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Perceived Benefits and Risks of Korean Digital Health Devices: Exploring Adoption in Indonesia's Growing Healthcare Market

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Abstract

As digital health technologies continue to grow worldwide, Korean digital health devices are receiving greater recognition for their advanced technology and user-friendly design. With its fast-growing digital health landscape, Indonesia stands out as a promising market for global adoption of digital health technologies. This study examines how Indonesian consumers evaluate the perceived benefits and perceived risks of Korean digital health devices and how these perceptions shape their intention to adopt such technologies. Guided by the Net Value Model, a quantitative survey was administered to 175 Indonesian respondents. SmartPLS 4.0 was employed for reliability testing and hypothesis assessment. Results indicate that all perceived benefit dimensions performance expectancy (β = 0.335, p < 0.001), effort expectancy (β = 0.296, p < 0.001), compatibility (β = 0.290, p < 0.001), and image (β = 0.286, p < 0.001) significantly enhance perceived benefits. Meanwhile, multiple risk dimensions, performance risk (β = 0.292, p < 0.001), financial risk (β = 0.281, p < 0.001), time risk (β = 0.273, p < 0.001), privacy risk (β = 0.198, p < 0.001), and security risk (β = 0.155, p < 0.001) strongly increase perceived risk. In turn, both perceived benefits (β = 0.403, p < 0.001) and perceived risks (β = 0.530, p < 0.001) significantly influence consumers' intention to adopt Korean digital health devices.

Keywords: digital health devices; perceived benefits and risks; technology adoption; korean healthcare technology; Indonesian market

1. Introduction

The market shares of Korean medical devices are expected to grow from USD 7.57billion in 2025 to USD 12.58billion by 2032 (Fortune Business Insight, 2025). The rapid expansion of digital health technologies has reshaped global healthcare delivery, offering new opportunities for remote monitoring, chronic disease management, and preventive healthcare (Awad et al., 2021). In recent years, Korean digital health devices which includes sensors-based healthcare devices have gained global attention for their high-quality technology, user-friendly design, and strong government support under Korea's Digital Healthcare Strategy (Lee et al., 2025). As international demand grows, emerging markets such as Indonesia represent a significant opportunity for cross-border digital health adoption.

Indonesia's healthcare landscape is undergoing accelerated digital transformation, driven by rising healthcare costs, uneven access to medical services, high smartphone penetration, and increasing government interest in telemedicine and digital healthcare modernization (Pitaloka & Nugroho, 2021). Despite these advancements, challenges remain in improving patient access, early detection, and continuous monitoring. However, the adoption of foreign digital health devices in Indonesia depends heavily on individual users' perceived benefits and perceived risks, shaping their willingness to integrate such technologies into health-related routines (Li et al., 2016).

Variables such as performance expectancy, effort expectancy, compatibility and image plays a central role in shaping technology perceived benefit (Wang et al., 2020), particularly towards adoption intention. On the other hand, perceived risks include privacy concerns, data security, financial cost, system performance, and time barriers may limit adoption, especially when technologies originate from overseas providers (Jain et al., 2022). Understanding how Indonesian consumers evaluate these benefits and risks in relation to Korean digital health devices is therefore critical.

Although Korea has become a global leader in smart health innovation, there is limited empirical research addressing how foreign users, particularly in Southeast Asia, perceive Korean digital health products. Existing studies tend to focus on domestic Korean users or general digital health adoption (Kim et al., 2017; Zin et al., 2023), but little attention has been given to cross-cultural acceptance, market-specific concerns, and consumer decision-making in developing healthcare ecosystems like Indonesia.

To address this gap, this study aims to explore Indonesian consumers' perceptions of the benefits and risks associated with adopting Korean digital health devices, providing insights into factors that may promote or hinder adoption. By focusing on the Indonesian healthcare context as one of the fastest-growing digital health markets in Southeast Asia, this research contributes to both academic understanding and practical strategies for market expansion, product adaptation, and user education.

This study offers a timely examination of how perceived benefits and perceived risks jointly shape technology adoption intentions, providing actionable implications for Korean device manufacturers, healthcare policymakers, and digital health innovators seeking sustainable entry into Indonesia's rapidly evolving healthcare environment.

