behavioral intentions, thus influencing usage behaviors (Menon and Shilpa, 2023). However, the primary aim of these two models is to investigate the general acceptance of conventional technologies by individuals, placing excessive emphasis on the effort required in adopting new technologies while affording inadequate attention to the distinctive features of AI, such as anthropomorphism. Additionally, the roles of cognitive and affective attitudes in the process of human-computer interaction are often overlooked. To forecast users' intentions to use AI devices, a theoretical model of AIDUA is put forth by Gursoy et al. (2019) and explains the three steps customers take to decide if they are prepared to accept AI devices. When it comes to services, according to Gursoy (Gursoy et al. 2019), the first stage is primary evaluation, which includes hedonic motivation, social influence, and perceived anthropomorphic characteristics of AI. In the following phase, users will measure the benefits versus costs and effort of using AI based on their initial evaluation and form an emotional perception of AI. Finally, users will decide whether to accept AI based on their evaluations in the previous two stages. Previous studies have verified the applicability of the theoretical model in various service contexts, including hotel services (Lin et al. 2019), restaurant services (Pande and Gupta, 2022), and travel services (Ribeiro et al. 2021). This demonstrates the model's potential to predict the psychological assessment mechanism of user acceptance of AI devices in various service environments.

In the context of healthcare in China, the relationship between patients and healthcare providers, particularly in outpatient settings, is frequently strained due to long waiting times and queues, which can erode patients' tolerance. Thus, it is imperative to offer more personalized and efficient services to patients during the outpatient stage. We assert that medical service robots utilized in outpatient care must possess not only advanced intelligent functionalities but also the capacity to engage in empathetic communication with patients. Given the research background and objectives, we contend that the AIDUA model is more suitable than conventional technology acceptance models for elucidating patients' behavioral inclinations regarding the acceptance or rejection of medical service robots. To further explore the emotional factors in patient acceptance of the medical service robot, we added empathy and interaction quality to the original model and subdivided anthropomorphism into four potential variables to determine which anthropomorphic dimensions of the medical service robot are more important to the emotional experience of the user in their interactions with the robot.

Hypotheses

Anthropomorphism. Anthropomorphism is the tendency or mental process by which people ascribe human characteristics, motives, intentions, or mental states to non-human objects (Airenti, 2018). To increase the effectiveness of human-robot interaction, robots must be personified to a certain extent (Zhang et al. 2022). Anthropomorphism includes not only physical characteristics, such as appearance, voice, expression, and behavior, but also psychological characteristics. Appearance anthropomorphism is one of the most visible and distinctive attributes of service robots, and it is also the most intuitive anthropomorphic feature for users (Mende et al. 2019). People tend to perceive robots as more anthropomorphic when they exhibit higher levels of socially interactive behavior (Fraune et al. 2020). The human-like voice of the robot is also an important social cue (Złotowski et al. 2014). With the deep application of AI technology, service robots are becoming more human-like emotionally and psychologically, exhibiting human personality traits such as extroversion and humor (Zhang et al. 2021). Humans possess multiple mental abilities, and they also tend to distinguish between multiple dimensions of anthropomorphic traits when assessing whether a robot is human-like (Kühne and Peter, 2023). Therefore, this study considers the anthropomorphism of medical service robots specifically in four aspects: appearance, voice, behavior, and personality.

Appearance traits. Appearance anthropomorphism is one of the most prominent anthropomorphic features of social robots. Walters et al. (2007) classified the physical appearances of robots based on the level of anthropomorphic features: mechanoid, humanoid, and android. A human-like appearance leads to higher performance expectation, while a mechanical appearance leads to higher effort expectancy (Zhang et al. 2021). People react more positively when robots look similar to humans, but when the human appearance level exceeds a certain limit, it triggers the uncanny valley effect, which leads to negative user emotions (Mori et al. 2012).

Voice traits. The human voice is the sound that has the most impact on our lives. It conveys highly relevant information about the speaker and represents a substantial component of interpersonal communication (Kuhne et al. 2020). Kim and Kim (2020) found that the tone of the robot's voice affects the user's degree of liking for the robot. Pitch makes the robot more engaging for the user and also influences their perceived quality and overall enjoyment of the interaction (Niculescu et al. 2013). A social robot with a human female voice is more pleasant to listen to (Leung et al. 2023). The anthropomorphic character of a robot's voice is closely associated with its ability to connect with humans. Specifically, native language-speaking robots are more likely to influence customer behavior than those that speak a second language (Van Vaerenbergh and Holmqvist, 2013).

Behavioral traits. Assigning human behavioral traits to non-human entities, such as gestures and facial expressions, is recognized as behavioral anthropomorphism (Kim et al. 2019). If a robot can perform human-like behavioral actions, it will elicit a stronger emotional response from people, and even subtle gestures may affect people's perceptions of robot anthropomorphism (Salem et al. 2013). Chatbots utilizing emojis are perceived as equally dependable as those engaging in conversations with real individuals (Beattie et al. 2020). The fundamental attribute of a service robot is its capability to execute tasks. Should it possess self-awareness or demonstrate heightened human-like behaviors, the resulting communication and interaction with customers are poised to enhance customer satisfaction.

Personality traits. In human-robot interactions, the personality of social robots is a key factor influencing human responses (Lee et al. 2006). Personality shapes the very nature of social relationships, even impacting how satisfying an interaction is for the participants (Dryer, 1999). Robot designers use this to manipulate perceived personalities to create more enjoyable interactions. It has been found that personalized robots can involve users in several tasks, such as post-stroke rehabilitation (Tapus et al. 2008) or restaurant recommendations. Researchers commonly develop robot identities based on the five human personality traits—extroversion, ableness, openness, conscientiousness, and neuroticism—owing to the complex nature of human personality dimensions. Some service robots even have human personality traits, such as a sense of humor, which is a human characteristic that increases user satisfaction (Zhang et al. 2021).

