Asia Business & Service Innovation

ABSI

Information about the Journal & Article could be found at https://absi-official.github.io/absi/

User Acceptance of AI-Based Smart Healthcare Devices: An Integrated TAM–ISSM Model with Perceived Risk

Yinai Zhong[1], Dat Hung Ho[1], Jue Wang[2], Byungkwon Jeon[3] and Hak-Seon Kim[4], Byeong-Hoon Lee[3]*

[1] *Department of Global Business, Kyungsung University, Busan, Republic of Korea*
[2] *School of Global Studies, Kyungsung University, Busan, Republic of Korea*
[3] *Cheil Electric Co., Ltd., Busan, Republic of Korea*
[4] *School of Hospitality & Tourism Management, Kyungsung University, Busan, Republic of Korea*
* Corresponding author: bhlee@cheilelec.com

Abstract

The rapid advancement of artificial intelligence (AI) has accelerated the development of smart healthcare devices capable of providing continuous, contactless monitoring through radar-based sensing and automated data analysis. Despite their potential to enhance personal health management and support early detection of abnormalities, user acceptance of these technologies remains uncertain due to concerns related to usability, information reliability, and perceived risks. This study develops and empirically validates an integrated model that combines the Technology Acceptance Model (TAM) and the Information Systems Success Model (ISSM), while incorporating perceived risk as a moderating variable. Data were collected from 223 respondents through an online survey and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results show that system quality and information quality significantly influence perceived usefulness and perceived ease of use, which subsequently shape users' attitudes and behavioral intentions. Perceived usefulness emerged as the strongest determinant of adoption intention. The moderation analysis further reveals that perceived risk weakens the positive effect of perceived usefulness on attitude but does not alter the influence of perceived ease of use. These findings highlight the combined importance of technical performance, cognitive evaluations, and psychological concerns in promoting user acceptance of AI-enabled smart healthcare devices.

Keywords: Artificial Intelligence; Smart Healthcare Device; Technology Acceptance Model; Information Systems Success Model; Perceived Risk; Radar-Based Monitoring; User Adoption

1. Introduction

Artificial intelligence (AI) has increasingly transformed the healthcare industry by enabling intelligent, data-driven solutions for personal health monitoring and disease prevention (Majeed & Hwang, 2022). Among various innovations, smart healthcare devices, particularly non-contact systems powered by radar sensors and AI algorithms, offer the ability to detect movement, heart rate, and respiration in real time without requiring users to wear any device (Kim et al., 2024). These systems provide continuous health tracking in home environments, enabling early detection of potential issues such as falls or abnormal inactivity. As societies face aging populations and growing demands for remote healthcare, such technologies represent an important step toward more accessible and preventive health management.

Radar sensors stand out among these technologies for their ability to monitor key health indicators such as heart rate and respiration remotely, thus promoting comfort and convenience for both patients and healthcare providers. The Non-Invasive Monitoring Device Market, valued at USD 21.5 billion in 2024, is projected to grow at a compound annual growth rate (CAGR) of 7%, reaching USD 36.39 billion by 2031 (Verified Market Research, 2025). This growth is largely driven by the demand for remote patient monitoring and the rising prevalence of chronic diseases, reinforcing the critical role of these technologies in modern healthcare systems (Coye et al., 2009).

Despite these advantages, user acceptance of AI-based healthcare technologies remains uncertain. Many individuals express hesitations due to concerns about privacy, data security, and trust in automated systems. The successful adoption of smart healthcare devices therefore depends not only on their technical performance but also on users' perceptions of usefulness, ease of use, and overall system quality (Al-rawashdeh et al., 2022).

User acceptance of emerging healthcare technologies has long been studied through behavioral models such as the Technology Acceptance Model (TAM), which posits that perceived usefulness and perceived ease of use are key determinants of users' attitudes and intentions (Davis, 1989). While TAM has proven effective across various digital contexts, including telemedicine, e-learning, and AI applications, it often overlooks technical system attributes that shape these perceptions. To address this limitation, the Information Systems (IS) Success

Model by Delone and McLean (2003) introduces system quality and information quality as fundamental predictors of user satisfaction and technology effectiveness. Integrating these perspectives allows researchers to link the technical performance of AI-based devices with users' psychological acceptance mechanisms.

Additional factors such as perceived risk have become increasingly critical. Users must rely on AI-generated health insights and automated alerts, yet they may remain skeptical about data privacy, reliability, and potential errors. Prior studies have emphasized that while trust can facilitate technology adoption, perceived risk can undermine positive attitudes even when usefulness and ease of use are high (Rouibah et al., 2016; Glassberg et al., 2025). Thus, combining TAM and IS Success constructs with risk perception provides a comprehensive framework to explain how both technological quality and psychological concerns jointly influence behavioral intention toward adopting AI-enabled healthcare solutions.

Previous research has widely applied the Technology Acceptance Model (TAM) to explain users' behavioral intentions toward adopting new technologies across diverse contexts such as e-learning, telemedicine, and automated vehicles (Ho et al., 2025). Scholars have further integrated TAM with the Information Systems (IS) Success Model to highlight how system quality (SQ) and information quality (IQ) influence perceived usefulness (PU) and perceived ease of use (PEOU). Studies by Delone and McLean (2003), and Hasija and Esper (2022) confirmed that high-quality information and system design enhance user satisfaction and technology acceptance. More recently, extensions of TAM in smart service environments have incorporated constructs such as trust and perceived risk to account for emotional and cognitive uncertainty when interacting with AI-driven systems (Koivumäki et al., 2008). Bibliometric evidence suggests that user acceptance and trust have emerged as prominent themes in home IoT and smart system research, highlighting the relevance of integrating technical and psychological factors when examining adoption behavior (Wang & Kim, 2023).

However, most existing studies have focused on digital learning or online service settings, leaving limited empirical evidence in the smart healthcare domain, especially for non-contact radar-based devices that collect sensitive biometric data. While research by Jayashankar et al. (2018) and Wang et al. (2021) emphasized the role of trust and perceived risk in technology adoption, these variables have rarely been tested jointly within an integrated TAM–IS Success framework. Consequently, there remains a research gap in understanding how system and information quality, mediated by users' cognitive evaluations and moderated by perceived risk, jointly determine attitudes and behavioral intentions toward AI-enabled healthcare devices. This study seeks to address this gap by developing a comprehensive model that integrates technical, psychological, and behavioral factors influencing smart healthcare adoption.

The present study aims to develop and empirically validate an integrated model explaining users' behavioral intentions to adopt AI-based smart healthcare devices. Building upon the Technology Acceptance Model (TAM) and the Information Systems Success Model (ISSM), this research examines how system quality and information quality influence users' perceptions of usefulness and ease of use, which in turn shape their attitudes and intentions to use. Furthermore, the study incorporates perceived risk as a moderating variable to capture users' psychological concerns regarding data reliability and privacy when interacting with AI-driven health technologies. By combining technical, perceptual, and behavioral dimensions, this research seeks to provide both theoretical insight and practical guidance for enhancing user acceptance and trust in smart healthcare innovations.

2. Literature Review

2.1. Information Systems Success Model (ISSM) in Healthcare

The Information Systems Success Model (ISSM), proposed by Delone and McLean (1992) and later updated in 2003, serves as a comprehensive theoretical framework to evaluate the effectiveness and impact of information systems. The model identifies six interrelated dimensions, system quality, information quality, service quality, use, user satisfaction, and net benefits, to assess how system design and performance contribute to successful implementation (Delone & McLean, 2003). In healthcare settings, where technological reliability and informational accuracy are critical for patient safety and decision-making, the ISSM provides a valuable lens through which to understand user satisfaction and system effectiveness. Scholars have confirmed that when medical information systems deliver high-quality, reliable, and accessible data, users experience higher satisfaction and trust in digital healthcare technologies (Walle et al., 2023; Ho et al., 2024).

