Humanities & Social Sciences Communications

ARTICLE

https://doi.org/10.1057/s41599-024-03388-5 OPEN

Consumer acceptance of robotic surgeons in health services

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Over the course of the preceding half-century, specific advancements in robotic technologies have been assimilated into the continuum of human life in a seamless manner, demonstrating the profound impact of robotics on society. Nevertheless, the actual consumer response to service robots remains a subject of ongoing research, with scant attention paid to it thus far. This study focuses on the potential factors influencing the acceptance of robots in the realm of health services. Specifically, a model has been developed to explain individuals' willingness to use a robot as a surgeon to correct visual impairment in one eye. The Partial Least Squares Structural Equation Modeling (PLSc-SEM) technique is deployed to validate the proposed hypotheses. The model proposed exhibits a robust explanatory power concerning the intention to utilize the robot surgeon, as evidenced by a high R-squared value of 0.817. The findings show the influence of effort expectancy, performance expectancy, social influence, and perceived risk on the intention to adopt robot services. However, the emotional dimensions, specifically pleasure and arousal, were not observed to exert any significant impact on the intention to employ the proposed robot surgeon. The proposed and tested model serves as a roadmap for future research and holds significant practical implications for the industry, paving the way for a more robot-friendly future in health services.

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Introduction

Strategic orientation toward digitalization plays a key role in the successful creation and maintenance of client relationships (Cuesta-Valiño et al. 2023). In the health services industry, robots are a cornerstone of this digitalization. Robots are replacing frontline employees in many services (Belanche et al. 2020). A new automated service digital environment is emerging, in which no face-to-face contact exists between employees and customers based on an innovative Frontline Service Technology (De Keyser et al. 2019). Complex robots and other emerging technologies, such as Artificial Intelligence, are representing a disruptive innovation in the healthcare sector (Chaudhuri, Thrassou & Vrontis, 2022). Smart healthcare devices such as self-managing robots, automatic issues of drug prescriptions, or self-learning machines are transforming medical services, provoking a paradigm shift in health services (Patrício et al. 2020; Lee, 2019). In the domain of health services, the advent of robotic technology has engendered a transformative shift, ushering in a novel and positive paradigm in therapeutic (Beasley, 2012; Mois and Beer, 2020). Additionally, advancements in the field of medical robotics have culminated in the advent of a diverse array of medical devices, which can be deployed in both proximate and distant robotic surgical procedures. A new reltationship paradigm between users and robots in health services emerges (Amarillo et al. 2021; Bayro-Corrochano et al. 2020; Onnasch and Roesler, 2020). These robots are used to enhance and imitate human capabilities. Although some regard the performance of entire surgical procedures or parts thereof as a potential futuristic use of robots (Pessaux et al. 2015), in fact, it is already a reality. For instance, surgeons operating from a console can use remote-controlled robotic arms to perform laparoscopic surgeries. This not only enhances healthcare quality and surgical outcomes but also improves surgeon performance, all while reducing the risk of infections due to blood transfusions (Barbash and Glied, 2010). In December 2016, robot-assisted surgery was performed for the first time on a human eye, with the robot performing semiautomated tasks (Parkin, 2017).

Almost 20 million cataract surgeries are performed each year around the world, costing around USD 10 billion in the USA alone (Lindstrom, 2015). Contemporary research endeavors have been directed toward the conceptualization and development of systems with the potential to supplant human surgeons with their robotic counterparts (Hoeckelmann et al. 2015). To date, the majority of the extant systems have been employed to bolster and enhance the capabilities of surgeons, thereby augmenting the quality of life and safety of patients (Diana and Marescaux, 2015). The assimilation of such technological advancements is not solely contingent upon healthcare institutions and robotic designers, but also intricately linked to the consumers' intent and actual utilization of robots within the healthcare services (Alaiad et al. 2013). The question thus becomes: will consumers accept surgical robots? And, what factors influence that acceptance?

In addition to the superior technical capabilities that consumers expect from robots, their envisioned use in the service sector requires them to have certain features related to the ability to interact with people socially. Consequently, the factors affecting robot service acceptance, which will determine the successful deployment of robots in service settings, may include both technical and social aspects. Previous studies have focused on robot acceptance from a technology acceptance perspective; little attention has been paid to social and emotional factors even though the use of robots can involve direct interaction with consumers, as in the cases of healthcare (e.g., Alaiad and Zhou, 2013, 2014; Alaiad et al. 2013) or service robots (e.g., Homburg and Merkle, 2019; Stock and Merkle, 2017, 2018a, 2018b).

