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Factors Affecting Doctors' and Nurses' Adoption of Surgical Robots in Thai Hospitals

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Abstract

Purpose: This study examines factors affecting doctors' and nurses' adoption and use of surgical robots in Thailand's top 10 hospitals. Based on the Technology Acceptance Model, the Unified Theory of Acceptance and Use of Technology, and the Almere model, it investigates perceived ease of use, perceived usefulness, attitude, perceived risk, social influence, facilitating conditions, intention to use, and use. **Research design, data, and methodology:** A quantitative cross-sectional design was used. Data were collected from 500 doctors and nurses in Thai tertiary hospitals using a structured questionnaire and multi-stage sampling. Confirmatory factor analysis and structural equation modeling were applied to assess reliability, validity, model fit, and hypothesized relationships. **Results:** Perceived ease of use positively affected perceived usefulness (β = .639) and attitude (β = .350). Perceived usefulness influenced attitude (β = .543) and intention to use (β = .349). Attitude (β = .325), social influence (β = .192), and facilitating conditions (β = .282) positively affected intention, while perceived risk had a negative effect (β = −.330). Social influence (β = .336) and intention to use (β = .539) predicted use. All ten hypotheses were supported. **Conclusions:** The integrated model was empirically supported, showing that psychological, social, and organizational factors jointly shape surgical robot adoption in Thai hospitals.

Keywords: Surgical Robots, Technology Adoption, Thai Hospitals, Intention to Use, Use

JEL Classification Code: I11, I18, M15, O33, D83

1. Introduction

Surgical robots have become an important innovation in modern healthcare by integrating medical science, engineering, imaging, and intelligent technologies to support minimally invasive and high-precision procedures. Since the first robot-assisted surgical application in 1985, surgical robotics has expanded across specialties such as urology, orthopedics, vascular surgery, and general surgery. Compared with conventional techniques, surgical robots provide enhanced precision, flexibility, three-dimensional visualization, tremor reduction, and improved instrument control, supporting surgical performance and patient outcomes (Rivero-Moreno et al., 2023; Reddy et al., 2023). Advances in imaging, artificial intelligence, sensor integration, telemedicine, 5G communication, and multisensory feedback are further expanding robotic surgery, including remote operations and advanced human-computer interaction (Attanasio et al., 2020; Picozzi et al., 2023; Tappero et al., 2024; Wu et al., 2022; Xie et al., 2025).

The global surgical robotics market has grown steadily due to rising demand for minimally invasive procedures, aging populations, the prevalence of chronic diseases, and healthcare modernization. This growth is evident in both developed and emerging economies, where hospitals invest in robotic-assisted systems to improve clinical quality and efficiency (Mehta et al., 2022; Perera & Wickramarachchi, 2024). In Thailand, universal health coverage, healthcare modernization, medical tourism, and policy support for medical technology have encouraged investment in robotic surgery. Major hospitals such as Siriraj, Ramathibodi, Bumrungrad, Bangkok Hospital, and other leading institutions have introduced robotic surgical systems, reflecting the growing role of robotics in Thai healthcare

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services.

Despite this progress, effective implementation depends not only on technology availability but also on healthcare professionals' willingness to accept and use surgical robots in clinical practice. Doctors and nurses are key users, and their perceptions, attitudes, and readiness influence whether robotic surgery can be integrated into hospital workflows. However, adoption in Thailand remains constrained by high costs, limited training, insufficient certified programs, and resistance to workflow changes (Duensing et al., 2023; Edmondson et al., 2001; Wongkietkachorn et al., 2018). Although prior studies have examined technological development, clinical applications, and hospital investment, limited research has focused on doctors' and nurses' behavioral intentions and actual use of surgical robots in Thai hospitals. Therefore, this study investigates the factors affecting doctors' and nurses' intention to use and actual use of surgical robots in top-tier hospitals in Thailand.

The formal research objectives of this study are as follows: 1) to examine the effect of perceived ease of use on perceived usefulness; 2) to examine the effect of perceived ease of use on attitude; 3) to examine the effect of perceived usefulness on attitude; 4) to examine the effect of perceived usefulness on intention to use; 5) to examine the effect of attitude on intention to use; 6) to examine the effect of perceived risk on intention to use; 7) to examine the effect of social influence on intention to use; 8) to examine the effect of social influence on use; 9) to examine the effect of facilitating conditions on intention to use; and 10) to examine the effect of intention to use on use.

The research questions are as follows: 1) Does perceived ease of use significantly affect perceived usefulness? 2) Does perceived ease of use significantly affect attitude? 3) Does perceived usefulness significantly affect attitude? 4) Does perceived usefulness significantly affect intention to use? 5) Does attitude significantly affect intention to use? 6) Does perceived risk significantly affect intention to use? 7) Does social influence significantly affect intention to use? 8) Does social influence significantly affect use? 9) Do facilitating conditions significantly affect intention to use? and 10) Does intention to use significantly affect actual use of surgical robots among doctors and nurses in Thai hospitals?

2. Literature Review

2.1 Perceived Ease of Use

Perceived ease of use refers to the belief that a particular system is simple and user-friendly to operate (Davis, 1989). In technology acceptance research, it reflects how easy, understandable, and manageable a system appears to users. When a system is perceived as easy to learn and operate, users are more likely to recognize its practical value and develop favorable perceptions. Venkatesh and Davis (1996) further argued that perceived ease of use reflects users' expectations about the effort required to interact with a system. In healthcare settings, ease of use influences clinicians' acceptance of electronic health records, mobile health applications, and collaborative systems because user-friendly technologies reduce resistance and increase confidence in clinical adoption (Schnall et al., 2015; Tubaishat, 2017).

In surgical robotics, perceived ease of use is especially important because the technology involves advanced interfaces, instruments, and clinical workflows. When doctors and nurses perceive robotic systems as easy to understand and operate, they are more likely to recognize their usefulness and develop positive attitudes toward them. Prior studies have consistently found that perceived ease of use positively influences both perceived usefulness and attitude in technology adoption contexts (King & He, 2006; Venkatesh & Davis, 2000). Therefore, the following hypotheses are proposed.

H1: Perceived Ease of Use has a significant impact on Perceived Usefulness.

H2: Perceived Ease of Use has a significant impact on Attitude.

2.2 Perceived Usefulness

Perceived usefulness is defined as the degree to which a person believes that using a system would enhance his or her job performance (Davis, 1989). It is one of the most important constructs in the Technology Acceptance Model and is commonly applied to explain the integration of information systems and healthcare technologies. Users tend to develop positive attitudes and stronger intentions to use a technology when they perceive it as effective, efficient, and capable of improving work performance (Venkatesh & Bala, 2008).