Among the core dimensions, System Quality (SQ) and Information Quality (IQ) are particularly important in determining user acceptance of healthcare technologies. System quality refers to the technical excellence of a system, its reliability, response time, and ease of navigation, while information quality pertains to the completeness, accuracy, and relevance of the data generated. In medical contexts, a system with high-quality architecture ensures operational stability and usability, whereas precise and up-to-date information supports clinical accuracy and patient confidence. Empirical studies in healthcare informatics demonstrate that both SQ and IQ significantly influence healthcare professionals' and patients' trust and perceived value of digital systems (Al-assaf et al., 2024; Ouajdouni et al., 2024). These findings underscore the dual technical and informational foundations required for successful digital transformation in healthcare environments.

Furthermore, integrating the ISSM with behavioral frameworks such as the Technology Acceptance Model (TAM) strengthens our understanding of how technical quality translates into user perception and behavioral intention. Chirchir et al. (2019) demonstrated that SQ and IQ are antecedents of perceived usefulness and perceived ease of use, linking system performance to users' psychological evaluations. In smart healthcare contexts, this relationship becomes even more pronounced as users' interaction with AI-enabled devices that autonomously collect and analyze biometric data. When such systems are perceived as reliable, efficient, and capable of producing accurate information, users are more likely to find them useful and effortless to operate, thus increasing their intention to adopt and continue using them (Mohd et al., 2008). Consequently, the ISSM complements TAM by bridging technical quality and behavioral acceptance, offering a holistic view of success factors in digital health innovations. Consistent with the Information Systems Success Model, system quality and information quality are conceptualized as key technical antecedents shaping users' cognitive evaluations. In AI-based smart healthcare devices, higher system reliability and information accuracy are expected to enhance perceived usefulness and ease of use. Accordingly, the following hypotheses are proposed:

H1: System quality positively affects perceived usefulness.

H2: System quality positively affects perceived ease of use.

H3: Information quality positively affects perceived usefulness.

H4: Information quality positively affects perceived ease of use.

2.2. Technology Acceptance Model (TAM) in Healthcare

The Technology Acceptance Model (TAM), originally proposed by Davis (1989), is one of the most widely used frameworks to explain individuals' acceptance and usage of new technologies. TAM postulates that two cognitive beliefs, Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), jointly shape users' Attitude toward Use (ATT), which subsequently influences their Behavioral Intention (BI) to use a technology (Zin et al., 2023). Over time, TAM has been validated across various domains, including education, e-commerce, and healthcare, for its ability to capture psychological determinants of user behavior (Kang & Hwang, 2022). It provides a parsimonious yet powerful explanation of how users' perceptions and attitudes determine their willingness to adopt innovative systems.

In the healthcare context, TAM has been extensively applied to study the adoption of digital tools such as electronic health records (EHRs), telemedicine platforms, mobile health (m-Health) applications, and AI-assisted diagnostic systems (Jacob et al., 2020). Research consistently shows that when medical professionals and patients perceive a technology as both useful and easy to use, they demonstrate stronger adoption intentions and satisfaction (Pan et al., 2018). Specifically, perceived usefulness reflects the extent to which a system enhances healthcare performance or decision-making accuracy, while perceived ease of use reflects the effort required to learn and operate the system. In clinical settings, where efficiency, accuracy, and time sensitivity are crucial, these perceptions directly affect not only behavioral intention but also long-term continuance usage.

However, despite its theoretical strength, the traditional TAM has been criticized for focusing primarily on individual cognitive beliefs, often overlooking contextual, technical, and social dimensions that influence acceptance. To enhance its explanatory power, researchers have proposed integrating TAM with other theoretical frameworks, such as the Information Systems

Success Model (ISSM). This integration is particularly relevant in smart healthcare environments, where users must rely on AI algorithms to interpret sensitive health data. Factors such as system quality, information quality, and perceived risk play critical roles in shaping users' confidence and willingness to adopt such technologies. Therefore, extending TAM beyond its original boundaries provides a more holistic understanding of how users form positive attitudes toward AI-based smart healthcare devices, especially when interacting with automated systems that directly impact personal well-being and data security. According to the Technology Acceptance Model, perceived ease of use enhances perceived usefulness, while both beliefs shape users' attitudes toward technology adoption and subsequent behavioral intention. In smart healthcare contexts, these relationships are expected to remain robust due to the functional and health-related value of AI-based devices. Therefore, the following hypotheses are proposed:

H5: Perceived ease of use positively affects perceived usefulness.

H6: Perceived ease of use positively affects attitude.

H7: Perceived usefulness positively affects attitude.

H8: Perceived usefulness positively affects behavioral intention.

H9: Attitude positively affects behavioral intention.

2.3. Perceived Risk in Smart Healthcare Technologies

Perceived risk represents users' apprehension about potential negative consequences arising from using technology, such as privacy breaches, data misuse, system malfunction, or social discomfort (Almaiah et al., 2023). In healthcare, where personal data are extremely sensitive, perceived risk can severely hinder adoption despite users' acknowledging the usefulness of the system. Research has identified several dimensions of perceived risk, functional, financial, social, psychological, and time-related, that collectively influence user attitudes and decisions (Engelberg, 2007). For instance, if individuals fear that their medical information may be leaked or misinterpreted by AI algorithms, they may resist engaging with such technologies even when they recognize their potential health benefits. Hence, perceived risk operates as a counterbalancing force to trust, shaping whether users ultimately form positive or negative attitudes toward innovative healthcare systems.

Recent studies have begun to examine the interactive effects of perceived risk within technology adoption models such as TAM and UTAUT, particularly in the context of intelligent or autonomous systems (Namahoot & Jantasri, 2022; Lee et al., 2025). In smart healthcare scenarios, where users rely on AI to interpret physiological data, the dual presence of perceived risk becomes pivotal, also perceived risk may erode confidence and discourage engagement. Integrating these constructs into the extended TAM–ISSM framework therefore provides a more comprehensive understanding of user behavior by acknowledging not only technological and cognitive determinants but also the emotional and ethical concerns surrounding the adoption of AI-enabled healthcare innovations.

In addition, perceived risk plays a particularly salient role in smart healthcare contexts because AI-enabled devices often operate autonomously and generate health-related insights without direct human oversight (Williamson & Prybutok, 2024). This autonomy can intensify users' concerns about accountability, error attribution, and potential harm resulting from inaccurate alerts or false reassurance. Scholars have argued that as the level of system autonomy increases, users experience greater psychological uncertainty, leading them to scrutinize the credibility and transparency of AI-generated outputs more carefully (Yu et al., 2025).

Moreover, because radar-based monitoring devices continuously collect biometric signals in private home environments, perceived intrusiveness may heighten apprehensions regarding surveillance and personal vulnerability (Casmin & Oliveira, 2025). Such concerns extend beyond traditional notions of data privacy and enter the realm of emotional safety and personal boundaries. Consequently, perceived risk in AI-driven healthcare is not merely a technical construct but a multidimensional psychological evaluation that can substantially undermine trust and weaken favorable perceptions of system quality, information quality, and usefulness. Understanding how these risk perceptions interact with cognitive and emotional factors is therefore essential for designing user-centered, ethically aligned smart healthcare solutions. Despite potential benefits, perceived risk related to privacy, data accuracy, and system malfunction may weaken favorable evaluations of smart healthcare devices. Prior studies indicate that perceived risk can constrain the translation of cognitive beliefs into positive attitudes. Thus, perceived risk is proposed as a moderating factor:

H10a: Perceived risk negatively moderates the relationship between perceived usefulness and attitude.