In this context, technology acceptance research is normally conducted with products already on the market. A limited number of scholars exhibit interest in the acceptance of technologies that are currently in the emergent stage of development (Reinares-Lara et al. 2018). The acceptance of robots by workers has been analyzed (Turja and Oksanen, 2019) but few studies focus on the acceptance by consumers in health services such as the surgical ones. Consequently, the current study pivots its attention towards these technologies, aiming to bridge this existing gap and proffering invaluable foundational knowledge to society regarding forthcoming technological advancements, especially in the field of healthcare services acceptance by consumers. It looks at the acceptance of robot surgeons in the healthcare sector. Since this application will require direct robot–human interaction, the research will consider technology acceptance factors, such as performance expectancy, effort expectancy, social influence, and perceived risk. The expectations of value related to the expectations of surgical services performed by robots are another potential factor to consider (Hamilton and Tee, 2015). It will also examine social capabilities, such as empathy and emotions, as the research on human-robot interactions indicates that humans treat robots as social entities with specific social roles and characteristics. Therefore, robots should be designed to be social in structure to better integrate into the human-owned environment (Broadbent et al. 2009; Sharkey, 2016).

Specifically, the research aims to answer the following question: What are the primary factors that facilitate the acceptance of robot services in surgical procedures? It will do this by fulfilling three research objectives, namely: to propose a theoretical framework to define and explain the factors influencing the intention to use robot services; to offer recommendations to technology developers and service providers based on the model validation and results; and to provide guidelines for future research, especially for researchers interested in frontier products (i.e., those on the cutting edge of new technological developments). The model proposed herein can be perceived as both a foundational reference point and a benchmark for ensuing investigations within this discipline.

Literature review and hypotheses

Influence of effort expectancy and performance expectancy on the intention to use health robot services. Effort expectancy is related to the simplicity of using and interacting with a new technology, while performance expectancy is related to an individual's beliefs about the ability of a new technology to improve his or her performance (Venkatesh et al. 2003). The Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al. 2003), and its extension (UTAUT2) (Venkatesh et al. 2012), established the impact of these variables on the acceptance of new technologies. Both constructs are an evolution of constructs from the Technology Acceptance Model (TAM) (Davis, 1989): perceived ease of use and perceived usefulness, respectively. Various studies on healthcare services have examined new technology acceptance by applying these two constructs and have confirmed their impact on intention and use behavior (Chang et al. 2015; Chen et al. 2013; Sun et al. 2013). For instance, some studies have found that effort expectancy is the major influencer on the acceptance of such technologies, either through its direct impact on behavioral intention or indirectly through its impact on performance expectancy (Chow et al. 2013; Keikhosrokiani et al. 2018; Pai and Huang, 2011).

Both constructs have also been employed in research to analyze the acceptance and proliferation of robot technology within the healthcare industry. For instance, Alaiad et al. (2013) and Alaiad and Zhou (2014) use the UTAUT to investigate the acceptance of humanoid healthcare robots and find that performance expectancy holds the greatest importance, becoming the best predictor of the intention to use them. They further confirm the impact of effort expectancy through its direct impact on performance expectancy, proving the usefulness of these robotic systems, and highlighting their potential to enhance daily living and expedite the process of treatment and recovery. Their study argues that, once patients perceive these benefits, they may be more willing to accept healthcare robots. In contrast, other studies highlight the importance of effort expectancy in the early stages of use (Heerink et al. 2008, 2009, 2010a) and performance expectancy for long-term use of service and social robots (de Graaf et al. 2015; Park and del Pobil, 2013).

In light of these previous findings, the following hypotheses are proposed in the context of robot service use in the healthcare sector:

H1a: *The patient's intention to have a surgery done by a robot is positively affected by effort expectancy.*

H1b: *The patient's intention to have a surgery done by a robot is positively affected by performance expectancy.*

Influence of social influence on the intention to use robot services. Social influence is defined as the degree to which a person perceives that others believe that he or she should use a specific technology (Venkatesh et al. 2003). Since individuals are members of their social groups, other members' opinions and advice regarding a behavior or decision can make a difference and can guide that behavior or decision. It thus makes sense to investigate the effect of social influence in the study of new technology acceptance (Ajzen, 1991). Social influence was introduced by the Theory of Reasoned Action (TRA) (Fishbein and Ajzen, 1975) and the Theory of Planned Behavior (TPB) (Ajzen, 1991), and it has been integrated into technology acceptance models, including the TAM and UTAUT and their extensions, the acceptance of cyborg technologies (Pelegrín-Borondo et al. 2015; Pelegrín-Borondo et al. 2017; Pelegrín-Borondo et al. 2016; Reinares-Lara et al. 2018; Reinares-Lara et al. 2016), and the acceptance of new technologies in healthcare services (Chu et al. 2018; Guo et al. 2012; Hossain et al. 2019).

In the realm of robotic acceptance, the role of social influence, particularly from friends and family members, appears to be a critical determinant in shaping an individual's intention to use a robot (Conti et al. 2017; Heerink et al. 2009). For instance, the likelihood of fostering a positive human–robot collaboration in working environments can be enhanced by favorable counsel and endorsements from those who have had a satisfactory prior experience or have been persuaded of the robots' efficacy as co-workers (Bröhl et al. 2016). Simultaneously, the anticipated impact of social influence is projected to be positively substantial in relation to both the acceptance of robots in frontline works (Wirtz et al. 2018) and the adoption of social robots by the elderly population (Alaiad and Zhou, 2013; Alaiad et al. 2013; Chen, 2018). This underscores the pervasive role of social factors in shaping perceptions and attitudes toward robotic technology across diverse contexts and demographic groups.