In healthcare, perceived usefulness has been found to influence the integration of electronic health records, telemedicine, mobile health systems, and clinical decision-support tools because healthcare professionals are more likely to accept technologies that support patient care and work performance (Gagnon et al., 2016; Rahimi et al., 2018). In the context of surgical robots, perceived usefulness may include beliefs that robotic systems improve surgical precision, enhance safety, reduce complications, and support better clinical outcomes. Studies on robotic-assisted surgery have also shown that when users perceive robotic systems as useful, their attitudes become more positive and their intention to use them becomes stronger (Kao et al., 2022; Nayak et al., 2024). Therefore, the following hypotheses are

proposed.

H3: Perceived Usefulness has a significant impact on Attitude.

H4: Perceived Usefulness has a significant impact on Intention to Use.

2.3 Attitude

Attitude is defined as a person's positive or negative evaluation of another person, object, or behavior (Ajzen & Fishbein, 1980). In the Technology Acceptance Model, attitude reflects users' affective judgment toward technology use and is shaped by perceived ease of use and perceived usefulness (Davis et al., 1989). A favorable attitude generally increases willingness to adopt technology. In healthcare technology research, attitude has been shown to influence intention to use telemedicine, mobile health applications, electronic records, and smart hospital technologies (Hu et al., 1999; Tu et al., 2022). In the context of surgical robots, attitude refers to whether doctors and nurses evaluate robotic systems positively or negatively in clinical practice. When healthcare professionals perceive surgical robots as useful, manageable, and beneficial to patient care, they are more likely to develop positive attitudes toward their use. Prior literature also supports the positive effect of attitude on intention to use technology (Teo & Noyes, 2011). Therefore, the following hypothesis is proposed.

H5: Attitude has a significant impact on Intention to Use.

2.4 Perceived Risk

Perceived risk refers to users' belief that using a technology may lead to negative consequences. The concept was first introduced by Bauer (1960) in consumer behavior research and was later extended to information systems by Featherman and Pavlou (2003), who described it as the potential negative outcomes that may arise when using a system. In technology use contexts, perceived risk commonly includes concerns related to privacy, security, system failure, uncertainty, and other possible negative consequences.

In healthcare, perceived risk is particularly important because technology-related errors may affect patient safety, confidentiality, and trust. Previous studies have shown that perceived risk negatively affects the adoption of online health systems, patient portals, mobile health applications, and other digital technologies (Klaver et al., 2021; Sinha et al., 2021). In surgical robotics, perceived risk may include concerns about technical malfunction, operational errors, lack of control, and uncertainty regarding surgical outcomes. When doctors and nurses perceive robotic systems as risky, their willingness to adopt them is likely to decrease. This leads to the following research hypothesis.

H6: Perceived Risk has a significant impact on Intention to Use.

2.5 Social Influence

Social influence describes the social forces that influence an individual's decision to use a technological device or system. It is defined as the degree to which an individual perceives that important others believe he or she should use a new system (Venkatesh et al., 2003). This influence may come from supervisors, colleagues, professional peers, family members, or institutional expectations. In technology acceptance research, social influence is considered an important factor shaping both behavioral intention and actual use, especially in organizational contexts.

In healthcare, social influence can be particularly strong because doctors and nurses often work within formal systems, professional norms, and team-based environments. Previous studies have shown that peer opinions, institutional pressure, and support from important others influence the adoption of healthcare technologies and healthcare robots (Alaiad & Zhou, 2014; Cao et al., 2024). In the case of surgical robots, support from hospital management, senior surgeons, colleagues, and professional networks may increase both willingness to adopt the technology and actual usage in practice. Therefore, the following hypotheses are proposed.

H7: Social Influence has a significant impact on Intention to Use.

H8: Social Influence has a significant impact on Use.

2.6 Facilitating Conditions

Facilitating conditions refer to the organizational, technical, and individual resources that support a person in completing a task or using a system (Venkatesh et al., 2003). These conditions include training, technical support, equipment availability, institutional readiness, compatible systems, and reliable infrastructure. When users perceive that sufficient support is available, they are more confident in adopting and using technology.

In healthcare technology research, facilitating conditions have been shown to affect the use of health information systems, telemedicine, mobile health tools, and clinical technologies because successful implementation requires strong organizational and technical support (Kijsanayotin et al., 2009; Kruse & Heinemann, 2022). In surgical robotics, facilitating conditions may include access to robotic platforms, hospital investment, professional training, maintenance support, and workflow integration. When doctors and nurses perceive that these supports are available,

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they are more likely to intend to use robotic systems and apply them in practice. Therefore, the following hypothesis is proposed.

H9: Facilitating Conditions have a significant impact on Intention to Use.

2.7 Intention to Use

Intention to use refers to a user's willingness and readiness to use a particular system or technology to achieve a desired purpose (Venkatesh et al., 2003). In technology acceptance research, it represents the motivational tendency that precedes actual technology use. In healthcare, intention to use has been applied to explain the adoption of electronic health records, mobile health services, telemedicine, artificial intelligence systems, and robotic technologies (AlQudah et al., 2021; Kwak et al., 2022). In surgical robotics, intention to use reflects the willingness of doctors and nurses to adopt robotic systems in clinical practice. Previous studies consistently support that stronger behavioral intention leads to greater actual use of a system (Dwivedi et al., 2017; Venkatesh et al., 2003). Therefore, the following hypothesis is proposed.

H10: Intention to Use has a significant impact on Use.

2.8 Use

Use refers to the actual behavior of applying a technology in practice and is commonly treated as the final outcome showing whether intention becomes real action (Venkatesh et al., 2003). In healthcare, actual use is critical because successful implementation depends on whether professionals routinely apply the system in clinical settings (Holden & Karsh, 2010).

In this study, use refers to doctors' and nurses' actual engagement with surgical robots during surgical procedures and related clinical activities. Since robotic surgery requires technical skill, training, institutional readiness, and workflow integration, actual use reflects the real integration of robotic systems into clinical practice (Fuller et al., 2025). Therefore, this study proposes that use is directly influenced by social influence and intention to use.

3. Research Methods and Materials

3.1 Research Framework

The conceptual framework of this research is based on theoretical concepts and prior studies related to surgical robot adoption. It was adapted from three major theories and three empirical research frameworks. First, the Technology Acceptance Model (TAM) by Davis (1989) contributed the cognitive variables of perceived ease of use and perceived usefulness. Second, the Almere model by Heerink et al. (2010) contributed socio-psychological factors, particularly attitude and social influence, in the context of robot acceptance. Third, the Extended Unified Theory of Acceptance and Use of Technology (UTAUT) supported the inclusion of facilitating conditions, intention to use, and actual use (Venkatesh et al., 2003).

In addition, previous studies supported the framework by emphasizing different factors in technology and service robot adoption. Verelst (2019) examined technology adoption of service robots in elderly care and emphasized attitude and perceived usefulness. Park and Del Pobil (2013) studied individuals' attitudes toward service robots in South Korea and highlighted perceived usefulness, perceived ease of use, and social influence. Cokins et al. (2020) examined intention to use accounting platforms and emphasized perceived risk and facilitating conditions.