Anthropomorphism, performance expectation, and effort expectancy. Anthropomorphism is an antecedent in the AIDUA model and is thought to influence performance expectations and effort expectations (Gursoy et al. 2019). To enhance user satisfaction in the service field, service robots are becoming more physiologically and psychologically similar to humans (Shin et al. 2022). Anthropomorphism is important for human-service robot interaction. The impact of service robots' anthropomorphism on user acceptance is debated. Studies concluded that the impact of anthropomorphic features of service robots on people's attitudes and behaviors depends on the type of service environment (Qiu et al. 2019). As evidenced in the literature review, the anthropomorphic appearance, behavior, personality, and voice of service robots contribute to a positive user experience, enhancing user convenience and efficiency when interacting with the robots (Kim and Kim, 2020; Salem et al. 2013; Tapus et al. 2008; Zhang et al. 2021). When service robots exhibit reduced anthropomorphism, users may perceive them as less intelligent, resulting in increased communication costs. Thus, the following two hypotheses are proposed:

H1: Appearance anthropomorphism (H1a), voice anthropomorphism (H1b), behavior anthropomorphism (H1c), and personality anthropomorphism (H1d) positively impact performance expectancy.

H2: Appearance anthropomorphism (H2a), voice anthropomorphism (H2b), behavior anthropomorphism (H2c), and personality anthropomorphism (H2d) negatively impact effort expectancy.

Anthropomorphism and perceived empathy. Scholars believe that increasing the anthropomorphic attributes of robots gives us a sense that robots have more empathy (Leite et al. 2013). Perceived Empathy is an important emotional element in service interactions, including unique human emotional characteristics and social cues (Xie et al. 2022). This emotional connection enhances the user's experience with the robots, thus increasing their acceptance (Pelau et al. 2021). In technical service environments (e.g., banks, hotels), the anthropomorphic features of service robots can enhance users' perception of empathy and thus mitigate abnormal consumer behavior. Medical robots also increase patient recognition of their empathy when using human-like language and behaviors, leading to increased satisfaction (Johanson et al. 2023). Similarly, the more medical robots behave like people, the more they can attend to patients' emotions and understand their needs. As a result, we suggest the following hypothesis:

H3: Appearance anthropomorphism (H3a), voice anthropomorphism (H3b), behavior anthropomorphism (H3d), and personality anthropomorphism (H3d) positively impact perceived empathy.

Hedonic motivation. Hedonic motivation is related to the perceived enjoyment that individuals would have as a result of the AI device's services (Allam et al. 2019). Personally motivated by the hedonic experience of a new technology, users lower their effort expectancy and increase their performance expectations for the technology (Koenig-Lewis et al. 2015). Research in robots has supported the idea that the pleasant experience of the user interacting with the robot builds positive emotions between the two, thus increasing the user's acceptance (Wood et al. 2013). scholar investigated how Gen Z employees intended to interact with service robotics and proposed that hedonic motivations actively drove those interactions (Yuan et al. 2022). Gursoy ascertained that the anthropomorphic and affinity advantages of AI assistants will awaken users' intrinsic hedonic motivation and satisfy their emotional needs to benefit from the experience of interacting with their smart devices (Chi et al. 2020). When people are in a healthcare environment, they may be concerned about whether service robots are entertaining when performing services such as providing medical guidance and escorting patients. Thus, the following hypotheses are put forward:

H4a: Hedonic motivation positively affects patients' performance expectancy of medical service robots.

H4b: Hedonic motivation negatively affects patients' effort expectancy of medical service robots.

Social influence. As the social impact theory (SIT) suggests, people who value social groups will be more congruent with their group norms (Latané, 1981). Prior research revealed that social network norms and customs are important predictors of users behavioral intentions (Rather, 2018), especially when they lack the information necessary to make an informed choice (Voramontri and Klieb, 2019). When people close to them are favorable or encouraging of the use of the medical service robot, patients will tend to evaluate the service robot favorably; thus, the perceived difficulty of utilizing the robot is reduced and its perceived value as a tool is increased. Previous research has argued that consumers' performance expectancy and effort expectancy are highly influenced by social influence (Lin et al. 2019). Therefore, this study puts forward two hypotheses:

H5a: Social influence positively impacts patients' performance expectancy of medical service robots.

H5b: Social influence negatively impacts patients' effort expectancy of medical service robots.

Perceived empathy. Perceived Empathy is typically referred to as an emotional response or a cognitive comprehension of people's experiences (Simon, 2013). Emotional response connects to the sentiments of compassion and concern for others, and cognitive comprehension comprises both individual understanding and the capacity to comprehend and respond to the thoughts and feelings of others (McBane, 1995; Pelau et al. 2021). Service staff with a high level of empathy pay deeper attention to consumers' needs and desires, thus providing them with a pleasant interactive experience (Aggarwal et al. 2015). Considering that service robots have the ability to analyze big data and learn relevant interactive knowledge (Ashfaq et al. 2020), it can be assumed that medical service robots are capable of focusing on complex patient needs to bring them better and more personalized services. It has also been shown that building empathy modules in robots can significantly increase the level of robot interaction and enhance people's adoption. Consequently, the following hypothesis is put forth:

H6: Perceived Empathy positively influences the quality of patients' interactions with medical service robots.

Performance expectation and effort expectancy. Perceived product benefits and cost are two key factors in the TAM theory, which suggests that the tendency of customers to utilize a product is impacted by how helpful and easy it is to use (Davis et al. 1989). Based on this, previous research proposed two similar factors, performance expectancy and effort expectancy (Venkatesh et al. 2003). Performance expectancy refers to how patients evaluate the consistency and accuracy of the services provided by medical service robots (Lin et al. 2019). Effort expectancy describes the amount of effort or usefulness patients anticipate when utilizing medical service robots (Vitezić and Perić, 2021). While deeper levels of effort expectancy produce unpleasant emotions, higher levels of performance expectancy contribute to favorable emotional experiences. Accordingly, two hypotheses are presented as follows:

H7: Performance expectancy positively impacts patients' emotions.