Based on the above, the following hypothesis is proposed:

H2: *The patient's intention to have surgery done by a robot is positively affected by a favorable social influence.*

Influence of the pleasure and arousal emotional dimensions on the intention to use robot services. Integrating emotions into models breaks away from traditional frameworks of technology acceptance that prioritize rationality and logic in explaining human behavior. Recognizing the intricate relationship between emotions and cognition broadens the scope of modeling by adding a dynamic element. Emotions enhance comprehension of complex phenomena, including consumer behavior. Within the framework of technology adoption, the CAN model was formulated by Pelegrín-Borondo et al. (2016) and Olarte et al. (2017) as a means to evaluate the acceptance of technological implants. Using the CAN model, they demonstrate the influence of both positive and negative emotions on the acceptance of new technologies. Nonetheless, arousal and pleasure are considered by some scholars as the most fitting indicators of the human emotional condition (Cohen et al. 2008). The PAD emotional state model incorporates these emotional variables (Mehrabian and Russell, 1974). The levels of emotional pleasure and emotional arousal are the emotional dimensions most supported by the literature (Pelegrín-Borondo et al. 2015; Russell, 1980, 2003). Pleasure is related to the state of feeling good, happy, joyful, or content in a certain situation. Arousal refers to the state of feeling excited, alert, stimulated, wakeful, or active in a certain situation (Das, 2013; Mehrabian and Russell, 1974). In relation to both utilitarian and hedonic tasks, arousal and pleasure are deemed significant in shaping attitudes toward robotic technology (Kulviwat et al. 2007). Furthermore, the emotional arousal and pleasure experienced by a human during an interaction with social robots can notably influence acceptance in either a positive or negative manner, as well as affect the individual's emotional state (Damholdt et al. 2015).

In the provision of health services, patients' emotions can influence their decision to continue or end the service-buying process. The perception of arousal and pleasure can be linked to their behavioral intention, while negative emotions can be associated with the rejection of the service (Ladhari et al. 2017). Within the same framework, the discernment of service quality and the emergence of positive emotions can be attributed to efficacious interactions with the personnel engaged in the provision of the service (Ladhari and Rigaux-Bricmont, 2013). Feelings of arousal and pleasure thus promote behavioral engagement, as can be seen in the use of social robots in autism therapy (Rudovic et al. 2017). Conversely, the interactive features of robots can amplify the emotional response of consumers. This is evident in elderly health services, where an elderly individual's intent to use a social robot is closely tied to their experience of arousal and pleasure emotions. Simultaneously, a positive emotional reaction from the robot towards patients can encourage their acceptance of robotic technologies (Zhang et al. 2010, 2009).

In light of these previous studies on the impact of emotional dimensions on robot service acceptance, the following hypotheses are proposed:

H3a: *The patient's intention to have surgery done by a robot is positively affected by pleasure.*

H3b: *The patient's intention to have surgery done by a robot is positively affected by arousal.*

Influence of perceived risk on the intention to use robot services. Perceived risk is associated with uncertain situations (Gadeikiene et al. 2012). For instance, it has been included in technology acceptance models looking at online transactions and has been found to be an important predictor of the intention to use such technology (Nathan et al. 2019; Pavlou, 2003). Similarly, it has been employed in the examination of the acceptance of wearable technologies for healthcare purposes (Li et al. 2016; Yang et al. 2016) and the electronic exchange of information across the health services industry (Ahadzadeh et al. 2015; Chu et al. 2018; Hsieh, 2014). Certain authors emphasize the significance of perceived risk in human-robot interactions, contending that customers may refrain from using robots entirely if they believe the risks surpass the benefits (Hancock et al. 2011). The influence of risk has also been assessed using other variables (e.g., trust and social-robot characteristics). However, the impact of the construct on its own still needs to be investigated, and the conceptual models expanded to include perceived risk in the assessment of robotic technology acceptance (Blut et al. 2018). suggest that risk is viewed as a consequence (or side effect) of utilizing such technologies, rather than a factor perceived by users. Consequently, it is often not incorporated into their research models, such as those pertaining to healthcare applications (Kates et al. 2015; McColl et al. 2013; Young et al. 2009).