H10b: Perceived risk negatively moderates the relationship between perceived ease of use and attitude.

2.4. Integration of TAM and ISSM with Perceived Risk

Building upon the foundations of both Technology Acceptance Model (TAM) and Information Systems Success Model (ISSM), an integrated framework enables a holistic understanding of how technical and psychological factors jointly determine user acceptance of smart healthcare technologies. User satisfaction and technology acceptance are complementary streams, ISSM emphasizes system and information quality as design determinants, while TAM captures users' cognitive and attitudinal responses (Kanungo & Bhatnagar, 2002; Tate et al., 2015). Integrating these models bridges the gap between system performance and user behavior by demonstrating that System Quality (SQ) and Information Quality (IQ) function as antecedents to Perceived Ease of Use (PEOU) and Perceived Usefulness (PU). This synthesis thus connects system design attributes directly to the intention to adopt and use healthcare technologies, offering both diagnostic and predictive power in modeling user behavior.

In the healthcare context, this integration becomes essential because users' interactions with AI-based devices involve both functional evaluation and risk assessment. High-quality systems provide reliable information, intuitive interfaces, and responsive operations that enhance perceived usefulness and ease of use (Al-assaf et al., 2024). Simultaneously, these factors strengthen trust in the system, which acts as a stabilizing mechanism that offsets perceived risks such as data privacy, technical malfunction, or misinformation.

Furthermore, incorporating perceived risk into the TAM–ISSM framework enhances its explanatory depth by recognizing that users' acceptance decisions are contingent not only on cognitive evaluations, but also on their tolerance for uncertainty when engaging with AI-enabled healthcare systems (Salih et al., 2025). While SQ and IQ strengthen perceptions of usefulness and ease of use, perceived risk acts as a boundary condition that may diminish these positive effects (Almahamid et al., 2010). This moderating mechanism reflects a more realistic representation of technology adoption in healthcare, where the stakes of inaccurate monitoring or privacy violations are inherently higher than in other digital contexts. As a result, even a system with excellent technical performance may face resistance if users perceive substantial risk in allowing continuous, automated monitoring of their personal health data. Integrating perceived risk thus creates a more comprehensive model that better captures the interplay among system design, cognitive evaluations, and emotional responses, offering deeper insights into the drivers and inhibitors of user acceptance in smart healthcare environments (Pan et al., 2018).

3. Methodology

3.1. Data Collection

Data for this study were collected using an online self-administered questionnaire designed to measure users' perceptions, attitudes, and behavioral intentions toward AI-based smart healthcare devices. Prior to data collection, respondents were provided with a brief and standardized description of the target technology, a non-contact, radar-based smart healthcare device capable of monitoring respiration, heart rate, movement, and potential emergency conditions through AI algorithms. This ensured that all participants evaluated the same conceptual device, regardless of their prior experience with health technologies.

The survey was distributed through university networks, social media platforms, and community groups to reach a diverse population, including students, working adults, and individuals familiar with digital or healthcare technologies. Participation was entirely voluntary, and no incentives were offered. Respondents were informed that the study was anonymous and conducted solely for academic purposes. No personally identifiable information was collected.

A total of 238 responses were initially received. After data screening procedures, removal of incomplete responses, patterned answers, or unrealistic completion times, 223 valid responses remained and were used for analysis. This sample size exceeds the recommended minimum for

PLS-SEM and is adequate for detecting medium effect sizes across complex structural models. The data collection process adhered to general ethical standards for human-subject research. Informed consent was obtained at the beginning of the questionnaire, and participants retained the right to withdraw at any time.

3.2. Measurement Instrument

The measurement instrument consisted of multiple constructs adapted from well-established scales in the Information Systems and technology acceptance literature. All items were measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The questionnaire was designed to evaluate users' perceptions of AI-based smart healthcare devices, particularly non-contact radar systems that monitor vital signs and movement through embedded AI algorithms (see Table 1).

Table 1. Variables and Questionnaire Items Measurement.

Variable	Questionnaire Items		References
Information Quality (IQ)	IQ1	The health information that smart healthcare device provides is complete	(Alzahrani et al., 2019; DeLone & McLean, 2003; Lin et al., 2011; Sharma et al., 2017; Yakubu & Dasuki, 2018)
	IQ2	The health information that smart healthcare device provides is easy to understand	
	IQ3	The smart healthcare device provides relevant information I need for my healthcare	
	IQ4	The information within smart healthcare device is secure	
	IQ5	The health information that smart healthcare device provides is accurate	
System Quality (SQ)	SQ1	The smart healthcare device offers flexibility in use as to time and place	
	SQ2	The smart healthcare device provides convenient access	
	SQ3	The smart healthcare device system is reliable	
	SQ4	The response time of the smart healthcare device is reasonable	
	SQ5	The smart healthcare device enables interactive communication between users and the system	
Perceived Usefulness (PU)	PU1	Using the smart healthcare device improves my health management performance	(Davis,1989; Venkatesh et al., 2003)
	PU2	Using the smart healthcare device increases my productivity in managing health-related tasks	
	PU3	Using the smart healthcare device enhances my effectiveness in health management	

	PU4	Using the smart healthcare device is useful for health management	
Perceived Ease of Use (PEOU)	PEOU1	The interaction with smart healthcare device is clear and understandable	
	PEOU2	Interaction with smart healthcare device does not require a lot of mental effort	
	PEOU3	I find the smart healthcare device easy to use	
	PEOU4	It is easy to use the smart healthcare device to do what I want	
Attitude (ATT)	ATT1	Using smart healthcare devices for health management is a good idea	(Belanche et al., 2019; Chua et al., 2023; Hu et al., 1999)
	ATT2	Using smart healthcare devices for health management is a wise idea	
	ATT3	I am open to using the smart healthcare device for making health management decisions	
	ATT4	Using smart healthcare devices for health management is pleasant.	
Perceived Risk (PR)	PR1	I believe that using smart healthcare device is risky because the functions delivered may fail to meet my expectations	(Corbitt et al., 2003; Hsin et al., 2008)
	PR2	I believe that using smart healthcare device is risky because the readings/alerts may be inaccurate or unreliable	
	PR3	I believe that using smart healthcare device is risky because it may lead to financial loss for me (e.g., purchase, subscription, or maintenance costs)	
	PR4	I believe that using smart healthcare device is risky because it may cause others to think less highly of me	
	PR5	I believe that using smart healthcare device is risky because it may fail to fit well with my personal image or self-concept	
	PR6	I believe that using smart healthcare device is risky because it may lead to a loss of time (e.g., setup, troubleshooting, handling alerts)	
Behavioral Intention to Use (BI)	BI1	I intend to use smart healthcare devices for health management in the future	(Gold et al., 2015; Venkatesh et al., 2003; Zhang et al., 2019)
	BI2	I predict I would use smart healthcare devices for health management the future	
	BI3	I plan to use the smart healthcare devices for health management in the future	
	BI4	I will purchase the smart healthcare devices for health management in the future	

3.3. Data Analysis

The measurement instruments and data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4, which is appropriate for predictive modeling and theory development, especially when studying complex relationships among latent variables. To mitigate potential common method bias associated with the single-source, self-reported survey design, several procedural remedies were applied, including assuring anonymity and excluding responses that failed reverse-coded items or exhibited straight-lining behavior. In addition, a full collinearity assessment was conducted using inner model variance inflation factor (VIF) values. All inner model VIF values ranged from 1.144 to 1.580, below the recommended threshold of 3.3, suggesting that common method bias is unlikely to materially affect the findings.