H8: Effort expectancy negatively impacts patients' emotions.

Interaction quality. Interaction quality is one of the components of service quality (Brady and Cronin Jr, 2001), which relates to how well customers perceive the process and the customer-provider relationship when receiving services (Choi et al. 2019). Communication and interaction between individuals are two of the most crucial elements of society (Pelau et al. 2021). In the secondary assessment phase of the AIDUA model, Gursoy posits that individuals primarily evaluate decision options and their outcomes from an emotional perspective, with perceived costs and benefits exerting a significant influence on emotions (Gursoy et al. 2019). To offer patients the services they require, medical service robots must interact with them. During human-robot interaction, users engage in an evaluation process where they form attitudes toward the robot based on both the objective assessment of cost and benefit as well as the cognitive perspective of the interaction experience. The robot's service quality can be represented by three dimensions of interactivity: communication direction, user control, and time (McMillan and Hwang, 2013). These elements hold promise in the exploration of the perceived interactivity of social robots, which stimulate different emotional experiences in patients. Choi found that the quality of the customer's interaction with the hotel service robot developed a "moment of truth" and significantly affected the customer's attitude toward the robot (Choi et al. 2019). Thus, we hypothesized that:

H9: The interaction quality positively impacts patients' emotions toward medical service robots.

Emotion. Schoefer defined emotions as subjective mental states that influence an individual's choice of emotional information (Schoefer and Diamantopoulos, 2007). According to cognitive assessment theory (Lazarus, 1991), after the complicated evaluation process, emotions toward medical service robots will develop and ultimately affect how well patients accept service robots. Specifically, positive emotions are generated if users perceive that both the emotional and functional dimensions exhibited by the medical service robots are consistent and accurate, enabling them to benefit from the service experience. However, when users do not receive sufficient benefits from their service experience, they may develop negative emotions such as dissatisfaction, dread, and wrath toward the service robot. This negativity can lead to users refusing to accept or use service robots in healthcare (Milner et al. 2021). We have defined the following hypotheses:

H10a: Emotion positively influences a patient's willingness to use medical service robots.

H10b: Emotion negatively influences a patient's objection to using medical service robots.

In Fig. 1, the conceptual model is displayed.

Methodology

Data collection. A cross-sectional design was used in our research, and data were obtained by using survey methods. The research was carried out in a hospital with tertiary care in Shanghai. Before the questionnaire was formally distributed, we went to the hospital site to conduct interviews and correct the unclear questions. To ensure the reliability of the questionnaire data, we collected data on two separate occasions: November-December 2022 and February-March 2023. This research investigates the use of medical service robots in hospitals for public service. The medical service robots shown in the questionnaire refer to public service robots that can help patients better realize self-service in the outpatient stage, such as providing consulting services through voice interaction and guiding patients to the relevant departments for medical treatment. In China's healthcare system, outpatients often need to go through multiple steps to reach the target department for medical treatment, so this type of medical service robot can reduce the burden and cost of manual care and improve the efficiency of patients' medical treatment.

During both data collection periods, the questionnaire included photographs of scenes depicting the medical service robot in operation, which were used to enhance patients' recall and perception of the robot. To enhance participants' comprehension of various attributes of anthropomorphism, we provided 12 detailed visual aids alongside the assessment of anthropomorphism-related variables, followed by the sequential presentation of four relevant videos. This approach aimed to facilitate participants' understanding of voice anthropomorphism, behavioral anthropomorphism, appearance anthropomorphism, and personality anthropomorphism before completing the assessment. Six pictures were placed next to the appearance anthropomorphism items, corresponding to high mechanical part exposure, low mechanical part exposure, high facial realism, and low facial realism, as well as high torso integrity and low torso integrity. Additionally, six pictures were placed next to the behavioral anthropomorphism items, representing low, medium, and high levels of behavioral anthropomorphism. Before participants answered questions about voice personification, researchers showed videos depicting varying levels of affability, naturalness, and accent. Prior to answering questions about personality personification, participants viewed three separate videos that showcased different personality traits through the service robot's interactions.

Researchers will provide clear explanations of the research object and study purpose to participants when distributing questionnaires, in order to ensure accurate responses. We conducted a pilot study with 10 students to evaluate the questionnaire's usability. The students were asked to complete the questionnaire, and based on their feedback, we determined that a reasonable time frame for completing the questionnaire is approximately 5 min. Before survey distribution, the researcher will inquire about participants' prior exposure to service robots in