The following hypothesis is thus proposed regarding the expected impact of perceived risk on the intention to use robot services in the healthcare context:

H4: *The patient's intention to have surgery done by a robot is affected negatively by the perceived risk.*

Influence of empathy on the intention to use robot services. Empathy is characterized by the comprehension of customers' viewpoints and the ability to engage with them on an emotional level (Davis, 1983; Mohtasham et al. 2017). The interaction between a customer and an employee during service experiences is a fundamental method for assessing the quality of service (Mosadeghrad, 2013). Moreover, the traits of employees, such as empathy, should be factored in during recruitment, as they significantly impact customer perceptions of the service's value (Namasivayam and Denizci, 2006). Within this framework, empathy is less of an inherent characteristic and more of a skill that can be cultivated and refined to improve the interaction between customer and employee, ultimately leading to customer satisfaction (Malle and Pearce, 2001). The SERVQUAL instrument is used to evaluate the perceptions of service quality from customers (Ghobehei et al. 2019). Robot acceptance models also apply it. For example, empathy positively influences human expectations about robot behavior and stimulates successful interactions with robots in service settings (Niculescu et al. 2013). Likewise, some authors view empathy as a crucial element of a robot's social skills, emphasizing its substantial role in influencing the intention to use social robots. They include it in technology acceptance models related to the adoption of social robots (Heerink et al. 2010b; Heerink et al. 2010a).

In light of this conceptual framework regarding how expectations of empathy impact the intention to use robot services in healthcare, the following hypothesis is proposed:

H5: *The patient's intention to have a surgery done by a robot is positively affected by perceived empathy.*

The Unified Theory of Acceptance and Use of Technology (UTAUT) model and the Cognitive—Affective—Normative model provide a robust theoretical framework that enables us to comprehensively assess the factors influencing users' acceptance and adoption of technological innovations within the health service context. The proposed theoretical model of variables influencing the intention to use robot services in the healthcare sector is shown in Fig. 1.

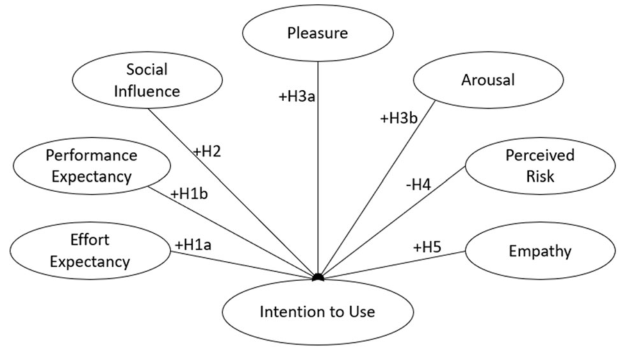

Fig. 1 The proposed theoretical model (pg. 7).

Method

A quantitative methodology was used for the research. To empirically test the proposed hypotheses, a digital questionnaire was constructed utilizing the Google Forms platform. The data collection process yielded responses from a sample of 379 individuals, all of whom were affiliated with various Jordanian universities. Studies focusing on young people are relevant because they exhibit specific behaviors that may differ from other age groups (Cuesta-Valiño et al. 2022). A noteworthy observation from the demographic distribution of the respondents was that a significant majority, precisely 92%, were of Jordanian nationality. The remaining 8% comprised students originating from other Arab nations, currently pursuing their education in Jordan. Furthermore, the gender distribution of the respondents was fairly balanced, with women constituting 47% of the total, and men accounting for the remaining 53%.

A structural equation modeling (SEM) tool was employed to execute the model. SEM allows researchers to analyze both the structural component (path model) and measurement component (factor model) concurrently within a single framework (Ringle et al. 2015; Cuesta-Valiño et al. 2022). The consistent partial least squares (PLSc) SEM technique was used to test the proposed hypotheses using SmartPLS 3 software. The Partial Least Squares Consistent (PLSc) method exhibits a lower susceptibility to both Type I and Type II errors in comparison to the traditional Partial Least Squares (PLS) technique. Therefore, it is recommended to employ the PLSc method in scenarios where all constructs within the model are reflective (Dijkstra and Henseler, 2015), as in the present research. PLS tends to skew factor loadings upwards and underestimate regression coefficients (Gefen et al. 2011). The selection of the PLS technique was primarily driven by its robustness against deviations from the assumption of normality, a characteristic that is particularly advantageous in the context of social science research (Chin, 1998a). Moreover, the application of partial least squares consistent structural equation modeling (PLSc-SEM) is particularly suitable for research endeavors aimed at both prediction and explanation, as is the case in this study (Mosquera et al. 2018).

The measurement scale was developed based on the literature review using an 11-point scale (0–10). the measurement scales employed for the constructs of effort expectancy, performance expectancy, and social influence were derived and adapted from a scale previously developed by Venkatesh et al. (2012). These scales have been previously employed in research studies within the domains of health services and robotics (Alaiad and Zhou, 2013, 2014; Alaiad et al. 2013; de Graaf et al. 2019; Hossain et al. 2019; Lu et al. 2019; Talukder et al. 2019). In contrast, to measure the intention to use, the measurement scale developed by Venkatesh and Davis (2000) was used. Various prior studies on technology acceptance, encompassing robotics and diverse service settings, have employed and validated this scale (Chen et al. 2017; Chow et al. 2013; Im et al. 2007; van der Heijden, 2004).