First, the measurement model is assessed to examine the reliability and validity of all constructs. Indicator reliability is confirmed as all factor loadings exceed the acceptable threshold of 0.70. Internal consistency reliability is evaluated using Cronbach's alpha and Composite Reliability (CR), both of which exceed 0.80 across all constructs. Convergent validity is established because all Average Variance Extracted (AVE) values are above 0.50. Discriminant validity is examined using both the Fornell–Larcker criterion and the Heterotrait–Monotrait ratio (HTMT). The square roots of AVE for each construct are greater than their inter-construct correlations, and all HTMT values remain below the conservative threshold of 0.85, indicating satisfactory discriminant validity (Hair et al., 2019).

Following the measurement assessment, the structural model is evaluated to test the hypothesized relationships. Path coefficients, t-values, and p-values are obtained through a bootstrapping procedure with 5,000 resamples. The analysis provides estimates of the significance and strength of each hypothesized path, including the moderating effects of perceived risk. The final model demonstrates strong explanatory power, accounting for a substantial proportion of variance in the key endogenous constructs: Perceived Usefulness, Attitude, and Behavioral Intention. Overall, the results validate the integrated TAM–ISSM–Risk framework and offer empirical insights into the determinants of users' acceptance of AI-based smart healthcare devices.

3.4. Research Model

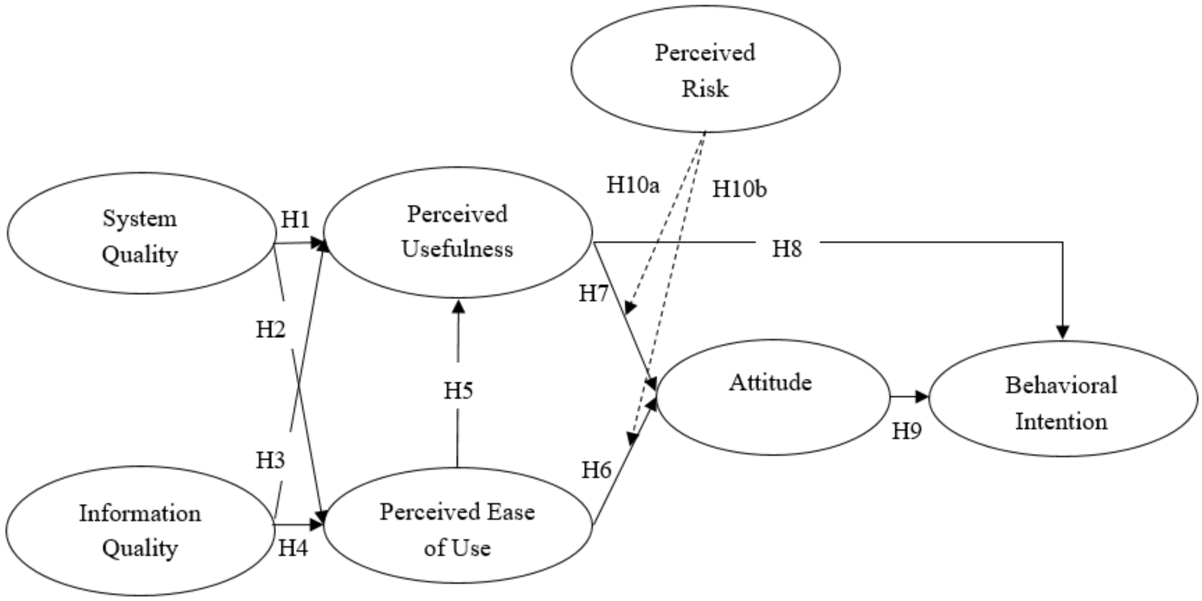

Figure 1. Research Model

The research model integrates the Technology Acceptance Model (TAM) with key constructs from the Information Systems Success Model (ISSM), while incorporating perceived risk as a moderating variable, to provide a comprehensive explanation of users' acceptance of AI-based smart healthcare devices. As depicted in Figure 1, System Quality (SQ) and Information Quality (IQ) are conceptualized as critical technological antecedents influencing users' cognitive evaluations, Perceived Ease of Use (PEOU) and Perceived Usefulness (PU). These two cognitive beliefs subsequently shape Attitude (ATT) toward using the device, which in turn affects Behavioral Intention (BI).

Consistent with TAM, PEOU is expected to enhance both PU and ATT, while PU is hypothesized to positively influence both ATT and BI. Attitude itself is expected to serve as a strong proximal predictor of behavioral intention. To capture the psychological uncertainties associated with AI-driven health monitoring, the model further incorporates Perceived Risk (PR) as a moderating variable. Specifically, PR is proposed to weaken the positive effects of PU and PEOU on ATT, reflecting the notion that privacy concerns, data insecurity, or perceived system malfunction may undermine users' favorable evaluations despite perceived usefulness or ease of use.

Together, this integrated framework explains adoption behavior through the joint influence of technical system attributes, cognitive beliefs, and risk-related psychological factors, offering a holistic lens for understanding users' acceptance of AI-enabled smart healthcare technologies.

4. Results

4.1. Demographic Information

The demographic information in Table 2 shows that the respondents are almost evenly split by gender, with 51.1% female and 48.9% male. In terms of age, 38.1% of the respondents are between 18 and 29 years old, 32.3% are between 30 and 39 years old, and 29.6% are between 40 and 49 years old. This indicates that the study mainly focuses on young and middle-aged adults. Regarding educational attainment, 48.9% of the participants hold a bachelor's degree, 18.8% graduated from a three-year college, 18.4% have a master's degree, and 3.6% have a doctoral degree, whereas 10.3% report having a high school education or less. The monthly income level is relatively low, as 46.6% of the respondents have a monthly income of less than USD 1,000 and 43.0% have an income ranging from USD 1,000 to 1,999. Overall, the respondents are relatively young and highly educated. However, they primarily belong to a low-income group.

Table 2. Demographic Information (n = 223).

Item	Variables	Frequency	Percent (%)
Gender	Male	109	48.9
	Female	114	51.1
Age	18-29	85	38.1
	30~39	72	32.3
	40~49	66	29.6
Education Level	High school graduate and below	23	10.3
	3-year college	42	18.8
	Bachelor's degree	109	48.9
	Master's degree	41	18.4
	Doctoral degree	8	3.6

Monthly Income (USD)	Less than $1,000	104	46.6
	$1,000~ $1,999	96	43.0
	$2,000 ~ $2,999	17	7.7
	$3,000 ~ $3,999	6	2.7

4.2. Reliability and Validity Test

The reliability and validity of the reflective measurement model were assessed using PLS-SEM. As shown in Table 3, standardized factor loadings range from 0.611 to 0.871. With the exception of item ATT4 (0.611), all items exceed the recommended threshold of 0.70, indicating satisfactory indicator reliability. ATT4 is retained because its loading remains acceptable in an exploratory context and its content is theoretically important for capturing users' overall attitudinal evaluation. To assess the robustness of this decision, an additional analysis was conducted by re-estimating the model after removing ATT4. The results indicate that the significance, direction, and magnitude of the main structural relationships remain substantively unchanged, and the overall conclusions are consistent. At the construct level, composite reliability (CR) values range from 0.848 to 0.919, thus exceeding the 0.70 criterion. Average variance extracted (AVE) values range from 0.585 to 0.721, surpassing the 0.50 benchmark and demonstrating adequate convergent validity (Fornell & Larcker, 1981). Cronbach's alpha coefficients vary from 0.764 to 0.892, all of which are above the widely accepted threshold of 0.70 (Nunnally, 1978), confirming strong internal consistency. In summary, these results indicate that the measurement model demonstrates good reliability and convergent validity, supporting its use in the subsequent evaluation of the structural model (Hair et al., 2019).

Table 3. Reliability and Validity Test.