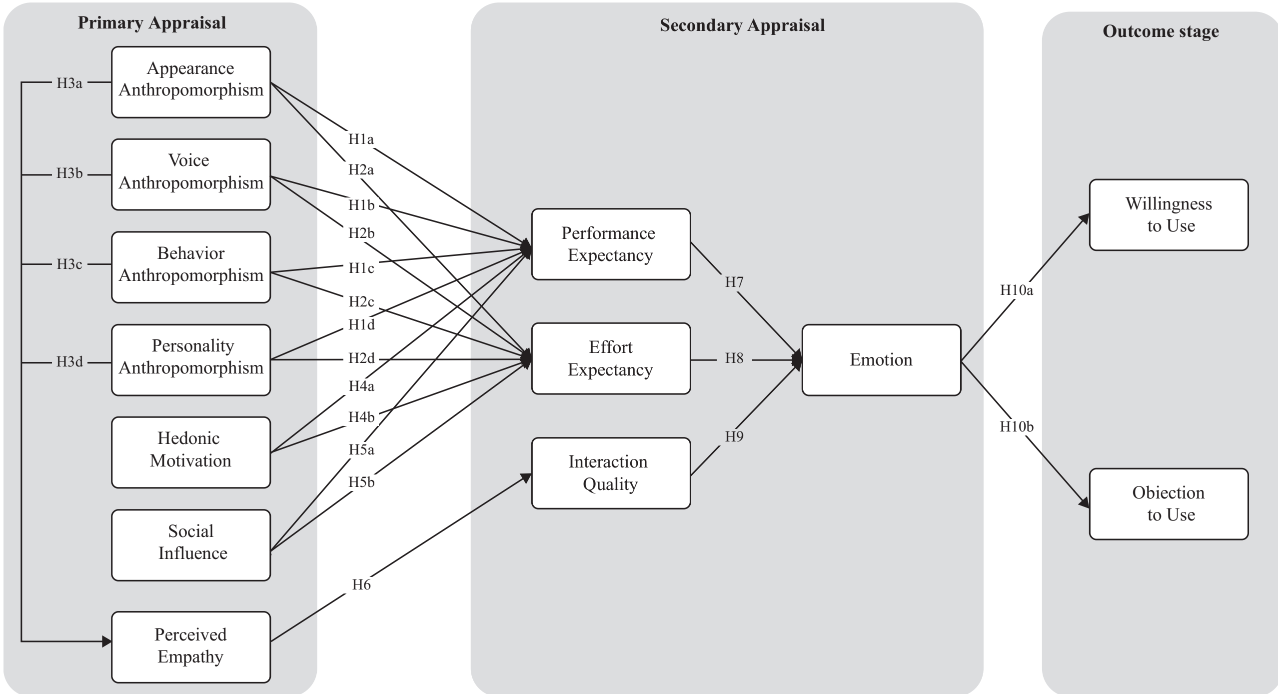

Fig. 1 The conceptual model of the study. This figure presents a theoretical framework of Patient Acceptance or Rejection of medical Service Robots. The diagram consists of several key components. At the center of the model is the "Patient Acceptance or Rejection" decision, which represents the ultimate outcome of the psychological process. The arrows in the diagram reflect the potential causal relationships and pathways between these constructs, indicating the direction and magnitude of their influence.

Table 1 Demographic profile of the survey participants.

Variables (*N* = 400)	Category	Number	Percentage (%)
Gender	Male	188	47%
	Female	212	53%
Age	18–25	45	11.3%
	26–34	67	16.7%
	35–54	128	32%
	55–64	69	17.3%
	Over 65	91	22.7%
Education	Below high school	23	5.8%
	High school	79	19.7%
	Bachelor's or college degree	211	52.8%
	Master's degree or above	87	21.7%
Occupation	Employed	195	48.7%
	Unemployed	132	33%
	Student	73	18.3%

healthcare to ensure that the respondents selected align with the study objectives. The first page of the questionnaire provides an introduction and an illustrative picture of the medical service robot relevant to the research objectives, designed to refresh the participants' memories. Our questionnaire includes a screening question: "Have you come into contact with a service robot in the healthcare field in the past year?" Only those who answered "yes" were permitted to proceed to the subsequent sections of the survey, while those who answered "no" were directed to end the survey. The questionnaire also contains two attention checks, and if a participant fails either of these checks, their responses were discarded. Additionally, we excluded questionnaires that took less than 5 min to complete, had missing responses, and had consecutively repeated answers to questions, resulting in a sample of 400 valid questionnaires.

Data description. The participants in this study were patients who had interacted with medical service robots in the past year (see Table 1). This sample consisted of 188 men (47%) and 212 women (53%). 128 subjects (32%) were aged between 35 and 54, 91 subjects (23.3%) were aged over 65, 69 subjects (17.3%) were aged between 55 and 64, 67 subjects (16.7%) were aged between 26 and 34, and 45 subjects (11.3%) were aged between 18 and 25. The largest number of subjects had a bachelor's degree (52.8%), while a small number had an education level below high school (5.8%). 79 subjects (19.7%) were educated at high school, and 87 subjects (21.7%) had a master's degree or higher. Most participants had a professional occupation (48.7%), and 73 subjects were students.

Instruments and measures. The questionnaire consisted of study constructs derived from prior studies (see Appendix A). The original seven latent variables in the AIDUA model were directly adapted from the scales developed by Gursoy et al. (2019). Empathy was evaluated using the scale created by Czaplewski et al. (2002). The scales of personality anthropomorphism were derived from three studies (Golossenko et al. 2020; Lu et al. 2019; Wang, 2017). The scales of voice anthropomorphism and behavior anthropomorphism were derived from Vernuccio et al. (2022). The measurement items of interaction quality and appearance anthropomorphism were self-designed according to McMillan and Hwang (2013) and Jie et al. (2021). This questionnaire uses a seven-point Likert scale to measure all items.

Analysis. The current study used structural equation models (SEMs) to validate the proposed research model. First, we performed reliability analysis, convergent validity analysis, and

Table 2 Reliability and convergent validity test.

Construct	Item	Ste	Cα	CR	AVE
Social Influence (SI)	SI1	0.789	0.717	0.797	0.567
	SI2	0.756			
	SI3	0.712			
Hedonic Motivation (HM)	HM1	0.752	0.787	0.831	0.552
	HM2	0.707			
	HM3	0.767			
	HM4	0.745			
Voice Anthropomorphism (VA)	VA1	0.752	0.787	0.788	0.554
	VA2	0.711			
	VA3	0.769			
Appearance Anthropomorphism (AA)	AA1	0.701	0.709	0.761	0.515
	AA2	0.722			
	AA3	0.729			
Behavioral Anthropomorphism (BA)	BA1	0.736	0.763	0.791	0.558
	BA2	0.718			
	BA3	0.786			
Personality Anthropomorphism (PA)	PA1	0.706	0.783	0.852	0.536
	PA2	0.752			
	PA3	0.724			
	PA4	0.728			
	PA5	0.748			
Perceived Empathy (E)	E1	0.753	0.784	0.813	0.592
	E2	0.793			
	E3	0.761			
Performance Expectancy (PE)	PE1	0.726	0.799	0.840	0.568
	PE2	0.709			
	PE3	0.780			
	PE4	0.797			
Effort Expectancy (EE)	EE1	0.710	0.720	0.744	0.534
	EE2	0.700			
	EE3	0.780			
Interaction quality (IQ)	IQ1	0.795	0.766	0.826	0.613
	IQ2	0.764			
	IQ3	0.789			
Emotion (EB)	EB1	0.711	0.799	0.856	0.543
	EB2	0.72			
	EB3	0.775			
	EB4	0.773			
	EB5	0.703			
Willingness to Use (W)	W1	0.73	0.763	0.811	0.588
	W2	0.784			
	W3	0.786			
Objection to Use (O)	O1	0.737	0.744	0.790	0.557
	O2	0.703			
	O3	0.796			

discriminant validity analysis on the collected data based on SPSS 23.0 and Amos 24.0. After that, we apply Amos 24.0 to verify all hypothetical model results.