The scale used by Loureiro (2015), established by Mazaheri et al. (2011), was used to measure the emotional dimensions arousal and pleasure. Various contexts of technology acceptance studies have also made use of it. (Chen et al. 2017; Pelegrín-Borondo et al. 2017; Ruiz-Mafe et al. 2018). The measurement scale used to measure the empathy construct was adapted from

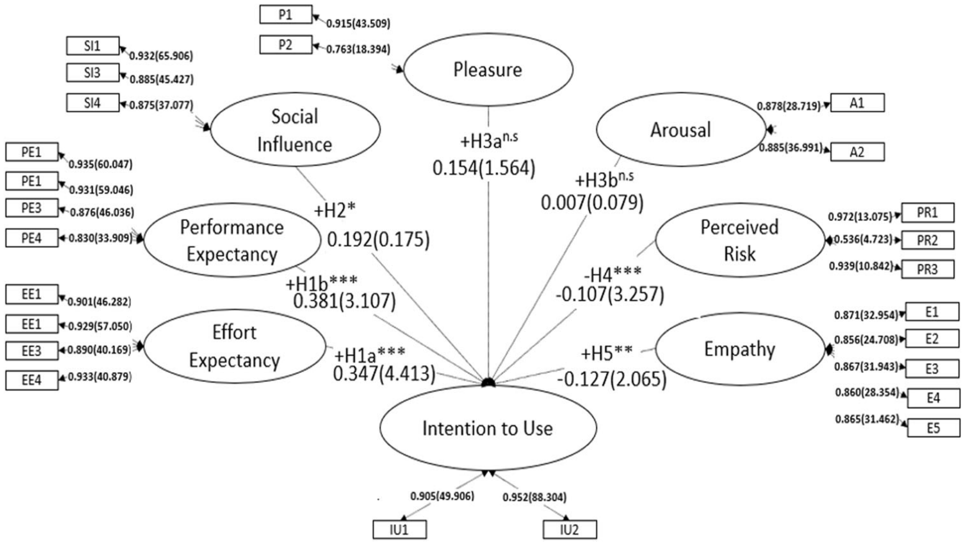

Fig. 2 Sign, magnitude, and significance (t-value) of the path coefficients of the robot service model. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$; n.s. not significant.

Homburg and Merkle (2019), who developed their scale based on Davis (1983), Hogan et al. (1984), and Parasuraman et al. (1991), in their study of attitudes towards humanoid robots.

The measurement scale for perceived risk was formulated drawing upon the scale adapted by Faqih (2016). This scale traces its origins back to the work of Shim et al. (2001). Its validity has been confirmed through various studies on technology acceptance (Agag and El-Masry, 2017; Pelegrin-Borondo et al. 2017; Yang et al. 2015).

Results

Measurement model assessment. The evaluation began with the criterion of internal consistency reliability. By employing Cronbach's alpha and composite reliability, the constructs' reliability was confirmed to be adequate (Hair et al. 2017). Hair et al. (2013) recommend a threshold of more than 0.70 for both Cronbach's alpha and composite reliability. The Cronbach's alpha and composite reliability values for all the constructs in the measurement model exceeded the threshold of 0.70, thereby confirming the internal consistency reliability. It is recommended that the standardized loading of the indicators exceed 0.70 and the t-value surpasses 1.96 to ensure the reliability of the indicators in the measurement model. Nonetheless, values ranging from 0.4 to 0.7 may be deemed acceptable, provided that the t-value is above 1.96. As can be seen in Fig. 2, all the measurement model indicators had standardized loading values greater than 0.7 and t-values greater than 1.96, except one Perceived Risk item, which had standardized loadings less than 0.7. Nevertheless, its t-values were greater than 1.96, and, as noted by Chin (1998a), the 0.7 standardized loading rule is flexible, particularly when indicators contribute to a factor's content validity. Therefore, the item was kept.

The attainment of convergent validity is corroborated by a positive correlation between an indicator and its alternative indicators within the same constructs. In order for this to hold, the average variance extracted (AVE) value must be at least 0.50 (Hair et al. 2017). The convergent validity of the measurement models is confirmed as all constructs of the research model demonstrated AVE values exceeding 0.50.

The last stage in evaluating the measurement model involved assessing the discriminant validity. This process ensures that the indicators of each construct only measure their respective construct and not others (Hair et al. 2017). Discriminant validity was evaluated using two methods. The initial method employed was the Fornell–Larcker criterion, which involves a comparison of the latent variable's correlation with the square root of the AVE values. For the discriminant validity criterion to be satisfied, the square root of each construct's AVE value must exceed its correlation with other constructs (Roldán and Sánchez-Franco, 2012). The second approach involved evaluating the Heterotrait-Monotrait ratio (HTMT) of the correlations. For validity, this ratio's value should be less than 0.90 (Gold et al. 2001; Henseler et al. 2015). While the criterion for the first method was not satisfied in one instance, all cases adhered to the limit set by the second method. These outcomes thus validate the discriminant validity of the construct indicators. The construct reliability, convergent validity, and discriminant validity are presented in Table 1.