2. Literature Review

2.1. Net Valence Model

The Net Valence Model explains consumer acceptance as a result of individuals evaluations of both the perceived benefitsand perceived risks associated with a product or service (Mascarenhas et al., 2021). The Net Valence Model also aligns with the cost- benefit perspective of customer value, which suggests that customers evaluate value by weighing the benefits they receive against the sacrifices or costs they incur Li et al. (2018). To provide a systematic analysis of how perceived benefits and risks affect individuals' intentions to adopt smart home devices, this study proposes a Net Valence Model Wang et al. (2020)

2.2. Digital Health Devices and Global Healthcare Transformation

Healthcare 5.0, with its integration of advanced sensors and emerging digital technologies, has the potential to revolutionize healthcare delivery. However, achieving true resilience and robustness within this ecosystem requires overcoming significant organizational, technological, and regulatory barriers (Mbunge et al., 2021). Digital health devices have become a crucial component of modern healthcare ecosystems, transforming how individuals monitor, manage, and improve their health (Bhavnani et al., 2016). These technologies include wearable sensors, mobile health (mHealth) applications, AI-enabled diagnostic tools, remote monitoring systems, and smart medical devices that collect real-time physiological data (Mitchell & Kan, 2019).

Previous studies indicate that digital healthcare technologies, particularly wearable devices which hold substantial potential to transform geriatric care by enabling continuous remote monitoring, enhancing preventive health management, and supporting greater independence among aging populations (Chen et al., 2023). Despite their promising benefits, the adoption of digital healthcare devices is also accompanied by notable concerns. Current regulatory frameworks and clinical guidelines remain insufficiently mature to fully guarantee patient safety, data security, and clinical validity. These regulatory gaps contribute to users' perceived risks, particularly in healthcare contexts where accuracy and reliability are essential. As a result, the need for stronger oversight, standardized evaluation procedures, and evidence-based guidelines has become increasingly important to support safe and trustworthy integration of digital health technologies (Fleming et al., 2020)

2.3. Korean Digital Health Technologies and International Market Expansion

The current Korean government support and clear regulatory guidance are critical for advancing the digital therapeutics industry both domestically and globally, with priorities including increased R&D funding, streamlined licensing procedures, and standardized evaluation protocols (Kim et al., 2022). It is also noted that major technology corporations, advancements in big data analytics, and Asia's emergence as a leading digital health hub are accelerating the shift toward consumer-centric healthcare, reshaping traditional delivery models and driving innovation across the sector (Thomason, 2021).

Existing literature highlights that digital healthcare is undergoing rapid transformation, driven by continuous technological innovation, increasing stakeholder engagement, and evolving regulatory frameworks that seek to modernize traditional healthcare delivery models (Lee & Kim, 2024). Studies on foreign patients' experiences in South Korea underscore persistent cultural and communication gaps, particularly across different language groups which shape perceptions of care quality and highlight the importance of culturally competent digital health services (Sung & Park, 2019). At the same time, Korean healthcare information systems have gained international traction, being adopted in countries such as Saudi Arabia, the UAE, and the Philippines to reduce maintenance costs and enhance patient care efficiency (Chae, 2014).

2.4. Perceived Benefits in Digital Health Device Adoption

Perceived benefits can be understood as system-wide advantages that enhance the overall healthcare ecosystem (Ordoobadi & Mulvaney, 2001). These benefits may contribute value to patients, caregivers, and healthcare providers, yet they are not always directly measurable or easily quantifiable in traditional economic terms. Perceived benefits play a central role in shaping users' willingness to adopt digital health devices, particularly wearables and remote monitoring tools (Kim & Kyung, 2023). There are several constructs under the perceived benefits which are performance expectancy, effort expectancy, compatibility, and image. The full operational definition of each construct can be found in the Table 1.

Table 1. Perceived benefit constructs operational definition

Construct	Operational Definition	Source
Performance Expectancy	The degree to which individuals believe that using digital health devices.	(Wang et al., 2020)
Effort Expectancy	The degree to which individuals perceive digital health devices as easy to learn, operate, and integrate into their daily routines.	
Compatibility	The degree to which digital health devices fit with an individual's lifestyle, health needs, and existing technological habits.	
Image	The degree to which using digital health devices is perceived to enhance social image or is influenced by recommendations from peers, family, or healthcare providers.	

2.5. Perceived Risks in Digital Health Device Adoption

Perceived risk plays a critical role in shaping individuals' decisions to adopt new technologies, particularly in sensitive domains such as digital health. It has been broadly defined as "the amount that would be lost (i.e., that which is at stake) if the consequences of an act were not favorable, and the individual's subjective feeling of certainty that the consequences will be unfavorable (Dowling, 1986). Prior studies further demonstrate that perceived risk interacts with a range of individual and contextual factors that influence technology adoption. Research shows that variables such as technology type and gender can significantly shape users' acceptance of digital tools, while prior user experience often plays only a marginal role once measurement errors are accounted for (Im et al., 2008).