Results

Reliability and validity. The study evaluated the measurement model with a CFA in order to confirm the quality of the data analysis. First, the results of the CFA show the goodness of fit: x2/df = 1.351; RMSEA = 0.076, NFI = 0.916, GFI = 0.962, TLI = 0.862. Second, further analysis satisfied discriminant and convergent validity. Using the SPSS 23.0 software, we examined each construct's reliability. The findings revealed that all constructs had Cronbach's alpha values greater than 0.7 (see Table 2), above the suggested level of reliability (Cronbach, 1951). The standardized loadings for all constructs ranged from 0.709 to 0.799, all above the suggested value of 0.7 (Fornell and Larcker, 1981). In terms of data validity, all constructs' average variance extracted (AVE) values are above 0.50, and composite reliability (CR) was more than 0.7, confirming the expected convergent validity (Fornell and Larcker, 1981). Also, the results matched the requirements for distinguishing validity since the squared roots of the AVEs for each construct were over the correlation between themselves and other latent variables (see Table 3).

Hypothesis Testing Results. The findings of the proposed model are shown in Fig. 2, and Table 4 contains the estimated path coefficients of the hypothetical relationships. The results revealed that effort expectancy was affected by hedonic motivation ($\beta = -0.083$, $p < 0.01$), voice anthropomorphism ($\beta = -0.395$, $p < 0.001$), appearance anthropomorphism ($\beta = -0.176$, $p < 0.001$), behavior anthropomorphism ($\beta = -0.161$, $p < 0.001$), and personality anthropomorphism ($\beta = -0.189$, $p < 0.001$), but not related to social influence ($\beta = -0.042$, $p = 0.222$). Hence, H2 and H4b are supported, but H5b is rejected. Social influence ($\beta = 0.27$, $p < 0.001$) and hedonic motivation ($\beta = 0.668$, $p < 0.001$) significantly influenced performance expectancy, supporting H4a and H5a. Appearance ($\beta = -0.011$, $p = 0.84$) and personality anthropomorphism ($\beta = 0.04$, $p = 0.523$) did not affect performance expectations, voice anthropomorphism ($\beta = 0.147$, $p < 0.05$) was positively related to performance expectations, and behavioral anthropomorphism ($\beta = -0.125$, $p < 0.05$) was negatively related to performance, so H1 was partially supported.

In addition, perceived empathy was influenced by voice anthropomorphism ($\beta = 0.224$, $p < 0.001$), behavioral

Table 3 Discriminant validity test.

	1	2	3	4	5	6	7	8	9	10	11	12	13
1PA	0.73												
2BA	0.00	0.75											
3AA	0.00	0.00	0.72										
4 VA	0.00	0.00	0.00	0.74									
5SI	0.00	0.00	0.00	0.00	0.75								
6E	0.35	0.64	0.11	0.33	0.00	0.77							
7HM	0.00	0.00	0.00	0.00	0.00	0.00	0.74						
8PE	0.05	−0.14	−0.01	0.17	0.33	−0.02	0.61	0.75					
9IQ	0.27	0.51	0.08	0.26	0.00	0.71	0.00	−0.02	0.78				
10EE	−0.34	−0.29	−0.32	−0.70	−0.08	−0.57	−0.16	−0.24	−0.45	0.73			
11EB	0.23	0.27	0.09	0.33	0.17	0.53	0.43	0.52	0.64	−0.52	0.74		
12 O	−0.17	−0.20	−0.06	−0.24	−0.13	−0.39	−0.31	−0.38	−0.47	0.38	−0.73	0.75	
13 W	0.16	0.18	0.06	0.23	0.12	0.36	0.29	0.36	0.44	−0.36	0.68	−0.50	0.77