Structural model assessment. The evaluation of the structural model was conducted using the coefficient of determination (R^2), which represents the variance in the endogenous variable explained by the exogenous variables (Chin, 2010). It is generally accepted that the values 0.67, 0.33, and 0.19 are interpreted as substantial, moderate, and weak, respectively. An increase in the R^2 value corresponds to an enhancement in the model's predictive capability (Chin, 1998b; Mosquera et al. 2018). The R^2 value for the robot service model was 0.817. The Q^2 of the PLS Predict was 0.675. Table 2 shows the R^2, Q^2, path coefficients, and t-values and whether support was found for the hypotheses.

An evaluation was conducted on the path coefficient for all exogenous variables. For the path coefficient to be significant, it is required that the p-value must be less than 0.01, and the t-value must be equal to or exceed 1.65 (Hair et al. 2017; Roldán and Sánchez-Franco, 2012). The research findings provided evidence in support of Hypothesis 1 (influence of effort expectancy and performance expectancy), Hypothesis 2 (influence of social influence), and Hypothesis 4 (influence of perceived risk), but not for Hypothesis 3 (influence of pleasure and arousal) or Hypothesis 5 (influence of empathy).

Discussion

Robotics emerge as a potential solution for many societal challenges, such as aging, productivity, and climate change (Michalec et al. 2021). Different studies have investigated robot acceptance

Table 1 Robot service model construct reliability, convergent validity, and discriminant validity.

Variables	Cronbach's alpha	Composite reliability	AVE	PE	EE	P	A	SI	PR	E	IU
PE	0.941	0.941	0.800	**0.894**	0.777	0.721	0.722	0.881	0.055	0.592	0.860
EE	0.953	0.953	0.834	0.777	**0.913**	0.614	0.619	0.774	0.049	0.711	0.795
P	0.822	0.829	0.709	0.719	0.612	**0.842**	0.856	0.690	0.058	0.601	0.710
A	0.875	0.875	0.778	0.722	0.619	0.849	**0.882**	0.706	0.100	0.602	0.698
SI	0.926	0.926	0.806	0.881	0.774	0.690	0.706	**0.898**	0.079	0.663	0.815
PR	0.873	0.871	0.704	0.007	0.047	−0.043	−0.105	0.070	**0.839**	0.240	0.109
E	0.936	0.936	0.746	0.592	0.712	0.599	0.602	0.663	0.246	**0.864**	0.543
IU	0.926	0.926	0.863	0.860	0.795	0.707	0.698	0.816	−0.113	0.543	**0.929**

Note: Values on the main diagonal (in bold) are the square roots of the AVEs. Values below the diagonal are the correlations between the constructs. Values above the diagonal are the HTMT values. *PE* performance expectancy, *EE* effort expectancy, *P* pleasure, *A* arousal, *SI* social influence, *PR* perceived risk, *E* empathy, *IU* intention to use.

Table 2 Structural model results.

Variable	R^2	Q^2	Path coefficient	*t*-Value	*p*-Value	Decision
Intention to use	0.817	0.675				
Performance expectancy → (+) Intention to use			0.381	3.107	0.002	Supported
Effort Expectancy → (+) Intention to use			0.347	4.413	0.000	Supported
Pleasure → (+) Intention to use			0.154	1.564	0.118	Not Supported
Arousal → (+) Intention to use			0.007	0.079	0.937	Not supported
Social Influence → (+) Intention to use			0.192	1.753	0.080	Supported
Perceived Risk → (+) Intention to use			−0.107	3.257	0.001	Supported
Empathy → (+) Intention to use			−0.127	2.065	0.039	Not supported

in terms of social interaction. However, consumers' reactions to service robots are still an emerging topic with scarce studies (Stock and Merkle, 2018b). Nevertheless, robots are evolving and are transforming the workforce. What remains uncertain is the magnitude of this development, its implications, and the perception of consumers toward robots in service environments. The service robot model was consequently designed to assess the willingness of patients to utilize them, specifically in the role of surgeons. The model was built based on technology acceptance models (e.g., UTAUT, TAM, and CAN models). Moreover, it incorporates certain additional elements that can be utilized to evaluate the suggested surgeon, facilitating the evaluation of acceptance towards robot services. The integration of emotions into models signifies a departure from traditional technology acceptance frameworks that prioritize rationality and logic in human behavior analysis. This integration enhances comprehension of multifaceted phenomena like the acceptance of robots as surgeons.

The first key finding is the model's power to explain patients' intention to use a robot surgeon ($R^2 = 0.817$). Research results showed that effort expectancy had the strongest impact on the intention to use robot services (p-value < 0.01, t-value = 4.413), while performance expectancy ranked third (p-value < 0.01, t-value = 3.107). This is to be expected as numerous prior studies on the acceptance of robot technology concur on the significance of these factors in encouraging the intention to utilize it (Alaiad and Zhou, 2013, 2014; Stock and Merkle, 2017). The significance of performance and effort expectancy can be explained by the notion that users often view ease of use and performance efficiency as key drivers in motivating their intention to adopt new technologies, particularly during the initial stages (Heerink et al. 2008, 2009, 2010a).