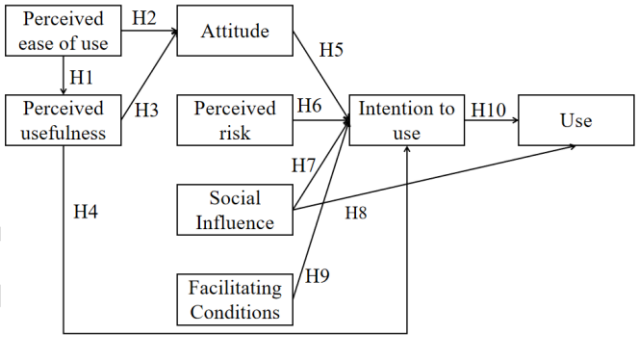

Figure 1: Conceptual Framework

Based on these theories and studies, the conceptual framework proposes that perceived ease of use, perceived usefulness, attitude, perceived risk, social influence, and facilitating conditions influence intention to use and use of surgical robots among doctors and nurses in Thai hospitals, as shown in Figure 1.

3.2 Methodology

A quantitative research design was used in this research. The study involved multi-stage sampling and incorporated both non-probability and probability sampling methods. The research constructs were measured on a five-point Likert scale, ranging from strongly disagree (1) to strongly agree (5). The respondents were doctors and nurses from selected leading tertiary hospitals in Thailand. To determine content validity, the research instrument was first assessed using the Index of Item-Objective Congruence (IOC) by three experts. The IOC values ranged from 0.67 to 1.00, meeting the acceptance criterion of IOC $\geq$ 0.67 for all questionnaire items. Therefore, all measurement items were retained. The

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clarity and preliminary reliability of the instrument were further assessed through a pilot test of 50 respondents. Cronbach's alpha was used to test internal consistency. The pilot-test Cronbach's alpha values ranged from 0.700 to 0.910, indicating acceptable to excellent reliability. Specifically, the Cronbach's alpha values were 0.747 for Perceived Usefulness, 0.717 for Perceived Ease of Use, 0.782 for Attitude, 0.726 for Perceived Risk, 0.716 for Social Influence, 0.802 for Facilitating Conditions, 0.910 for Intention to Use, and 0.700 for Use. These results confirmed that the questionnaire had adequate preliminary reliability before the final data collection. The final questionnaire was then distributed, resulting in 500 valid responses. Participation was voluntary, informed consent was obtained, and respondents could withdraw at any time. No personal information was collected, and all responses were kept anonymous and confidential. The data were used only for academic purposes. The collected data were analyzed using SPSS and AMOS. Confirmatory Factor Analysis was used to assess the validity of the measurement model and its overall fit, while Structural Equation Modeling was conducted to test the hypothesized relationships among perceived ease of use, perceived usefulness, attitude, perceived risk, social influence, facilitating conditions, intention to use, and use (Awang, 2012; Byrne, 2016; Hair et al., 2017).

3.3 Population and Sample Size

The target population of this study consisted of doctors and nurses who had been working for at least one year in the top 10 hospitals in Thailand, based on the World's Best Hospitals ranking for Thailand published by Newsweek and Statista (Newsweek & Statista, 2025). For Structural Equation Modeling, a sample size of 200 or more is generally considered acceptable for multivariate analysis and model estimation (Hair et al., 2017). Moreover, the minimum sample size calculated using Fisher's formula was 385 respondents. In addition, the A-priori Sample Size Calculator for Structural Equation Models indicated that at least 444 respondents were required for this study design, based on the number of observed variables, number of latent variables, anticipated effect size, desired probability level, and statistical power (Soper, 2026). Accordingly, the questionnaire was distributed to 500 respondents. After the data screening process, all 500 responses were retained and used in this study.

3.4 Sampling Technique

The researcher used multi-stage sampling to collect the data. First, purposive sampling was applied to select the top 10 hospitals in Thailand (Newsweek & Statista, 2025). Second, stratified random sampling was used to allocate the sample proportionally according to hospital size, based on the number of hospital beds. Finally, convenience sampling was employed to distribute the questionnaire in both online and paper-based formats to doctors and nurses who were available and willing to participate.

Table 1: Sample Units and Sample Size

Hospital Name	Number of Beds	Proportion	Sample
Bumrungrad International Hospital	580	0.106	53
Samitivej Sukhumvit Hospital	275	0.050	25
Siriraj Piyamaharajkarun Hospital	345	0.063	32
King Chulalongkorn Memorial Hospital	1,479	0.271	135
Bangkok Hospital	488	0.089	45
MedPark Hospital	550	0.101	50
Ramathibodi Hospital	1,000	0.183	91
Thonburi Hospital	435	0.080	40
Praram 9 Hospital	204	0.037	19
Bangkok Christian Hospital	110	0.020	10

Source: Compiled by the author.

4. Results and Discussion

4.1 Demographic Information

The demographic profile of the 500 respondents is presented in Table 2. Female respondents accounted for 78.80% of the sample, while male respondents represented 21.20%. Regarding age, the largest group was 25-35 years old, comprising 72.60% of the respondents, followed by 36-45 years old at 24.20%, more than 45 years old at 2.00%, and less than 25 years old at 1.20%. In terms of nationality, the vast majority of respondents were Thai, representing 99.40%, whereas non-Thai respondents accounted for 0.60%.

With respect to educational background, most respondents held a certificate or bachelor's degree, accounting for 89.20% of the sample. This was followed by those holding a master's degree at 8.80% and a doctoral degree at 2.00%. In terms of position, nurses constituted the majority of respondents at 87.40%, while doctors or physicians accounted for 12.60%. Regarding employment experience, the largest group had 6-10 years of experience, representing 57.60%, followed by 11-15 years at 34.60%, 1-5 years at 4.40%, 16-20 years at 2.20%, and over 20 years at 1.20%.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	106	21.20%
	Female	394	78.80%
Age	Less than 25 years old	6	1.20%
	25-35 years old	363	72.60%
	36-45 years old	121	24.20%
	More than 45 years old	10	2.00%
Nationality	Thai	497	99.40%
	Non-Thai	3	0.60%
Education	Certificate/Bachelor's degree	446	89.20%
	Master's degree	44	8.80%
	Doctoral degree	10	2.00%
Position	Doctors/Physicians	63	12.60%
	Nurses	437	87.40%
Employment Experience	1-5 years	22	4.40%
	6-10 years	288	57.60%
	11-15 years	173	34.60%
	16-20 years	11	2.20%
	Over 20 years	6	1.20%

Source: Compiled by the author.

4.2 Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis (CFA) was first conducted to assess the reliability and validity of the measurement model before the structural relationships among the latent variables were tested. Reliability was evaluated using Cronbach's alpha and composite reliability (CR), while convergent validity was assessed using standardized factor loadings and average variance extracted (AVE). Discriminant validity was also examined to ensure that the constructs were empirically distinct from one another (Byrne, 2016; Hair et al., 2010; Kline, 2016).