In addition, studies in the FinTech domain highlight that perceived risk, perceived value, and social influence jointly determine adoption intentions, with performance expectancy and effort expectancy exerting indirect effects through perceived value (Xie et al., 2021). Cultural factors also play a crucial role, as privacy and security risks tend to affect adoption differently across countries, reflecting variations in national norms, regulatory environments, and trust in technology. These findings collectively underscore the multifaceted nature of perceived risk and its strong, context-dependent influence on individuals' willingness to adopt emerging technologies (Chopdar et al., 2018).

Table 2. Perceived risk constructs operational definition

Construct	Operational Definition	Source
Privacy Risk	The risk that individuals' personal or health-related data may be accessed, shared, or misused without their consent.	
Perceived Risk	The perceived likelihood that digital health devices may experience data breaches, hacking, or unauthorized system access.	
Security Risk	The perceived likelihood that digital health devices may experience data breaches, hacking, or unauthorized system access.	(Wang et al., 2020)
Performance Risk	The risk that digital health devices may fail to function accurately, produce unreliable data, or not meet users' expectations for health monitoring.	
Time Risk	The risk that using digital health devices will require excessive time to set up, learn, maintain, or interpret data.	
Financial Risk	The risk that the purchase, subscription fees, maintenance, or replacement costs of digital health devices will be unreasonably high.	

2.6. Digital Health Adoption in Emerging Markets and the Indonesian Context

Digital health development in Indonesia shows uneven progress, with EMR adoption largely dependent on hospitals' technological infrastructure and the digital literacy of healthcare staff, particularly in more developed regions (Hossain et al., 2025). Personal health record implementation faces additional barriers related to security, privacy, interoperability, and infrastructure, although organizational commitment, competitive pressure, and vendor support help facilitate adoption (Harahap et al., 2022). At the user level, m-health uptake is strongly driven by performance expectancy and price value, while perceived risk continues to shape individuals' behavioral intentions toward adopting digital health services (Kwee et al., 2022).

Previous studies on digital health adoption in Indonesia highlight several important determinants across different healthcare technologies (Alviani et al., 2023). Prior research shows that performance expectancy, effort expectancy, social influence, e-health literacy, and trust significantly influence telemedicine adoption, whereas facilitating conditions, price value, and privacy concerns exhibit no meaningful effects (Binsar et al., 2025). Additionally, studies indicate that hospitals' digital adoption capability positively contributes to organizational performance, with digital leadership, ICT literacy, and patient-centric care emerging as essential enablers. Other research further demonstrates that initial trust, adequate facilitating conditions, and strong performance expectancy play a central role in shaping Indonesian consumers' intentions to adopt and recommend m-health applications (Octavius & Antonio, 2021).

To empirically test the proposed conceptual model, which is grounded in the Net Value Model (integrating elements from UTAUT and the Diffusion of Innovation theory), a set of eleven hypotheses were formulated. These hypotheses investigate the multi-dimensional relationships among the specific benefit antecedents (performance, effort, compatibility, and image), the various risk dimensions (privacy, security, performance, time, and financial), the two core cognitive constructs (Perceived Benefits and Perceived Risk), and the final behavioral outcome (Intention to Use) Korean digital health devices among Indonesian consumers.

H1: Performance expectancy positively influences perceived benefits
H2: Effort expectancy positively influences perceived benefits
H3: Compatibility positively influences perceived benefits
H4: Image positively influences perceived benefits
H5: Privacy risk positively influences perceived risk
H6: Security risk positively influences perceived risk
H7: Performance risk positively influences perceived risk
H8: Time risk positively influences perceived risk
H9: Financial risk positively influences perceived risk
H10: Perceived benefit positively influences intention to use
H11: Perceived risk positively influences intention to use