The findings also indicated that social influence has a notable, albeit moderate, positive effect on the intention to utilize robot services (p-value < 0.1, t-value = 1,753). This finding is in line with those of previous studies on robot acceptance involving direct interaction between humans and robots (e.g., Conti et al. 2017; Heerink et al. 2009). Typically, people may alter their emotions, perceptions, attitudes, or actions during interactions with others. As a result, they may base their decisions on the recommendations of others, particularly when the service or product is relatively novel and/or unfamiliar (Talukder et al. 2019). Therefore, the established influence of social factors on the intention to use the suggested services can be rationalized by the significance of advice from others. Furthermore, the effect of social influence provides a broad perspective on the healthcare landscape in Jordan, where a segment of the population places greater emphasis on the advice of others (such as family members, friends, or existing users) when selecting a surgeon. However, although this variable is significant, its influence is low. This is logical since the importance of other people's opinions of a product can decrease dramatically when that product is related to health.

The results did not indicate a substantial influence of emotions related to pleasure and arousal (H3) on the intention to utilize healthcare services offered by robots. This outcome diverges from previous studies on the acceptance of cutting-edge products, like cyborgs (Pelegrín-Borondo et al. 2017) or social robots (Zhang et al. 2009, 2010). The diminished importance of pleasure and arousal could be attributed to the use of technology in a healthcare setting, particularly in surgical procedures. People might prioritize the treatment of their illness over the experience being enjoyable or exciting. The diminished importance attributed to pleasure and arousal may arise from the unique characteristics of surgical services. Individuals undergoing medical procedures often prioritize effective treatment over seeking pleasurable experiences. This shift in focus reflects a heightened emphasis on the efficacy and outcomes of medical interventions rather than the immediate gratification or excitement associated with the healthcare process. Moreover, advancements in medical technology have increasingly streamlined surgical procedures, emphasizing precision, safety, and effectiveness, thereby overshadowing considerations of pleasure and arousal during the treatment process. Anyway, we consider that the inclusion of emotions in acceptance models could be relevant in other contexts, as it has been proved for the acceptance of social robots (Subero-Navarro et al. 2022).

With regard to the influence of perceived risk on the intention to use the robot service (H4), results showed its significance, as the second most relevant variable (p-value < 0.01, t-value = 3.257).

It's understandable that there might be inherent uncertainties about the robots' appearance, behavior, and effectiveness as surgeons. Despite this, the majority of prior studies on robot acceptance highlight the significance of perceived risk in accepting new technology, even though it has not been incorporated into the research models utilized (e.g., Destephe et al. 2015; Wirtz et al. 2018). If patients perceive a risk linked to the use of robots, they might choose to refrain from utilizing services provided by them (Blut et al. 2018).

Interestingly, the findings reveal that empathy (H5) significantly influences the intention to use robot services, but in an unexpected reverse direction. In certain service environments, it can be viewed as a major determinant of consumer buying behavior, particularly in scenarios that involve direct interaction between customers and employees. This is due to the expectation of customers in these scenarios for employees to comprehend their needs and respond appropriately (Malle and Pearce, 2001). Similarly, given that empathy is viewed as a crucial element in human social interactions, it has been extended to interactions between humans and robots as well. This empathy can be conveyed through facial expressions (Riek and Robinson, 2008), and human perception of a robot's empathy may be influenced by the robot's behavior during the interaction process (Gonsior et al. 2011). However, such displays of empathy could be viewed unfavorably, particularly as robots start to behave and look more like humans and less like machines (Leite et al. 2012; Złotowski et al. 2016). This could lead to the rejection of human-like robots if they behave too similarly to humans. Hence, additional research is needed to explore the ambiguous boundary of what is deemed normal and abnormal by consumers in both facets of robots, namely, their behavior and appearance. This will enable designers to align with consumers' expectations in terms of robot design. In this scenario, Mori (1970) proposed that humans might experience a sense of unease or discomfort (termed an "uncanny" feeling) when interacting with robots that closely resemble humans. In other words, consumers may positively perceive robots' ability to experience and detect emotions without expressing them (Koschate et al. 2016), i.e., without behaving as if they were human.

Conclusions and managerial implications

This study pushes forward a new line of research concerning the acceptance of robots as independent entities that can be employed in crucial service environments, such as health services and surgical procedures. Acquiring a profound understanding of robot acceptance in services broadly and in health services specifically will be extremely beneficial for robot developers, allowing them to concentrate their efforts on key factors of acceptance. Manufacturers of robot technology can leverage this valuable information to construct their designs. By focusing on the factors that most significantly influence consumer acceptance, they can tailor their robots to align with these key aspects. This not only ensures that the robots are well-received by consumers, but also that they effectively meet their needs. Furthermore, understanding these factors can guide manufacturers in making strategic decisions about future developments and improvements, ultimately leading to more successful and beneficial robot technology in the service sector.