As shown in Table 3, the standardized factor loadings ranged from 0.652 to 0.835, exceeding the recommended minimum value of 0.50. Cronbach's alpha values ranged from 0.793 to 0.874, and CR values ranged from 0.777 to 0.879, indicating adequate internal consistency and construct reliability. Although an AVE value of 0.50 or above is generally recommended for convergent validity (Fornell & Larcker, 1981; Hair et al., 2010), the AVE value for Intention to Use was 0.466, which is slightly below the conventional threshold but above 0.40. Previous methodological literature suggests that AVE is a conservative indicator and that convergent validity may still be considered adequate when CR is satisfactory, particularly when AVE is only slightly below 0.50 (Malhotra & Dash, 2011; Huang et al., 2013). Similar treatment has also been applied in previous empirical studies, where constructs with AVE values below 0.50 were retained because their CR values exceeded the recommended threshold (Pervan et al., 2018; Shafiq et al., 2020). Accordingly, the convergent validity of the Intention to Use construct was considered marginal but acceptable, and this result should be interpreted with caution.

Table 3: Reliability and Convergent Validity Results

Variables	Source of Questionnaire (Measurement Indicator)	No. of Items	Cronbach's Alpha	Factors Loadings	CR	AVE
Perceived Usefulness (PU)	Karahoca et al. (2018)	5	0.827	0.673-0.756	0.833	0.500
Perceived Ease of Use (PEOU)	Karahoca et al. (2018)	5	0.832	0.672-0.777	0.834	0.502
Attitude (ATT)	Sung and Jeon (2020); Fridin and Belokopytov (2014)	6	0.857	0.662-0.816	0.868	0.523
Perceived Risk (PR)	Featherman and Pavlou (2003)	5	0.874	0.662-0.835	0.879	0.593
Social Influence (SI)	Alaiad and Zhou (2014)	3	0.793	0.708-0.777	0.796	0.566
Facilitating Conditions (FC)	Sung and Jeon (2020)	4	0.838	0.686-0.804	0.840	0.568
Intention to Use (UI)	Sung and Jeon (2020); Karahoca et al. (2018); Chawla and Joshi (2019); Alaiad et al. (2013)	4	0.834	0.652-0.750	0.777	0.466
Use (U)	Sobti (2019); Lau et al. (2001)	3	0.794	0.684-0.826	0.800	0.573

Note: CR = Composite Reliability, AVE = Average Variance Extracted
Source: Compiled by the author.

Table 4: Discriminant Validity

	PU	PEOU	ATT	PR	SI	FC	UI	U
PU	**0.707**							
PEOU	0.32	**0.709**						
ATT	0.375	0.355	**0.723**					
PR	-0.086	-0.085	-0.103	**0.77**				
SI	0.337	0.353	0.371	-0.108	**0.752**			
FC	0.192	0.318	0.279	-0.196	0.287	**0.754**		
UI	0.358	0.317	0.374	-0.267	0.381	0.349	**0.683**	
U	0.317	0.337	0.355	-0.144	0.392	0.315	0.417	**0.757**

Note: The diagonal values are the square roots of AVE.
Source: Compiled by the author.

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As presented in Table 4, discriminant validity was confirmed because the square root of the AVE for each construct exceeded its correlations with other constructs. This result indicates that the constructs were sufficiently distinct from one another.

Table 5: Goodness-of-Fit Indices for Confirmatory Factor Analysis (CFA) Model

Fit Index	Acceptable criteria	Statistical Values
χ^2/df(CMIN/df)	< 5.00	1325.148/532 or 2.49
GFI	≥ 0.85	0.859
AGFI	≥ 0.80	0.833
NFI	≥ 0.80	0.852
CFI	≥ 0.80	0.905
TLI(NNFI)	≥ 0.80	0.894
RMSEA	≤ 0.08	0.055

Remark: CMIN/df denotes the chi-square-to-degrees-of-freedom ratio; GFI, the Goodness-of-Fit Index; AGFI, the Adjusted Goodness-of-Fit Index; NFI, the Normed Fit Index; CFI, the Comparative Fit Index; TLI, the Tucker-Lewis Index; and RMSEA, the Root Mean Square Error of Approximation.
Source: Compiled by the author.

The CFA model achieved an acceptable fit, with χ^2/df = 2.490, GFI = 0.859, AGFI = 0.833, NFI = 0.852, CFI = 0.905, TLI = 0.894, and RMSEA = 0.055. These results indicate that the measurement model demonstrated acceptable reliability, validity, and model fit. Therefore, the measurement model was considered appropriate for proceeding to the structural model assessment.

4.3 Structural Equation Model (SEM)

After the measurement model was validated, Structural Equation Modeling (SEM) was employed to test the hypothesized relationships among the latent variables and to evaluate the overall fit of the proposed structural model (Byrne, 2016; Hair et al., 2010; Kline, 2016).

As shown in Table 6, the SEM structural model demonstrated acceptable model fit, with χ^2/df = 2.948, GFI = 0.850, AGFI = 0.825, NFI = 0.831, CFI = 0.881, TLI = 0.869, and RMSEA = 0.062. All fit indices met the acceptable criteria, indicating that the proposed structural model adequately represented the relationships among the constructs. Therefore, the structural model was considered suitable for hypothesis testing.

Table 6: Goodness-of-Fit Indices for the Structural Equation Model (SEM) Model

Fit Index	Acceptable Criteria	Statistical Values
χ^2/df(CMIN/df)	< 5.00	1591.777/540 or 2.948
GFI	≥ 0.85	0.850
AGFI	≥ 0.80	0.825
NFI	≥ 0.80	0.831
CFI	≥ 0.80	0.881
TLI(NNFI)	≥ 0.80	0.869
RMSEA	≤ 0.08	0.062

Remark: CMIN/df denotes the chi-square-to-degrees-of-freedom ratio; GFI, the Goodness-of-Fit Index; AGFI, the Adjusted Goodness-of-Fit Index; NFI, the Normed Fit Index; CFI, the Comparative Fit Index; TLI, the Tucker-Lewis Index; and RMSEA, the Root Mean Square Error of Approximation.
Source: Compiled by the author.

4.4 Research Hypothesis Testing Results

The structural model was evaluated using standardized path coefficients, t-values, and p-values. As presented in Table 7, all ten hypothesized relationships were statistically significant at the $p < 0.001$ level, indicating full support for the proposed model. Among the positive relationships, the strongest effect was observed from perceived ease of use to perceived usefulness ($\beta = 0.639$), followed by perceived usefulness to attitude ($\beta = 0.543$) and intention to use on actual use ($\beta = 0.539$). In contrast, perceived risk exerted a significant negative effect on intention to use ($\beta = -0.330$), suggesting that greater perceived risk reduced doctors' and nurses' willingness to adopt surgical robots.