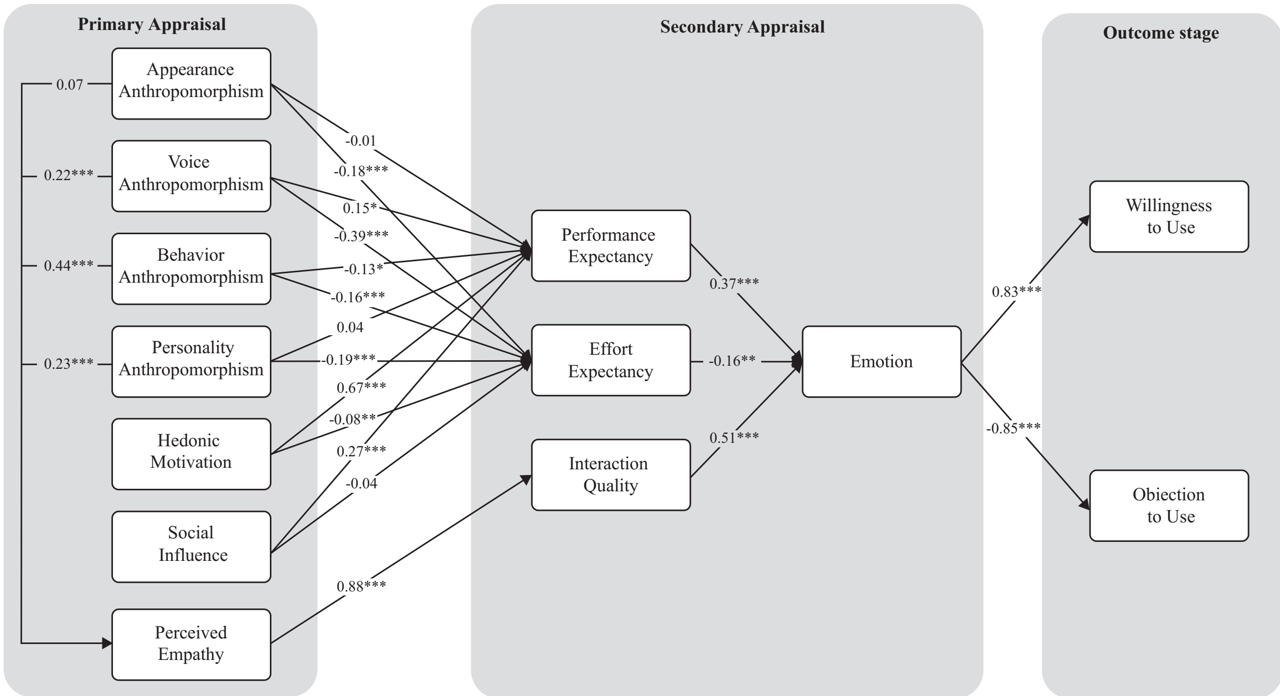

Fig. 2 Estimates of research model. This figure presents the results of our research model, demonstrating the estimated relationships and correlation levels between different variables. The analysis was conducted using AMOS statistical software. The strength and significance of the relationships between variables are indicated by asterisks, where * represents p < 0.05, ** represents p < 0.01, and *** represents p < 0.001.

Table 4 Hypotheses testing.

	Hypothesis	β	t-value	p	Result
H1a	Appearance Anthropomorphism → Performance Expectancy	−0.011	−0.201	0.840	Reject
H1b	Voice Anthropomorphism →Performance Expectancy	0.147	2.543	*	Support
H1c	Behavior Anthropomorphism → Performance Expectancy	−0.125	−02.161	0.031	Reject
H1d	Personality Anthropomorphism → Performance Expectancy	0.040	0.638	0.523	Reject
H2a	Appearance Anthropomorphism → Effort Expectancy	−0.176	−5.509	***	Support
H2b	Voice Anthropomorphism → Effort Expectancy	−0.395	−11.428	***	Support
H2c	Behavior Anthropomorphism → Effort Expectancy	−0.161	−4.673	***	Support
H2d	Personality Anthropomorphism → Effort Expectancy	−0.189	−5.132	***	Support
H3a	Appearance Anthropomorphism → Perceived Empathy	0.071	1.310	0.190	Reject
H3b	Voice Anthropomorphism → Perceived Empathy	0.224	3.918	***	Support
H3c	Behavior Anthropomorphism → Perceived Empathy	0.435	7.495	***	Support
H3d	Personality Anthropomorphism → Perceived Empathy	0.230	3.814	***	Support
H4a	Hedonic motivation → Performance Expectancy	0.668	12.981	***	Support
H4b	Hedonic motivation → Effort Expectancy	−0.083	−2.725	**	Support
H5a	Social Influence → Performance Expectancy	0.270	4.720	***	Support
H5b	Social Influence → Effort Expectancy	−0.042	−1.221	0.222	Reject
H6	Perceived Empathy → Interaction Quality	0.882	38.100	***	Support
H7	Performance Expectancy → Emotion	0.367	13.420	***	Support
H8	Effort Expectancy → Emotion	−0.157	−2.968	***	Support
H9	Interaction Quality → Emotion	0.505	10.267	***	Support
H10a	Emotion → Willingness to Use	0.830	30.927	***	Support
H10b	Emotion → Objection to Use	−0.854	−35.329	***	Support

*p < 0.05, **p < 0.01, and ***p < 0.001.

anthropomorphism ($\beta = 0.435$, $p < 0.001$), and personality anthropomorphism ($\beta = 0.23$, $p < 0.001$) but was not correlated with appearance anthropomorphism ($\beta = 0.071$, $p = 0.19$). Therefore, H3 was partly supported. Patients' perceived empathy ($\beta = 0.882$, $p < 0.001$) was found to have a positive effect on interaction quality, lending support to H6. Next, patients' performance expectancy ($\beta = 0.367$, $p < 0.001$) and interaction quality ($\beta = 0.505$, $p < 0.001$) caused a positive impact on their emotions to medical service robots, whereas the effort expectancy had the opposite result ($\beta = -0.18$, $p < 0.01$). Therefore, H7, H8, and H9 were supported. A higher level of emotion also increased acceptance willingness ($\beta = 0.83$, $p < 0.001$) and decreased opposition to the use of service robots ($\beta = -0.854$, $p < 0.001$), supporting H10a and H10b.

Discussion

Our study explored the mechanisms that psychologically influence patients' intentions to use medical service robots. The results demonstrate the applicability of the AIDUA model in the context of healthcare services and support the majority of the hypotheses.