Constructs	Items	Factor Loading	CR	AVE	Cronbach's Alpha
System Quality	SQ1	0.804	0.903	0.651	0.866
	SQ2	0.755			
	SQ3	0.818			
	SQ4	0.783			
	SQ5	0.870			
Information Quality	IQ1	0.837	0.919	0.696	0.892
	IQ2	0.779			
	IQ3	0.863			

	IQ4	0.816			
	IQ5	0.871			
Perceived Usefulness	PU1	0.806	0.889	0.667	0.834
	PU2	0.802			
	PU3	0.846			
	PU4	0.810			
Perceived Ease of Use	PEOU1	0.851	0.912	0.721	0.871
	PEOU2	0.840			
	PEOU3	0.834			
	PEOU4	0.870			
Perceived Risk	PR1	0.772	0.914	0.638	0.887
	PR2	0.747			
	PR3	0.831			
	PR4	0.781			
	PR5	0.819			
	PR6	0.840			
Attitude	ATT1	0.787	0.848	0.585	0.764
	ATT2	0.848			
	ATT3	0.794			
	ATT4	0.611			
Behavioral Intention	BI1	0.813	0.886	0.661	0.829
	BI2	0.782			
	BI3	0.866			
	BI4	0.787			

Note. CR: Composite Reliability; AVE: Average Variance Extracted

Discriminant validity was first assessed using the Fornell–Larcker criterion, as shown in Table 4. In this approach, the square root of the Average Variance Extracted (AVE) for each construct is compared with its correlations with other constructs. The diagonal elements in Table 4 represent the square roots of AVE, and all values exceed the corresponding inter-construct correlations in their rows and columns. For example, the square root of AVE for Attitude (0.765) is greater than its correlations with Perceived Usefulness (0.447), Behavioral Intention (0.447), and the remaining constructs. Similarly, System Quality shows a square root of AVE of 0.807, exceeding its correlations with Information Quality (0.400), Perceived Ease of Use (0.398), and Perceived Risk (0.358).

These results indicate that each construct shares more variance with its own indicators than with other latent variables, satisfying the Fornell–Larcker criterion. Therefore, discriminant validity is established, confirming that the constructs in the proposed model are conceptually distinct and do not exhibit problematic overlap.

Table 4. Discriminant Validity Test (Fornell-Larcker criterion).

	ATT	BI	IQ	PEOU	PR	PU	SQ
ATT	**0.765**						
BI	0.447	**0.813**					
IQ	0.365	0.324	**0.834**				
PEOU	0.335	0.314	0.353	**0.849**			
PR	0.348	0.410	0.280	0.278	**0.799**		
PU	0.447	0.418	0.312	0.358	0.291	**0.816**	
SQ	0.331	0.311	0.400	0.398	0.358	0.372	**0.807**

Note. Diagonal entries are the square root of each construct's average variance extracted (AVE)
ATT: Attitude; BI: Behavioral Intention; IQ: Information Quality; PEOU: Perceived Ease of Use; PR: Perceived Risk; PU: Perceived Usefulness; SQ: System Quality.

In addition to the Fornell–Larcker assessment, the heterotrait–monotrait ratio (HTMT) was calculated to further examine discriminant validity, as recommended by Henseler et al. (2015). The HTMT represents the ratio of between-construct correlations to within-construct correlations, where lower values indicate stronger discriminant validity. As shown in Table 5, all HTMT values range from 0.304 to 0.552, which are well below the conservative threshold of 0.85. These results provide additional support for discriminant validity, indicating that the constructs are conceptually distinct from one another. In summary, the results from both criteria confirm that the measurement model has good discriminant validity, allowing for the assessment of the structural model.

Table 5. Discriminant Validity using HTMT.

	ATT	BI	IQ	PEOU	PR	PU	SQ
ATT							
BI	0.533						
IQ	0.439	0.366					
PEOU	0.389	0.368	0.390				
PR	0.405	0.471	0.304	0.315			
PU	0.552	0.496	0.347	0.418	0.332		
SQ	0.393	0.360	0.447	0.452	0.412	0.433	

Note. Entries represent heterotrait–monotrait (HTMT) ratios of construct correlations.
ATT: Attitude; BI: Behavioral Intention; IQ: Information Quality; PEOU: Perceived Ease of Use; PR: Perceived Risk; PU: Perceived Usefulness; SQ: System Quality.

4.3. Hypotheses Testing Results

To examine the determinants of users' behavioral intention to adopt smart healthcare devices, the proposed structural model was tested using partial least squares structural equation modeling (PLS-SEM). The model integrates the Technology Acceptance Model with key constructs from the IS Success Model, namely system quality and information quality. As presented in Table 6, the bootstrapping results based on 5,000 subsamples provided strong empirical support for all nine hypothesized relationships (H1–H9). System Quality had a significant positive effect on both Perceived Usefulness ($\beta = 0.228$, $p = 0.005$) and Perceived Ease of Use ($\beta = 0.306$, $p < 0.001$), supporting H1 and H2. Similarly, Information Quality positively influenced Perceived Usefulness ($\beta = 0.144$, $p = 0.045$) and Perceived Ease of Use ($\beta = 0.231$, $p = 0.001$), confirming H3 and H4.

In line with the Technology Acceptance Model, Perceived Ease of Use significantly affected Perceived Usefulness ($\beta = 0.216$, $p = 0.004$) and Attitude toward adoption ($\beta = 0.143$, $p = 0.050$), supporting H5 and H6. Furthermore, Perceived Usefulness was a strong predictor of both Attitude ($\beta = 0.290$, $p < 0.001$) and Behavioral Intention ($\beta = 0.273$, $p < 0.001$), confirming H7 and H8. Finally, Attitude demonstrated the strongest direct effect on Behavioral Intention ($\beta = 0.325$, $p < 0.001$), supporting H9.

Overall, the results indicate that system quality and information quality affect technology adoption indirectly through perceived usefulness and perceived ease of use. Perceived Usefulness emerges as the most influential predictor of Behavioral Intention, exerting both direct and mediated effects, while Attitude functions as a key mediator in the decision to adopt smart healthcare devices.

Table 6. Summary of Hypotheses Results

	Path	**Path Coefficient (*β*)**	**Standard Deviation**	***t*-value**	***p*-value**	**Result**
H1	SQ → PU	0.228	0.080	2.834	0.005	Supported
H2	SQ → PEOU	0.306	0.084	3.647	<0.001	Supported
H3	IQ → PU	0.144	0.072	2.007	0.045	Supported
H4	IQ → PEOU	0.231	0.072	3.214	0.001	Supported
H5	PEOU → PU	0.216	0.076	2.845	0.004	Supported

H6	PEOU → ATT	0.143	0.073	1.963	0.050	Supported
H7	PU → ATT	0.290	0.071	4.076	<0.001	Supported
H8	PU → BI	0.273	0.073	3.744	<0.001	Supported
H9	ATT → BI	0.325	0.077	4.220	<0.001	Supported

Note. ATT: Attitude; BI: Behavioral Intention; IQ: Information Quality; PEOU: Perceived Ease of Use; PR: Perceived Risk; PU: Perceived Usefulness; SQ: System Quality.

4.4. Moderation Effect Results

The analysis examined the moderating effect of perceived risk on the relationships from perceived usefulness and perceived ease of use to attitude. As reported in Table 7, the interaction between perceived risk and perceived usefulness exerted a significant negative effect on attitude ($\beta = -0.362$, $p < 0.001$), thereby supporting H10a. This finding indicates that when perceived risk is higher, the positive influence of perceived usefulness on users' attitude toward adopting smart healthcare devices becomes weaker. By contrast, the interaction between perceived risk and perceived ease of use was not significant ($\beta = 0.127$, $p = 0.074$), and H10b was therefore not supported. This suggests that perceived risk does not significantly alter the relationship between perceived ease of use and users' attitude. In summary, these findings position perceived risk as a significant negative boundary condition for the role of perceived usefulness, but not for perceived ease of use, in shaping users' attitudes toward smart healthcare devices.