More specifically, perceived ease of use significantly influenced both perceived usefulness and attitude, while perceived usefulness significantly enhanced both attitude and intention to use. Attitude, in turn, had a positive effect on intention to use. Perceived risk negatively affected intention to use, whereas social influence significantly strengthened both intention to use and use. Facilitating conditions also showed a significant positive effect on intention to use. Finally, intention to use was found to significantly predict use. Overall, these findings confirm that perceptual, social, and organizational factors play important roles in explaining doctors' and nurses' adoption of surgical robots in Thai hospitals.

Table 7: Hypothesis Testing Results of the Structural Model

Hypotheses	Paths	Standardized Path Coefficients (β)	P-value	t-value	Test Result
H1	PU <--- PEOU	0.639	< 0.001	11.412	Supported
H2	ATT <--- PEOU	0.350	< 0.001	5.893	Supported
H3	ATT <--- PU	0.543	< 0.001	8.343	Supported
H4	UI <--- PU	0.349	< 0.001	4.504	Supported
H5	UI <--- ATT	0.325	< 0.001	4.226	Supported
H6	UI <--- PR	−0.330	< 0.001	−7.419	Supported
H7	UI <--- SI	0.192	< 0.001	4.422	Supported
H8	U <--- SI	0.336	< 0.001	6.986	Supported

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Hypotheses	Paths	Standardized Path Coefficients (β)	P-value	t-value	Test Result
H9	UI <--- FC	0.282	< 0.001	6.350	Supported
H10	U <--- UI	0.539	< 0.001	9.757	Supported

Source: Compiled by the author.

5. Conclusions and Recommendations

5.1 Conclusion and Discussion

This research analyzed the factors influencing doctors' and nurses' intention to use and actual use of surgical robots in Thai hospitals. This study integrated the Technology Acceptance Model, the Unified Theory of Acceptance and Use of Technology, and the Almere model to explain how perceived ease of use, perceived usefulness, attitude, perceived risk, social influence, and facilitating conditions determine intention to use and use behavior (Davis, 1989; Heerink et al., 2010; Venkatesh et al., 2003). Questionnaires were administered to doctors and nurses in major hospitals in Thailand who had at least one year of work experience, direct involvement in surgical practice, and prior awareness of surgical robots. Confirmatory Factor Analysis was used to assess the validity and reliability of the measurement model, and Structural Equation Modeling was implemented to test the hypothesized relationships among the variables (Byrne, 2016; Hair et al., 2010).

The results indicate that perceived ease of use had the strongest positive effect on perceived usefulness, whereas perceived usefulness had significant positive effects on attitude and intention to use. Attitude also positively influenced intention to use. These findings are aligned with the Technology Acceptance Model, which assumes that perceived ease of use and perceived usefulness are central cognitive predictors of users' attitudes and behavioral intention to adopt technology (Davis, 1989). This finding suggests that doctors and nurses are more likely to perceive surgical robots as useful when the systems are easy to understand, easy to operate, and compatible with surgical workflows, which is consistent with previous healthcare technology acceptance studies (BenMessaoud et al., 2011; Holden & Karsh, 2010). Conversely, perceived risk had a significant negative effect on intention to use, indicating that concerns about safety, uncertainty, and potential operational failure reduced clinicians' intention to adopt surgical robots (Featherman & Pavlou, 2003). This result is important because surgical robots are used in high-risk clinical environments where patient safety, legal responsibility, and system reliability directly affect clinicians' willingness to adopt the technology. Facilitating conditions significantly increased intention to use, indicating that organizational support, training, and technical infrastructure are important for technology adoption in hospital settings (Venkatesh et al., 2003). Social influence significantly affected both intention to use and use, showing that professional norms and encouragement from important others remain influential in clinical environments (Heerink et al., 2010; Venkatesh et al., 2003). Finally, intention to use had a strong positive effect on use, consistent with intention-based models of technology adoption (Ajzen, 1991; Davis, 1989; Venkatesh et al., 2003). In the Thai hospital context, this means that actual use depends not only on individual willingness but also on institutional readiness, professional training, and technical support. Since most respondents were nurses and aged 25-35 years, future studies should consider multi-group analysis by profession and age to examine whether perceived risk, perceived ease of use, and facilitating conditions have different effects across groups (Hair et al., 2017; Venkatesh et al., 2003). Overall, the study confirms that perceived usefulness, perceived ease of use, attitude, perceived risk, social influence, and facilitating conditions are key determinants of doctors' and nurses' adoption of surgical robots in Thai hospitals.

5.2 Recommendations

These findings provide evidence-based insights and guidance for Thai hospitals seeking to promote doctors' and nurses' intention to use and actual use of surgical robots. The results showed that perceived usefulness, facilitating conditions, perceived risk, social influence, and attitude significantly influenced intention to use, while perceived ease of use indirectly supported adoption through perceived usefulness and attitude. Intention to use was the strongest predictor of use. Therefore, hospitals should focus on these factors to strengthen surgical robot adoption in clinical practice (Ajzen, 1991; Davis, 1989; Venkatesh et al., 2003).

Hospitals should clearly demonstrate the clinical benefits of surgical robots to strengthen perceived usefulness, while structured training and simulation-based practice should be provided to improve perceived ease of use and positive attitudes (Holden & Karsh, 2010; Lanfranco et al., 2004). In addition, hospitals should reduce perceived risk through clear safety procedures, technical support, and credentialing systems (Featherman & Pavlou, 2003). Social influence and facilitating conditions should also be enhanced through support from senior clinicians, adequate infrastructure, and effective workflow integration (BenMessaoud et al., 2011; Park & Del Pobil, 2013; Verelst, 2019). For Thai public hospitals, especially under the Universal Coverage Scheme, adoption should focus on budget planning, cost-effectiveness evaluation, workforce training, infrastructure, maintenance, and equitable access to strengthen facilitating conditions and reduce perceived risk (National Health Security Office

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[NHSO], 2023; Venkatesh et al., 2003). For Thai private hospitals, adoption should emphasize service quality, medical tourism, patient communication, clinical benefits, ease of use, senior clinician support, and simulation-based training to improve perceived usefulness, attitude, and intention to use (Davis, 1989; Holden & Karsh, 2010). At the national healthcare system and Universal Coverage Scheme (UCS) levels, policymakers should support funding, reimbursement planning, workforce development, referral networks, and shared robotic surgery centers to improve access beyond top-tier hospitals (NHSO, 2023; Tangcharoensathien et al., 2018). In terms of regulation, the Thai FDA should provide clear registration guidelines, risk-based classification, safety and maintenance standards, post-adoption monitoring, and user training requirements to reduce perceived risk and increase clinicians' confidence (ASEAN Secretariat, 2015; Thai Food and Drug Administration, n.d.). If surgical robots are expanded to secondary hospitals, national training programs, referral systems, and shared robotic centers should be considered to overcome limited specialists, infrastructure, and technical support.