Specifically, it's crucial that consumers perceive the use of the robot as effortless. The technology should be designed in a way that its operation is intuitive and straightforward, eliminating any potential barriers to its use. Moreover, the robot must not only seem useful but also deliver substantial value. It should be capable of performing tasks efficiently and effectively, thereby justifying its adoption. The perceived usefulness extends beyond the robot's primary function; it should also enhance the user's overall experience, whether it's saving time, reducing effort, or providing a level of service that surpasses traditional methods. By ensuring these two key factors - ease of use and usefulness - manufacturers can significantly increase the likelihood of their robot technology being accepted and integrated into everyday routines. Another fundamental aspect is the absolute safety of the robots. It's essential that consumers perceive the robots as completely safe to use, with no risk of harm or error. This includes physical safety, such as the robot's movements and interactions, as well as data security, ensuring that any personal information handled by the robot is protected. If any of these aspects are lacking in the robots' design, it could lead to consumers rejecting them. Furthermore, designers must also consider the potential for rejection of robots that closely resemble humans. This phenomenon, known as the 'uncanny valley', suggests that when robots look and act almost, but not exactly, like humans, it can make people feel uneasy or even repulsed. Therefore, striking the right balance in the robot's appearance and behavior is crucial. Designers need to carefully consider how human-like their robots should be, taking into account the specific context and purpose of the robot. For instance, a robot designed to provide companionship might benefit from a more human-like appearance, while a robot designed for a task like surgery might be better off looking and behaving more like a machine. Finally, marketing campaigns should be created regarding the benefits of using the proposed services to help instill more confidence in the technology and thereby minimize customers' risk perception. In conclusion, it is recommended to develop marketing strategies that emphasize the advantages of our proposed services. This will foster greater trust in the technology and consequently reduce the perception of risk among customers.

Limitations and future research. The study, conducted in one country, suggests that cultural variations could influence the willingness to adopt robot technology. Cross-cultural aspects have proven their relevance in technology acceptance (Pierce and Jiang, 2021). Therefore, the research should be expanded to encompass multiple countries to assess how cultural disparities influence the intent to utilize the suggested service. Another limitation of the research is that focuses on a specific segment: young people. Different results could be obtained with samples from other age groups, which represents a limitation and underscores the need for future studies involving diverse age ranges. Furthermore, a potential limitation of the research could be that consumers possess only a basic understanding of robotic applications. This lack of knowledge might hinder their ability to fully comprehend the benefits and implications of the proposed service, thereby affecting their willingness to adopt such technology. This aspect warrants further investigation in future studies. Health services can be delivered through private or public initiatives. It is important for future studies to explore the role of each and the potential collaborations they can develop to ensure the proper advancement of health robotics, as seen in other sectors (Henche et al. 2020). The findings of the research mirror a common perception among consumers about cutting-edge technologies. Despite the fact that the suggested services are in the development phase, enhancing the respondents' understanding of the underlying technology could potentially alter their view of the proposed robotic service. Hence, subsequent studies should explore the possibility that equipping participants with a more comprehensive understanding of the robotic technology before the data collection phase (for instance, via video presentations and/or prototype demonstrations) could influence their viewpoint of these services and their propensity to utilize them. Finally, this study proposed a specific use of robot technology. The results could vary if the proposed use of robots were conducted in different health service settings due to the enormous differences between health services. For instance, it is difficult to compare a robot used for simple consultations with a complex surgical robot used in operations with potential life-threatening risks. Further comparative studies are required to gain a comprehensive understanding of the entire sector. Another limitation is that this research suggested a particular application of robotic technology. The outcomes might differ if the proposed usage were implemented in diverse service environments. Future research on doctors' acceptance willingness could be beneficial for both academic and professional development within the field of health services robotics.

Data availability

The datasets generated during and/or analyzed during the current study are not publicly available due to ongoing works but are available from the corresponding author on reasonable request.

Received: 25 February 2024; Accepted: 18 June 2024;
Published online: 11 July 2024

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Acknowledgements
This research was supported by Telefonica Chair on Smart Cities of the Universitat Rovira i Virgili and the Universitat de Barcelona (project number 42.DB.00.18.00).

Author contributions
All authors contributed equally to the research, design, and writing of this paper.

Competing interests
The authors declare no competing interests.

Ethical approval
The ethical aspects of the research were presented and discussed with the board of research and ethics of the Social and Business Research Lab (Spain). The presentation took place during the meeting held on January 15, 2020. After a comprehensive review, no objections were raised concerning the ethical considerations and methodology of the study, consenting to its development.

Informed consent
Informed consent was obtained from all participants through detailed explanations of the study's objectives prior to their enrollment and ensuring ethical compliance.

Additional information
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