Table 7. Results of Moderation Analysis

Path		Path Coefficient (β)	Standard Deviation	*t*-value	*p*-value	Result
H10a	PR x PU → ATT	-0.362	0.076	4.732	<0.001	Supported
H10b	PR x PEOU → ATT	0.127	0.071	1.784	0.074	Not Supported

Note. ATT: Attitude; PEOU: Perceived Ease of Use; PU: Perceived Usefulness; PR: Perceived Risk.

5. Conclusion

5.1. Discussion

The purpose of this study was to investigate the determinants of users' acceptance of AI-based smart healthcare devices by integrating the Technology Acceptance Model (TAM) with the

Information Systems Success Model (ISSM) and perceived risk. The findings provide several noteworthy insights into how system attributes and psychological factors jointly shape behavioral intention.

First, both system quality (SQ) and information quality (IQ) were found to significantly influence perceived usefulness (PU) and perceived ease of use (PEOU). These results align with the propositions of DeLone and McLean (2003), confirming that reliable system performance, responsive functions, and accurate health information are fundamental drivers of positive evaluations in digital health environments. The effects observed in this study reinforce the argument that high-quality technological infrastructures enhance users' cognition by reducing uncertainty and facilitating operational efficiency (Dong et al., 2017). Importantly, IQ exerted a slightly stronger effect on PEOU than on PU, suggesting that users may prioritize clarity, accuracy, and relevance of health data when assessing how intuitively the device can be operated.

Second, the relationships predicted by TAM were consistently supported. PEOU significantly improved PU and attitude, demonstrating that ease of interaction with AI-based devices reduces cognitive load and enhances users' perceptions of technological value (Khan & Shehawy, 2025). Meanwhile, PU emerged as the strongest predictor of both attitude and behavioral intention, echoing prior research indicating that users adopt smart healthcare technologies primarily when they believe that the system meaningfully improves their health management performance (Al-rawashdeh et al., 2022). This finding substantiates the centrality of usefulness in driving acceptance of AI-supported health systems, where perceived health benefits and functional utility outweigh other considerations.

Third, the study revealed that attitude is a key mediator in translating cognitive evaluations into behavioral intention. Attitude showed the strongest direct effect on intention, suggesting that even when users perceive the system as useful and easy to use, adoption ultimately depends on their affective orientation toward AI-enabled health monitoring (Al-Okaily et al., 2025). This emphasizes the importance of shaping positive users' attitudes through transparent communication, credible design, and user-centered interaction experiences.

Finally, the moderation analysis yielded important psychological insights. Perceived risk significantly weakened the effect of PU on attitude, indicating that when concerns about privacy, data misuse, or device malfunction are high, the perceived functional benefits of the system may be discounted. This is consistent with studies showing that risk perceptions can offset perceived advantages in health technology adoption (Li & Li, 2023). However, perceived risk did not moderate the effect of PEOU on attitude, implying that ease of use is evaluated more cognitively and remains relatively stable regardless of perceived uncertainty. This asymmetrical moderation effect suggests that risk perceptions mainly interfere with users' value assessments or usefulness, rather than their assessments of usability.

Overall, the findings highlight that the adoption of AI-based smart healthcare devices is not solely determined by system performance but also by users' emotional and psychological comfort. Even when a system is perceived as efficient and easy to use, high perceived risk can erode trust and limit acceptance. Therefore, addressing risk-related concerns is essential to strengthening the adoption of AI-enabled smart healthcare technologies. These findings primarily reflect acceptance mechanisms among relatively young and well-educated users, and further validation among older adults and actual users is needed.

5.2. Theoretical Implications

This study provides several contributions to the theoretical understanding of smart healthcare adoption. First, by integrating the Technology Acceptance Model with Information Systems Success Model constructs, the study extends existing TAM–ISSM research by empirically validating the role of system quality and information quality as significant antecedents of perceived usefulness and perceived ease of use in the smart healthcare context. The significant effects of these system-related variables support prior assumptions in TAM–ISSM integrations and demonstrate their applicability in AI-enabled healthcare technologies.

Second, the study contributes to theory by identifying a differentiated moderating role of perceived risk within the integrated framework. The results show that perceived risk significantly weakens the relationship between perceived usefulness and attitude, while its moderating effect on the perceived ease of use–attitude relationship is not supported. This asymmetric moderating pattern refines prior TAM–ISSM integrations by indicating that perceived risk does not uniformly constrain all cognitive pathways, but selectively affects the translation of usefulness perceptions into attitudinal responses.

Third, the findings reaffirm the theoretical relevance of attitude as a mediating construct in smart healthcare adoption. While some contemporary models place less emphasis on attitudinal mechanisms, the results indicate that attitude continues to play a meaningful role in linking perceived usefulness and perceived ease of use to behavioral intention in this context. Together, these contributions provide a more precise understanding of how system quality, cognitive beliefs, attitude, and perceived risk interact within an integrated TAM–ISSM framework for AI-based smart healthcare devices.

5.3. Managerial Implications

The findings offer several practical insights for developers, healthcare providers, and policymakers seeking to promote the adoption of AI-based smart healthcare technologies. First, the strong effects of system quality and information quality indicate that technical excellence should be treated as a strategic priority. Developers should ensure high reliability, rapid response time, stable connectivity, and accurate physiological monitoring, as shortcomings in any of these areas can undermine users' confidence and weaken perceived usefulness.

Second, given that perceived usefulness emerges as the strongest determinant of behavioral intention, companies should emphasize communicating the tangible benefits of AI-enabled smart monitoring, such as early detection of abnormalities, enhanced safety for older adults, and continuous passive monitoring without physical contact. Demonstrations, real-world case examples, and users' testimonials may effectively strengthen perceived value.

Third, perceived risk significantly weakens the impact of usefulness on attitude, suggesting that risk-reduction strategies are crucial. Developers and service providers should implement and visibly communicate privacy safeguards, encrypted data transmission, and transparent data-handling policies. User-controlled access settings, customizable alert thresholds, and clear explanations of AI decision-making can reduce uncertainty and build trust.

Fourth, healthcare organizations and policymakers should support public education programs that clarify the capabilities and limitations of AI-based devices. Training materials, informational campaigns, and interactive demonstrations can enhance both ease of use and confidence among potential users, particularly those unfamiliar with AI technologies.

Finally, because attitude strongly predicts behavioral intention, industry stakeholders should design users experiences that are not only functional but also emotionally reassuring. Aesthetic interface design, clear feedback messages, user-friendly apps, and empathetic communication can all contribute to shaping a positive affective response, thereby improving adoption likelihood

5.4. Limitations and Future Research

Despite its contributions, this study has several limitations that offer opportunities for future research. First, the study relied on a sample predominantly composed of young and highly educated participants, which may limit generalizability. However, this sample is appropriate for capturing early-stage acceptance and cognitive evaluation mechanisms of emerging AI-based healthcare technologies. Older adults, who represent a key target group for home health monitoring technologies, may exhibit different perceptions of usefulness, ease of use, or risk. Future studies should include more diverse demographic segments, especially elderly users and individuals with chronic health conditions. Second, the study employed a cross-sectional research design, capturing perceptions at a single point in time. Users' acceptance of smart healthcare devices may evolve as individuals gain experience with the technology. Longitudinal studies or experimental designs could provide deeper insights into changes in trust, perceived risk, and behavioral intention over time.