5.3 Limitations and Further Study

There were several limitations encountered in this study. First, the sample was limited to doctors and nurses in selected advanced hospitals in Thailand, so the findings may not fully represent other hospital settings with different resource levels (Vichitkraivin & Naenna, 2021; Yiengpruksawan et al., 2018). Second, the study focused only on surgical robots, and the results may differ for other types of healthcare robots (Huang et al., 2023; Li et al., 2024). Third, the use of a cross-sectional self-report questionnaire limited the ability to establish causal or time-based relationships among the variables (AlQudah et al., 2021; Rahimi et al., 2018). Fourth, only doctors and nurses were included, while other stakeholders may also influence robotic adoption (Li et al., 2024; Szabó et al., 2024). In addition, because the sample was dominated by nurses and younger respondents aged 25-35 years, future research should compare doctors and nurses and examine whether age moderates technology acceptance relationships, particularly the effects of perceived ease of use, perceived risk, and facilitating conditions (Hair et al., 2017; Venkatesh et al., 2003).

Future research should include different hospital types, other categories of healthcare robots, and broader stakeholder groups. Longitudinal and mixed-method approaches are also recommended to provide a more comprehensive understanding of robotic technology adoption in Thai healthcare settings (AlQudah et al., 2021; Lee et al., 2025). Future studies should also use qualitative inquiry, such as in-depth interviews or focus group discussions, to better understand perceived risk concerns that Likert-scale questionnaires may not fully capture. These concerns may include patient safety, legal responsibility, technical failure, workflow disruption, training adequacy, and trust in robotic systems. Future research should also compare top-tier hospitals with secondary hospitals to examine whether facilitating conditions become a major barrier when surgical robots are introduced into hospitals with fewer resources.

References

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179-211.

Ajzen, I., & Fishbein, M. (1980). *Understanding attitudes and predicting social behavior*. Prentice-Hall.

Alaiad, A., & Zhou, L. (2014). The determinants of home healthcare robots adoption: An empirical investigation. *International Journal of Medical Informatics, 83*(11), 825-840. https://doi.org/10.1016/j.ijmedinf.2014.07.003

Alaiad, A., Zhou, L., & Koru, G. (2013). *An empirical study of home healthcare robots' adoption using the UTAUT model.* Western Michigan University Scholar Works. https://scholarworks.wmich.edu/ichita_transactions/27

AlQudah, A. A., Al-Emran, M., & Shaalan, K. (2021). Technology acceptance in healthcare: A systematic review. *Applied Sciences, 11*(22), 10537. https://doi.org/10.3390/app112210537

ASEAN Secretariat. (2015). *ASEAN Medical Device Directive.* https://asean.org/wp-content/uploads/2016/06/22.-September-2015-ASEAN-Medical-Device-Directive.pdf

Attanasio, A., Scaglioni, B., De Momi, E., Fiorini, P., & Valdastri, P. (2020). Autonomy in surgical robotics. *Annual Review of Control Robotics and Autonomous Systems, 4*(1), 651- 679. https://doi.org/10.1146/annurev-control-062420-090543

Awang, Z. (2012). *A handbook on SEM: Overview of structural equation modeling (SEM)*. Academia.edu. https://www.academia.edu/34981086/A_Handbook_on_SEM_Overview_of_Structural_Equation_Modeling_SEM

Bauer, R. A. (1960). Consumer behavior as risk taking. In R. S. Hancock (Ed.), *Dynamic marketing for a changing world* (pp. 389-398). American Marketing Association

BenMessaoud, C., Kharrazi, H., & MacDorman, K. F. (2011). Facilitators and barriers to adopting robotic-assisted surgery: Contextualizing the unified theory of acceptance and use of technology. *PLoS ONE, 6*(1), e16395. https://doi.org/10.1371/journal.pone.0016395

Byrne, B. M. (2016). *Structural equation modeling with AMOS: Basic concepts, applications, and programming* (3rd ed.). Routledge. https://doi.org/10.4324/9781315757421

AU-GSB E-JOURNAL

Cao, J., Li, T., & Chen, S. (2024). How social influence promotes the adoption of mobile health among young adults in China: The mediating roles of trust, health consciousness, and user experience. *Behavioral Sciences, 14*(6), 498. https://doi.org/10.3390/bs14060498

Chawla, D., & Joshi, H. (2019). Consumer attitude and intention to adopt mobile wallet in India—An empirical study. *International Journal of Bank Marketing, 37*(7), 1590-1618. https://doi.org/10.1108/IJBM-09-2018-0256

Cokins, G., Oncioiu, I., Türkeș, M. C., Topor, D. I., Căpușneanu, S., Paștiu, C. A., Deliu, D., & Solovăstru, A. N. (2020). Intention to use accounting platforms in Romania: A quantitative study on sustainability and social influence. *Sustainability, 12*(15), 6127. https://doi.org/10.3390/su12156127

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319-340. https://doi.org/10.2307/249008

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science, 35*(8), 982-1003. https://doi.org/10.1287/mnsc.35.8.982

Duensing, I. M., Stewart, W., Novicoff, W. M., Meneghini, R. M., & Browne, J. A. (2023). The impact of robotic-assisted total knee arthroplasty on resident training. *The Journal of Arthroplasty, 38*(6), 227-231. https://doi.org/10.1016/j.arth.2023.02.016

Dwivedi, Y. K., Rana, N. P., Jeyaraj, A., Clement, M., & Williams, M. D. (2017). Re-examining the Unified Theory of Acceptance and Use of Technology (UTAUT): towards a revised theoretical model. *Information Systems Frontiers, 21*(3), 719-734. https://doi.org/10.1007/s10796-017-9774-y

Edmondson, A. C., Bohmer, R. M. J., & Pisano, G. P. (2001). Disrupted routines: Team learning and new technology implementation in hospitals. *Administrative Science Quarterly, 46*(4), 685-716. https://doi.org/10.2307/3094828

Featherman, M. S., & Pavlou, P. A. (2003). Predicting e-services adoption: A perceived risk facets perspective. *International Journal of Human-Computer Studies, 59*(4), 451-474. https://doi.org/10.1016/S1071-5819(03)00111-3

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39-50. https://doi.org/10.1177/002224378101800104

Fridin, M., & Belokopytov, M. (2014). Acceptance of socially assistive humanoid robot by preschool and elementary school teachers. *Computers in Human Behavior, 33*, 23-31. https://doi.org/10.1016/j.chb.2013.12.016

Fuller, P., Kennedy, S., Ball, M., Duffie, H., Gainey, M., Luo, Q., Joseph, A., Carbonell, A., & Cha, J. S. (2025). Understanding the challenges of robotic-assisted surgery adoption: Perspectives from stakeholders and the general population on human-interaction, built environment, and training. *Applied Ergonomics, 122*, 104403. https://doi.org/10.1016/j.apergo.2024.104403

Gagnon, M.-P., Ngangue, P., Payne-Gagnon, J., & Desmartis, M. (2016). m-Health adoption by healthcare professionals: A systematic review. *Journal of the American Medical Informatics Association, 23*(1), 212-220. https://doi.org/10.1093/jamia/ocu084

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate data analysis* (7th ed.). Pearson.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A primer on partial least squares structural equat ion modeling (PLS-SEM)* (2nd ed.). Sage.