First, at a preliminary stage, social influence, hedonic motivation, and anthropomorphism (traits of appearance, behavior, voice, and personality) all contribute to the assessment of performance expectations and effort expectations. Patients who are heavily impacted by social groups develop a greater performance expectancy to medical service robots. When their friends or family members recommend a service robot in the hospital, the patients' willingness to use that service robot is stronger. The need for hedonic benefits triggers patients to perceive higher performance and lower a cost of effort when using medical service robots. This finding is corroborated by existing literature, wherein researchers have explored the impact of hedonic factors on the user's willingness to sustain use of smart medical devices (Alzahrani et al. 2022). Even within critical service settings such as hospitals, patients retain certain hedonic requirements for service robots. This is particularly pertinent to the prolonged waiting times experienced during the outpatient stage in China, where patients necessitate service robots with entertaining features to alleviate feelings of anxiety and monotony. Anthropomorphism decreases patients' effort expectations. Patients find it easier to communicate with medical service robots when their level of anthropomorphism (appearance, behavior, voice, and personality) is perceived to be high. This indicates that robot anthropomorphism helps to eliminate patient concerns about the cost of their use in healthcare contexts. This finding is consistent with extant literature, where scholars discovered that anthropomorphism of AI devices in autonomous vehicles similarly diminishes users' negative risk perceptions (Tian and Wang, 2022). Amongst the findings related to anthropomorphism and performance expectations, it was observed that only the hypothesis indicating that voice anthropomorphism positively influences performance expectations was confirmed. Previous related studies have demonstrated that voice anthropomorphism leads users to become more intimate with the AI and perceive its perceived usefulness more strongly (Oh and Kwon, 2020). Previous studies have shown that anthropomorphism can enhance patients' performance expectations. In this study, we further found that the voice anthropomorphic attributes of medical service robots play a positive role in patients' perceived performance expectations. Prior research has emphasized the significance of voice in medical settings, revealing that the pitch and gender of virtual assistants can increase users' likelihood of following their advice (Goodman and Mayhorn, 2023). On the one hand, we think it has something to do with China's medical environment. In the context of China's healthcare environment, where public hospitals dominate and face high patient volumes and demand, providing personalized care is challenging. In this setting, a more anthropomorphic voice interaction from service robots can alleviate patients' anxiety, help them understand medical terminology, and address other challenges. On the other hand, medical service robots are primarily used during the pre-consultation stage, when patients seek medical guidance and preliminary consultation services. During this phase, patients are more likely to appreciate a professional and reassuring voice. Here, the personification of speech offers a clear advantage over anthropomorphism in behavior, appearance, and personality. Therefore, when patients engage with a medical service robot, it is the human-like voice interaction that initially attracts them, rather than the human-like appearance.

Second, the findings articulated that the voice, behavior, and personality anthropomorphic features of the service robot positively promote patients' perceived empathy. This positive affective judgment further improves patients' assessments of the interaction quality with the medical service robots. Lo et al. (2022) concluded that robots that have anthropomorphic features evoke more empathy than tablet computers. The results further indicated that anthropomorphic voice, behavior, and personality attributes positively influenced this relationship, with the exception of appearance anthropomorphism. Interactions with medical service robots featuring vocal, personality, and behavioral anthropomorphism elicited greater empathetic emotional responses from patients, thereby contributing to more satisfactory service experiences and interactions. In contrast, appearance anthropomorphism appeared to evoke feelings of a challenge to human uniqueness, instigating apprehension and potentially engendering negative attitudes towards the robot (Canqun and Weizhen, 2020).

Third, the results revealed performance expectancy, effort expectancy, and interaction quality as key factors in patients' emotions about using medical service robots. It could be claimed that patients' overall assessments of PE, EE, and IQ of medical service robots contribute to their decisions to use robotic services in medical institutions. Patients have a higher level of positive attitude towards medical service robots when they perceive consistency in the information and services provided by them. Choi confirmed that high-quality customer interactions in consumer services promote mood. In an environment of disease distress and epidemic stress, patients often develop a plethora of negative psychological emotions (Choi and Kim, 2020). If the medical service robot focuses on patients' needs and interacts with them empathetically, patients are more likely to have positive emotions towards the robot.

Interacting with a service robot is a special and emotionally nuanced experience. We found that emotions are a major driver of patients' use of medical service robots. This result corroborates prior studies' findings (Gursoy et al. 2019; Lin et al. 2019). High levels of positive emotions motivate patients to use healthcare robots, and conversely, high levels of negative emotions make patients more resistant to using robots. Prior research has verified that emotions predominantly impact an individual's cognitive processes, and that achieving equilibrium between cognition and emotion emerges as the optimal strategy for effective social adaptation to the environment (Chen and Girish, 2023). High levels of positive emotions motivate patients to use healthcare robots, and conversely, high levels of negative emotions make patients more resistant to using robots. Concurrently, it is observed that interaction quality and performance expectations exert a more significant influence on emotions than effort expectations. This implies that when patients perceive high levels of performance expectations and interaction quality, concerns regarding the potential excessive costs and efforts required to discontinue the use of medical service robots may be mitigated. This indicates that enhancing patients' positive experiences contributes more significantly to their motivation towards medical service robots than reducing their negative experiences.

Theoretical implications. The current study proposes and validates a conceptual framework based on the AIDUA model, which deepens our understanding of patients' willingness to employ medical service robots. Service robots in the healthcare industry have received little attention from research. Given that service robots will be a key driving force for the high-quality development of medical services in China, it is necessary to discuss medical service robots from the perspective of patients. This study elucidates the complex multi-stage assessment process of patients in the process of receiving robotic service at hospitals and reveals the important role of patients' emotional factors in this psychological mechanism.

Our research also advances the literature on robot anthropomorphism. This study investigated the role of appearance anthropomorphism, behavior anthropomorphism, voice anthropomorphism, and personality anthropomorphism in the interaction between patients and medical service robots. The results revealed the importance of three anthropomorphisms—voice, behavior, and personality—in the psychological assessment of patients' willingness to accept the service robot. However, the appearance anthropomorphism of the robot does not act as a positive element to make patients feel more empathetic and enhance their human-robot interaction experience. This adds to the evidence on the differential and erratic effects of anthropomorphism on the intentions of people accepting robots.

Finally, we further extend the applicable service context of the AIDUA model. The current study extends the AIDUA model to the healthcare service scenario for the first time, and the findings basically support the original conclusions. Patients also follow the psychological mechanism of a multi-stage assessment in the process of receiving a medical service robot.

Practical implications. In practice, our findings provide insights for healthcare managers and designers. Especially, the findings on the anthropomorphic attributes of service robots may help hospital administrators better improve patient acceptance of service robots.