Third, the study used self-reported behavioral intention rather than actual usage behavior. While intention is a strong predictor of behavior, future research should incorporate objective usage data, field trials, or experimental deployment to validate behavioral outcomes. Fourth, the model focused primarily on system quality, information quality, perceived usefulness, ease of use, and risk. Other psychological or contextual factors, such as perceived privacy, algorithmic transparency, health status, cultural norms, or caregiver influence, may also shape adoption decisions. Future models could include these constructs to provide a more comprehensive understanding.

Finally, the study examined a specific type of AI-enabled device based on radar technology. As smart healthcare ecosystems expand to include multimodal sensing, cloud-based diagnostics, and generative AI support, future research should explore whether similar acceptance patterns apply across different technological architectures.

Supplementary Materials: Not applicable.

Author Contributions: Conceptualization was conducted by Y.Z. and H-S.K. Methodology was led by B-H.L., while D-H.H. was responsible for software development. Validation was performed by J.W., and formal analysis was carried out by B.J. Investigation was jointly completed by Y.Z. and D-H.H. Resources were provided by H-S.K., and data curation was managed by B-H.L. The original draft was prepared by J.W., and the review and editing were performed collaboratively by B.J. and H-S.K. Visualization was handled by D-H.H., supervision was provided by H-S.K., and project administration was coordinated by Y.Z. No external funding was acquired. All authors (Y.Z., D-H.H., J.W., B-H.L., B.J., H-S.K.) have read and agreed to the published version of the manuscript. All authors have read and agreed to the published version of the manuscript. All authors have read and agreed to the published version of the manuscript.

Funding: Busan Regional Innovation System & Education (RISE) Project, supported by the Ministry of Education and Busan Metropolitan City and Medi-Storming (Medical-ICT Convergence Workshop / Research Forum) Project, supported by the Busan Economic Promotion Agency (BEPA).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

Conflicts of Interest: The author declares no conflicts of interest.

References

Al-Assaf, K., Bahroun, Z., & Ahmed, V. (2024). Transforming Service Quality in Healthcare: A Comprehensive Review of Healthcare 4.0 and Its Impact on Healthcare Service Quality. *Informatics*, *11*(4), 96. https://doi.org/10.3390/informatics11040096

Al-Okaily, M., Shiyyab, F. S., Salim, N. A., & Al-Rahayfeh, A. (2025). The role of AI-enabled health systems in the Jordanian context: the case of digital contact tracing apps. *Journal of Health Organization and Management,* *39*(4), 463–483. https://doi.org/10.1108/JHOM-06-2024-0252

Al-Rawashdeh, M., Keikhosrokiani, P., Belaton, B., Alawida, M., & Zwiri, A. (2022). IoT adoption and application for smart healthcare: a systematic review. *Sensors*, *22*(14), 5377. https://doi.org/10.3390/s22145377

Almahamid, S. O. U. D., Mcadams, A. C., TAHER, A. K., & MO'TAZ, A. S. E. (2010). The relationship between perceived usefulness, perceived ease of use, perceived information quality, and intention to use e-government. *Journal of Theoretical & Applied Information Technology*, *11*.

Almaiah, M. A., Al-Otaibi, S., Shishakly, R., Hassan, L., Lutfi, A., Alrawad, M., Qatawneh, M., & Alghanam, O. A. (2023). Investigating the Role of Perceived Risk, Perceived Security and Perceived Trust on Smart m-Banking Application Using SEM. *Sustainability*, *15*(13), 9908. https://doi.org/10.3390/su15139908

Alzahrani, A. I., Mahmud, I., Ramayah, T., Alfarraj, O., & Alalwan, N. (2017). Modelling digital library success using the DeLone and McLean information system success model. *Journal of Librarianship and Information Science*, *51*(2), 291-306. https://doi.org/10.1177/0961000617726123

Belanche, D., Casaló, L. V., & Flavián, C. (2019). Artificial Intelligence in FinTech: understanding robo-advisors adoption among customers. *Industrial Management & Data Systems, 119*(7), 1411-1430. https://doi.org/10.1108/IMDS-08-2018-0368

Casmin, E., & Oliveira, R. (2025). Survey on Context-Aware Radio Frequency-Based Sensing. *Sensors*, *25*(3), 602. https://doi.org/10.3390/s25030602

Chua, A. Y., Pal, A., & Banerjee, S. (2023). AI-enabled investment advice: Will users buy it?. *Computers in Human Behavior, 138*, 107481. https://doi.org/10.1016/j.chb.2022.107481

Chirchir, L. K., Aruasa, W. K., & Chebon, S. K. (2019). Perceived usefulness and ease of use as mediators of the effect of health information systems on user performance. *European Journal of Computer Science and Information Technology, 7*(1), 22–37.

Gold, C., Körber, M., Hohenberger, C., Lechner, D., & Bengler, K. (2015). Trust in automation–before and after the experience of take-over scenarios in a highly automated vehicle. *Procedia Manufacturing, 3*, 3025-3032. https://doi.org/10.1016/j.promfg.2015.07.847

Corbitt, B. J., Thanasankit, T., & Yi, H. (2003). Trust and e-commerce: a study of consumer perceptions. *Electronic Commerce Research and Applications, 2*(3), 203-215. https://doi.org/10.1016/S1567-4223(03)00024-3

Coye, M. J., Haselkorn, A., & DeMello, S. (2009). Remote patient management: technology-enabled innovation and evolving business models for chronic disease care. *Health Affairs, 28*(1), 126-135. https://doi.org/10.1377/hlthaff.28.1.126

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

DeLone, W. H., & McLean, E. R. (1992). Information systems success: The quest for the dependent variable. *Information Systems Research*, *3*(1), 60-95. https://doi.org/10.1287/isre.3.1.60

DeLone, W. H., & McLean, E. R. (2003). The DeLone and McLean model of information systems success: a ten-year update. *Journal of Management Information Systems*, *19*(4), 9-30. https://doi.org/10.1080/07421222.2003.11045748

Dong, X., Chang, Y., Wang, Y., & Yan, J. (2017). Understanding usage of Internet of Things (IOT) systems in China: Cognitive experience and affect experience as moderator. *Information Technology & People*, *30*(1), 117-138. https://doi.org/10.1108/ITP-11-2015-0272

Engelberg, E. (2007). The perception of self-efficacy in coping with economic risks among young adults: an application of psychological theory and research. *International Journal of Consumer Studies*, *31*(1), 95-101. https://doi.org/10.1111/j.1470-6431.2005.00494.x

Glassberg, I., Ilan, Y. B., & Zwilling, M. (2025). The key role of design and transparency in enhancing trust in AI-powered digital agents. *Journal of Innovation & Knowledge*, *10*(5), 100770. https://doi.org/10.1016/j.jik.2025.100770

Hair, J. F., Jr., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Annabel Ainscow.

Hasija, A., & Esper, T. L. (2022). In artificial intelligence (AI) we trust: A qualitative investigation of AI technology acceptance. *Journal of Business Logistics, 43*(3), 388–412. https://doi.org/10.1111/jbl.12301

Ho, D. H., Lee, B.-H., Jeon, B., & Kim, H.-S. (2025). Psychological Barriers and Perceptual Drivers of Sensor-Based Smart Health Technology Adoption. *Sensors*, *25*(22), 7029. https://doi.org/10.3390/s25227029

Ho, D. H., Seieun, K., Byeong-Hoon, L., Jeon, B., Kim, H.-S., & Wang, J. (2024). Exploring User Perceptions of a Radar Sensor-Based Smart Healthcare Device for Heart Rate and Breathing Rate Monitoring through Interviews. *Journal of Industrial Innovation, 40*(3), 82–95. https://doi.org/10.22793/indinn.2024.40.3.009

Hsin Chang, H., & Wen Chen, S. (2008). The impact of online store environment cues on purchase intention: Trust and perceived risk as a mediator. *Online Information Review, 32*(6), 818-841. https://doi.org/10.1108/14684520810923953

Hu, P. J., Chau, P. Y., 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

Jacob, C., Sanchez-Vazquez, A., & Ivory, C. (2020). Understanding clinicians' adoption of mobile health tools: a qualitative review of the most used frameworks. *JMIR mHealth and uHealth*, *8*(7), e18072.