Heerink, M., Kröse, B., Evers, V., & Wielinga, B. J. (2010). Assessing acceptance of assistive social agent technology by older adults: The Almere model. *International Journal of Social Robotics, 2*(4), 361-375. https://doi.org/10.1007/s12369-010-0068-5

Holden, R. J., & Karsh, B.-T. (2010). The Technology Acceptance Model: Its past and its future in health care. *Journal of Biomedical Informatics, 43*(1), 159-172. https://doi.org/10.1016/j.jbi.2009.07.002

Hu, P. J., Chau, P. Y. K., Sheng, O. R. L., & Tam, K. Y. (1999). Examining the Technology Acceptance Model using physician acceptance of telemedicine technology. *Journal of Management Information Systems, 16*(2), 91-112. https://doi.org/10.1080/07421222.1999.11518247

Huang, C.-C., Wang, Y.-M., Wu, T.-W., & Wang, P.-A. (2013). An empirical analysis of the antecedents and performance consequences of using the Moodle platform. *International Journal of Information and Education Technology, 3*(2), 217-221. https://doi.org/10.7763/IJIET.2013.V3.267

Huang, R., Li, H., Suomi, R., Li, C., & Peltoniemi, T. (2023). Intelligent physical robots in health care: Systematic literature review. *Journal of Medical Internet Research, 25*, e39786. https://doi.org/10.2196/39786

Kao, H., Yang, Y., Hung, Y., & Wu, Y. J. (2022). When does Da Vinci robotic surgical systems come into play?. *Frontiers in Public Health, 10*. https://doi.org/10.3389/fpubh.2022.828542

Karahoca, A., Karahoca, D., & Aksöz, M. (2018). Examining intention to adopt to Internet of Things in healthcare technology products. *Kybernetes, 47*(4), 742-770. https://doi.org/10.1108/K-02-2017-0045

Kijsanayotin, B., Pannarunothai, S., & Speedie, S. M. (2009). Factors influencing health information technology adoption in Thailand's community health centers: Applying the UTAUT model. *International Journal of Medical Informatics, 78*, 404-416. https://doi.org/10.1016/j.ijmedinf.2008.12.005

King, W. R., & He, J. (2006). A meta-analysis of the technology acceptance model. *Information & Management, 43*(6), 740-755. https://doi.org/10.1016/j.im.2006.05.003

Klaver, N. S., van Deursen, A. J. A. M., & Kramer, J. M. (2021). Relationship between perceived risks of using mHealth applications and the intention to use them among older adults in the Netherlands: Cross-sectional study. *JMIR mHealth and uHealth, 9*(8), e26845. https://doi.org/10.2196/26845

Kline, R. B. (2016). *Principles and practice of structural equation modeling* (4th ed.). The Guilford Press.

Kruse, C. S., & Heinemann, K. (2022). Facilitators and barriers to the adoption of telemedicine during the first year of COVID-19: Systematic review. *Journal of Medical Internet Research, 24*(1), e31752. https://doi.org/10.2196/31752

AU-GSB E-JOURNAL

Kwak, Y., Seo, Y. H., & Ahn, J. (2022). Nursing students' intent to use AI-based healthcare technology: Path analysis using the unified theory of acceptance and use of technology. *Nurse Education Today*, *119*, 105541. https://doi.org/10.1016/j.nedt.2022.105541

Lanfranco, A. R., Castellanos, A. E., Desai, J. P., & Meyers, W. C. (2004). Robotic surgery: A current perspective. *Annals of Surgery*, *239*(1), 14-21. https://doi.org/10.1097/01.sla.0000103020.19595.7d

Lau, A. S. M., Yen, J., & Chau, P. Y. K. (2001). Adoption of online trading in the Hong Kong financial market. *Journal of Electronic Commerce Research*, *2*(2), 58-65.

Lee, A. T., Ramasamy, R. K., & Subbarao, A. (2025). Understanding psychosocial barriers to healthcare technology adoption: A review of TAM (Technology Acceptance Model) and UTAUT frameworks. *Healthcare*, *13*(3), 250. https://doi.org/10.3390/healthcare13030250

Li, W., Guo, J., Liu, W., Tu, J., & Tang, Q. (2024). Effect of older adults' willingness on telemedicine usage: An integrated approach based on technology acceptance and decomposed theory of planned behavior model. *BMC Geriatrics*, *24*(1), 765. https://doi.org/10.1186/s12877-024-05361-y

Malhotra, N. K., & Dash, S. (2011). *Marketing research: An applied orientation* (6th ed.). Pearson.

Mehta, A., Ng, J. C., Awuah, W. A., & Huang, H. (2022). Embracing robotic surgery in low- and middle-income countries: Potential benefits, challenges, and scope in the future. *Annals of Medicine and Surgery*, *84*, 104803. https://www.sciencedirect.com/science/article/pii/S2049080122015631

National Health Security Office. (2023). *NHSO annual report 2023*. https://www.nhso.go.th/th/aboutus-th/reports-annual/2024-11-21-06-39-26/55632-nhso-annual-report-2023

Nayak, S., Nayak, V. C., & S, S. G. (2024). Exploring the acceptance of robotic assisted surgery among the Indian population: An empirical investigation. *F1000Research*, *13*, 544. https://doi.org/10.12688/f1000research.145052.3

Newsweek, A., & Statista, A. (2025). *World's best hospitals 2025 - Thailand*. Newsweek. https://rankings.newsweek.com/worlds-best-hospitals-2025/thailand

Park, E., & Del Pobil, A. P. (2013). Users' attitudes toward service robots in South Korea. *Industrial Robot: An International Journal*, *40*(1), 77-87. https://doi.org/10.1108/01439911311294273

Perera, N. D., & Wickramarachchi, R. E. (2024). Asia's robotic revolution: Redefining affordable surgery and challenging da Vinci's legacy. *Sri Lanka Journal of Urology*, *15*(1), 1-13. https://doi.org/10.4038/slju.v15i1.4107

Pervan, M., Curak, M., & Pavic Kramaric, T. (2018). The influence of industry characteristics and dynamic capabilities on firms' profitability. *International Journal of Financial Studies*, *6*(1), 4. https://doi.org/10.3390/ijfs6010004

Picozzi, P., Nocco, U., Puleo, G., Labate, C., & Cimolin, V. (2023). Telemedicine and robotic surgery: A narrative review to analyze advantages, limitations and future developments. *Electronics*, *13*(1), 124. https://doi.org/10.3390/electronics13010124

Rahimi, B., Nadri, H., Lotfnezhad Afshar, H., & Timpka, T. (2018). A systematic review of the technology acceptance model in health informatics. *Applied Clinical Informatics*, *9*(3), 604-634. https://doi.org/10.1055/s-0038-1668091