Considering the significant impact of social influence, additional public opinion campaigns are required to promote medical service robot adoption. Patients take full account of group norms and advice from opinion leaders when adopting new medical technologies. Currently, new media has emerged as the primary avenue through which individuals acquire information. Managers should proactively leverage social media platforms for the dissemination and promotion of medical service robots, while concurrently formulating effective communication strategies through the cultivation of relationships with experts or opinion leaders.

Second, performance expectations are stronger predictors of mood than effort expectations. The results imply that when patients find a service robot useful enough, they are going to put in the time and effort to use it. Medical institutions need to further improve the intelligence of service robots and other functions to provide convenient and efficient services for patients. For example, hospitals should integrate tailored service scenarios to elevate the cognitive performance and interactive capability of service robots, optimize the interaction interface, and afford them greater autonomy in their interactions with patients.

Third, designers ought to concentrate more on the anthropomorphic features of the medical service robots, especially the three anthropomorphic attributes of voice, behavior, and personality. Service robots with human-like voices, behaviors, and personalities may help hospitals create high-quality care. Most patients, as a vulnerable group in the medical environment, are prone to psychological phenomena such as consultation anxiety and emotional sensitivity due to external and internal factors. Therefore, the ability of robots to process language and understand patients is an important feature to increase their use in healthcare services (Pelau et al. 2021). Medical service robots should be designed with warm and friendly anthropomorphic attributes such as a welcoming voice, a personality that is approachable and empathetic, and intelligent mobility. This will help patients receive medical services that are more empathetic and compassionate. Simultaneously, designers should focus on cultivating anthropomorphism in the behavior and personality of medical service robots, enabling the development of refined behavioral feedback and adaptable personality expression. This approach will facilitate the provision of more personalized and natural services during the consultation phase, thus addressing the individualized and distinct requirements of patients. However, designers should avoid increasing the level of appearance anthropomorphism of service robots excessively. Patients do not improve their service experience because a service robot looks more like a human and may even raise issues such as ethical crises (Pollmann et al. 2023), identity threats, and privacy concerns.

Conclusion

This study explored the multi-stage decision of patients' intention to use a medical service robot and the interrelationship between significant predictors. The results demonstrate the AIDUA model's applicability in the Chinese healthcare setting and emphasize the importance of emotion in the patient's final decision to use the service robots. Findings further revealed the important role of voice, behavior, and personality anthropomorphic attributes in the patient assessment process, which increased positive patient emotions toward the robot by enhancing empathy and interaction quality. Our research will contribute to the available knowledge of medical service robots' use intentions and service robot anthropomorphism. Furthermore, the study provides managers with some insight that could benefit the future rollout and adoption of medical service robots.

Limitations

Currently, service robots in China's healthcare context are still in the early stages of adoption and popularization, and users' technical perceptions and emotional identification with medical service robots are still vague. This study utilized self-reported data, which, while facilitating the achievement of research objectives, is inevitably subject to biases of a broad nature. Future research should incorporate direct measurement data to comprehensively assess patients' acceptance or rejection behaviors towards healthcare service robots, thereby yielding more reliable and valid results. Besides, our study adopted a cross-sectional design, which makes establishing causality difficult. Temporal changes might occur in the patients' attitudes toward medical service robots and may affect their intentions. In light of this, prospective research should think about using a longitudinal experimental design or making causal inferences.

Second, the effects of cultural diversity were not examined. As the data sample is limited to Chinese patients, the results of this study may face challenges in being generalized across countries with significant differences in their healthcare environments. Prior literature conceded cultural differences as important variables to predict users' emotions toward robots (Abdelhakim et al. 2023). For example, the Japanese pay more attention to the emotional experience of human-computer interactions. Also, due to the different medical consultation processes in China and other countries, patients in different cultures will focus on different attributes of medical service robots. For instance, in the context of the U.S. healthcare delivery system, the presence of family doctors and the appointment systems may lead to a reduced likelihood of patients encountering medical service robots during outpatient services in public hospitals. Consequently, this dynamic may contribute to variability in patients' perceptions and attitudes toward such robotic systems. Future studies should fully explore how cultural variations affect patients' acceptance of medical service robots.

Third, this study did not explore the potential influence of patients' health literacy, education, or age on the hypothesized associations. As digital technology and social robots have penetrated deeply into the daily lives of Chinese people, there may not be much difference in the acceptance of robots by groups at different levels. Future studies should stratify different populations to obtain more precise conclusions.

In addition, this research primarily focuses on enhancing patients' acceptance of medical service robots. However, in real human-computer interactions, patients may experience service failures due to potential ethical risks associated with robots, inappropriate robot behavior, and other factors. Future research could delve deeper into the specific types of tasks and service scenarios patients encounter, aiming to uncover more personalized user needs.

Data availability

The datasets generated and analyzed during the current study are not publicly available due to privacy issues but are available from the corresponding author on reasonable request.

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Wenjia Li: Conceptualization, Methodology, Investigation, Data curation, Writing – original draft. Huangyi Ding: Methodology, Data curation, Software, Writing – origi-nal draft. Jingjing Gui: Software, Visualization. Qinghe Tang: Supervision, Validation, Writing – review & Editing

Competing interests
The authors declare no competing interests.

Ethical approval
The procedures used in this study adhered to the ethical standards set out in the Declaration of Helsinki. As this study was not medical research nor considered human experimentation as stated in the Declaration of Helsinki, and because the questionnaire did not adversely affect the mental health of the respondents, ethical approval was required for this questionnaire-based study according to the regulations of the authors' institution (the Academic Ethics Committee of the University of Shanghai for Science and Technology (decision of November 2022)). Moreover, by completing the questionnaire, each respondent who was at least 18 years old consented to participate in the research study. The information collected was used exclusively for the study and was treated as strictly confidential and anonymous.

Informed Consent
Informed consent was obtained from all participants involved in the study. The nature and objectives of the study, together with the participants ability to withdraw at any time, were explained to the participants. The informed consent process was conducted from November-December 2022 and February-March 2023, concurrently with the questionnaire distribution.

Additional information
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