Jayashankar, P., Nilakanta, S., Johnston, W. J., Gill, P., & Burres, R. (2018). IoT adoption in agriculture: the role of trust, perceived value and risk. *Journal of Business & Industrial Marketing*, *33*(6), 804-821. https://doi.org/10.1108/JBIM-01-2018-0023

Kang, M. J., & Hwang, Y. C. (2022). Exploring the Factors Affecting the Continued Usage Intention of IoT-Based Healthcare Wearable Devices Using the TAM Model. *Sustainability*, *14*(19), 12492. https://doi.org/10.3390/su141912492

Kanungo, S., & Bhatnagar, V. V. (2002). Beyond generic models for information system quality: the use of interpretive structural modeling (ISM). *Systems Research and Behavioral Science*, *19*(6), 531-549. https://doi.org/10.1002/sres.476

Khan, S. M. F. A., & Shehawy, Y. M. (2025). Perceived AI Consumer-Driven Decision Integrity: Assessing Mediating Effect of Cognitive Load and Response Bias. *Technologies*, *13*(8), 374. https://doi.org/10.3390/technologies13080374

Kim, S., Zhong, Y., Wang, J., & Kim, H.-S. (2024). Exploring Technology Acceptance of Healthcare Devices: The Moderating Role of Device Type and Generation. *Sensors*, *24*(24), 7921. https://doi.org/10.3390/s24247921

Koivumäki, T., Ristola, A., & Kesti, M. (2008). The effects of information quality of mobile information services on user satisfaction and service acceptance–empirical evidence from Finland. *Behaviour & Information Technology,* *27*(5), 375–385. https://doi.org/10.1080/01449290601177003

Lee, A. T., Ramasamy, R. K., & Subbarao, A. (2025). Understanding Psychosocial Barriers to Healthcare Technology Adoption: A Review of TAM Technology Acceptance Model and Unified Theory of Acceptance and Use of Technology and UTAUT Frameworks. *Healthcare*, *13*(3), 250. https://doi.org/10.3390/healthcare13030250

Li, C., & Li, Y. (2023). Factors Influencing Public Risk Perception of Emerging Technologies: A Meta-Analysis. *Sustainability*, *15*(5), 3939. https://doi.org/10.3390/su15053939

Lin, F., Fofanah, S. S., & Liang, D. (2011). Assessing citizen adoption of e-Government initiatives in Gambia: A validation of the technology acceptance model in information systems success. *Government Information Quarterly, 28*(2), 271-279. https://doi.org/10.1016/j.giq.2010.09.004

Majeed, A., & Hwang, S. O. (2022). Data-Driven Analytics Leveraging Artificial Intelligence in the Era of COVID-19: An Insightful Review of Recent Developments. *Symmetry*, *14*(1), 16. https://doi.org/10.3390/sym14010016

Namahoot, K. S., & Jantasri, V. (2023). Integration of UTAUT model in Thailand cashless payment system adoption: the mediating role of perceived risk and trust. *Journal of Science and Technology Policy Management*, *14*(4), 634-658. https://doi.org/10.1108/JSTPM-07-2020-0102

Ouajdouni, A., Chafik, K., Allioui, S., & Jbene, M. (2024). Patient Satisfaction with the Mawiidi Hospital Appointment Scheduling Application: Insights from the Information Systems Success Model and Technology Acceptance Model in a Moroccan Healthcare Setting. *Big Data and Cognitive Computing*, *8*(12), 180. https://doi.org/10.3390/bdcc8120180

Pan, J., Ding, S., Wu, D., Yang, S., & Yang, J. (2019). Exploring behavioural intentions toward smart healthcare services among medical practitioners: a technology transfer perspective. *International Journal of Production Research*, *57*(18), 5801–5820. https://doi.org/10.1080/00207543.2018.1550272

Rouibah, K., Lowry, P. B., & Hwang, Y. (2016). The effects of perceived enjoyment and perceived risks on trust formation and intentions to use online payment systems: New perspectives from an Arab country. *Electronic Commerce Research and Applications*, *19*, 33-43. https://doi.org/10.1016/j.elerap.2016.07.001

Salih, L., Tarhini, A., & Acikgoz, F. (2025). AI-Enabled Service Continuance: Roles of Trust and Privacy Risk. *Journal of Computer Information Systems*, 1–16. https://doi.org/10.1080/08874417.2025.2452544

Sharma, S. K., Gaur, A., Saddikuti, V., & Rastogi, A. (2017). Structural equation model (SEM)-neural network (NN) model for predicting quality determinants of e-learning management systems. *Behaviour & Information Technology*, *36*(10), 1053–1066. https://doi.org/10.1080/0144929X.2017.1340973

Tate, M., Evermann, J., & Gable, G. (2015). An integrated framework for theories of individual attitudes toward technology. *Information & Management*, *52*(6), 710-727. https://doi.org/10.1016/j.im.2015.06.005

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

Verified Market Research. (2025, August). *Non-invasive monitoring device market size & forecast*. *Verified Market Research*. https://www.verifiedmarketresearch.com/product/non-invasive-monitoring-device-market/

Walle, A. D., Demsash, A. W., Ferede, T. A., & Wubante, S. M. (2023). Healthcare professionals' satisfaction toward the use of district health information system and its associated factors in Southwest Ethiopia: using the information system success model. *Frontiers in Digital Health*, *5*, 1140933. https://doi.org/10.3389/fdgth.2023.1140933

Wang, J., & Kim, H.-S. (2023). Visualizing the Landscape of Home IoT Research: A Bibliometric Analysis Using VOSviewer. *Sensors*, *23*(6), 3086. https://doi.org/10.3390/s23063086

Wang, J., Zhao, S., Zhang, W., & Evans, R. (2021). Why people adopt smart transportation services: an integrated model of TAM, trust and perceived risk. *Transportation Planning and Technology*, *44*(6), 629–646. https://doi.org/10.1080/03081060.2021.1943132

Williamson, S. M., & Prybutok, V. (2024). Balancing Privacy and Progress: A Review of Privacy Challenges, Systemic Oversight, and Patient Perceptions in AI-Driven Healthcare. *Applied Sciences*, *14*(2), 675. https://doi.org/10.3390/app14020675

Yakubu, N., & Dasuki, S. (2018). Assessing eLearning systems success in Nigeria: An application of the DeLone and McLean information systems success model. *Journal of Information Technology Education: Research*, *17*, 183-203. https://doi.org/10.28945/4077

Yu, T., Tian, Y., Chen, Y., Huang, Y., Pan, Y., & Jang, W. (2025). How Do Ethical Factors Affect User Trust and Adoption Intentions of AI-Generated Content Tools? Evidence from a Risk-Trust Perspective. *Systems*, *13*(6), 461. https://doi.org/10.3390/systems13060461

Zhang, T., Tao, D., Qu, X., Zhang, X., Lin, R., & Zhang, W. (2019). The roles of initial trust and perceived risk in public's acceptance of automated vehicles. *Transportation Research Part C: Emerging Technologies*, *98*, 207-220. https://doi.org/10.1016/j.trc.2018.11.018

Zin, K. S. L. T., Kim, S., Kim, H.-S., & Feyissa, I. F. (2023). A Study on Technology Acceptance of Digital Healthcare among Older Korean Adults Using Extended Tam (Extended Technology Acceptance Model). *Administrative Sciences*, *13*(2), 42. https://doi.org/10.3390/admsci13020042