Reddy, K., Gharde, P., Tayade, H., Patil, M., Reddy, L. S., & Surya, D. (2023). Advancements in robotic surgery: A comprehensive overview of current utilizations and upcoming frontiers. *Cureus*, *15*(12), e50415. https://doi.org/10.7759/cureus.50415

Rivero-Moreno, Y., Echevarria, S., Vidal-Valderrama, C., Stefano-Pianetti, L., Cordova-Guilarte, J., Navarro-Gonzalez, J., Acevedo-Rodríguez, J., Dorado-Avila, G., Osorio-Romero, L., Chavez-Campos, C., & Acero-Alvarracín, K. (2023). Robotic surgery: A comprehensive review of the literature and current trends. *Cureus*, *15*(7), e42370. https://doi.org/10.7759/cureus.42370

Schnall, R., Higgins, T., Brown, W., Carballo-Dieguez, A., & Bakken, S. (2015). *Trust, perceived risk, perceived ease of use and perceived usefulness as factors related to mHealth technology use.* Studies in Health Technology and Informatics. https://doi.org/10.3233/978-1-61499-564-7-467

Shafiq, A., Pahlevan Sharif, S., & Jan, A. (2020). Psychometric analysis of a proposed model to determine factors influencing selection of a research supervisor. *International Journal of Doctoral Studies, 15,* 285-304. https://doi.org/10.28945/4567

Sinha, M., Fukey, L., Balasubramanian, K., Hanafiah, M. H., Kunasekaran, P., & Ragavan, N. A. (2021). Acceptance of consumer-oriented health information technologies (CHITs): Integrating technology acceptance model with perceived risk. *Informatica, 45*(6). https://doi.org/10.31449/inf.v45i6.3484

Sobti, N. (2019). Impact of demonetization on diffusion of mobile payment service in India. *Journal of Advances in Management Research*, *16*(4), 472-497. https://doi.org/10.1108/JAMR-09-2018-0086

Soper, D. S. (2026). *A-priori sample size calculator for structural equation models*. https://www.danielsoper.com/statcalc

Sung, J., & Jeon, H. J. (2020). Untact: The new normal and the role of service robots in South Korea. *Service Business*, *14*(4), 713-735. https://doi.org/10.1007/s11628-020-00448-5

Szabó, B., Őrsi, B., & Csukonyi, C. (2024). Robots for surgeons? Surgeons for robots? Exploring the acceptance of robotic surgery in the light of attitudes and trust in robots. *BMC Psychology*, *12*(1). https://doi.org/10.1186/s40359-024-01529-8

Tangcharoensathien, V., Witthayapipopsakul, W., Panichkriangkrai, W., Patcharanarumol, W., & Mills, A. (2018). Health systems development in Thailand: A solid platform for successful implementation of universal health coverage. *The Lancet*, *391*(10126), 1205-1223. https://doi.org/10.1016/S0140-6736(18)30198-3

AU-GSB E-JOURNAL

Tappero, S., Fallara, G., Chierigo, F., Micalef, A., Ambrosini, F., Diaz, R., Dorotei, A., Pompeo, E., Limena, A., Bravi, C. A., Longoni, M., Piccinelli, M. L., Barletta, F., Albano, L., Mazzone, E., & Dell'Oglio, P. (2024). Intraoperative image-guidance during robotic surgery: Is there clinical evidence of enhanced patient outcomes?. *European Journal of Nuclear Medicine and Molecular Imaging*, *51*(10), 3061-3078. https://doi.org/10.1007/s00259-024-06706-w

Teo, T., & Noyes, J. (2011). An assessment of the influence of perceived enjoyment and attitude on the intention to use technology among pre-service teachers: A structural equation modeling approach. *Computers & Education*, *57*(2), 1645-1653. https://doi.org/10.1016/j.compedu.2011.03.002

Thai Food and Drug Administration. (n.d.). *Medical devices. Ministry of Public Health.* https://en.fda.moph.go.th/cat2-health-products/category/health-products-medical-devices

Tu, J., Luo, S. C., Lee, Y., Shih, M., & Chiu, S. (2022). Exploring usability and patient attitude towards a smart hospital service with the technology acceptance model. *International Journal of Environmental Research and Public Health*, *19*(10), 6059. https://doi.org/10.3390/ijerph19106059

Tubaishat, A. (2017). Perceived usefulness and perceived ease of use of electronic health records among nurses: Application of technology acceptance model. *Informatics for Health and Social Care*, *43*(4), 379-389. https://doi.org/10.1080/17538157.2017.1363761

Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision Sciences*, *39*(2), 273-315. https://doi.org/10.1111/j.1540-5915.2008.00192.x

Venkatesh, V., & Davis, F. D. (1996). A model of the antecedents of perceived ease of use: Development and test. *Decision Sciences*, *27*(3), 451-481. https://doi.org/10.1111/j.1540-5915.1996.tb00860.x

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, *46*(2), 186-204. https://doi.org/10.1287/mnsc.46.2.186.11926

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425-478. https://doi.org/10.2307/30036540

Verelst, L. (2019). Technology adoption of service robots in the elderly care sector [Master's dissertation]. Ghent University. https://libstore.ugent.be/fulltxt/RUG01/002/790/868/RUG01-002790868_2019_0001_AC.pdf

Vichitkraivin, P., & Naenna, T. (2021). Factors of healthcare robot adoption by medical staff in Thai government hospitals. *Health and Technology*, *11*(1), 139-151. https://doi.org/10.1007/s12553-020-00489-4

Wongkietkachorn, A., Wongkietkachorn, N., & Rhunsiri, P. (2018). Preoperative needs-based education to reduce anxiety, increase satisfaction, and decrease time spent in day surgery: A randomized controlled trial. *World Journal of Surgery*, *42*, 666-674. https://doi.org/10.1007/s00268-017-4207-0

Wu, J., Chen, W., Guo, D., Ma, G., Wang, Z., He, Y., Zhong, F., Lu, B., Wang, Y., Cheung, T. H., & Liu, Y. (2022). Robot-enabled uterus manipulator for laparoscopic hysterectomy with soft RCM constraints: Design, control, and evaluation. *IEEE Transactions on Medical Robotics and Bionics*, *4*(3), 656-666. https://doi.org/10.1109/TMRB.2022.3181497

Xie, X., Tian, Y., Huang, J., Luo, Q., & Chen, T. (2025). Surgery without distance: Will 5G-based robot-assisted telesurgery redefine modern surgery?. *Translational Lung Cancer Research*, *14*(5), 1821-1829. https://doi.org/10.21037/tlcr-2025-16

Yiengpruksawan, A., Akaraviputh, T., Methasate, A., & Chinswangwatanakul, V. (2018). Robotic surgery in Thailand: Current status and future development. *Siriraj Medical Journal, 70*(5), 466-470. https://doi.org/10.14456/smj.2018.74

AU-GSB E-JOURNAL