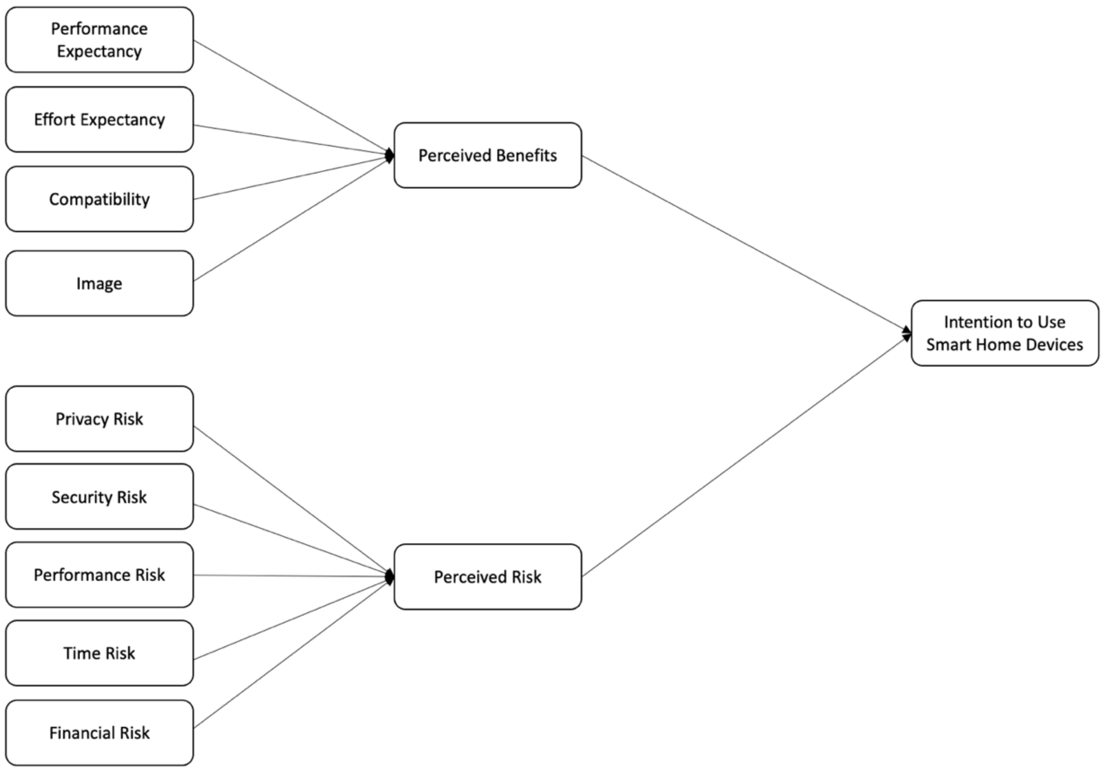

Figure 1. Research Model

3. Methodology

3.1. Data Collection

This study surveyed Indonesian consumers to assess their perceptions of Korean digital health devices. Because no comprehensive sampling frame exists for Indonesian users of foreign digital health devices, the study employed a convenience sampling approach. Data were collected between 12th November and 17th November 2025, following the research flow presented in the study design.

Participants were recruited through an online questionnaire distributed via Google Forms. The survey link was disseminated through social media platforms and online communities commonly used by Indonesian people including WhatsApp groups. To ensure respondent suitability, screening questions were included at the beginning of the questionnaire to confirm that participants had awareness of digital health devices. The questionnaire measured key constructs related to perceived benefits, performance expectancy, effort expectancy, compatibility, image, perceived risk, privacy risk, security risk, performance risk, time risk, financial risk, intention to use Korean smart health monitoring devices and demographic characteristics.

A total of 175 valid responses were retained for further analysis. Participation in the study was voluntary and anonymous, and all respondents were informed about the research purpose before completing the questionnaire, following ethical research guidelines. Data analysis followed the structured procedure shown in the research design. SPSS 26.0 was used to conduct demographic analysis, while SmartPLS 4.0 was used for reliability and validity testing as well as hypothesis testing through the measurement and structural model assessments.

3.2. *Variables and Measurements*

Perceived Benefits (four items) was adapted from Wang et al. (2020) and Xu et al. (2009) to assess users' perceived advantages, usefulness, and efficiency gained from using smart health-monitoring devices. Performance Expectancy (four items), adapted from Wang et al. (2020) and Venkatesh et al. (2003), measured the extent to which users believe the devices enhance their health-management performance. Effort Expectancy (five items) from Wang et al. (2020) evaluated the ease of learning and using the devices.

Compatibility (four items), adapted from Wang et al. (2020) and Moore and Benbasat (1991), assessed the degree to which the devices align with users' lifestyles and health-management routines. Image (four items), taken from Wang et al. (2020), measured users' perceptions of enhanced social status associated with device usage.

Perceived Risk (four items) integrated items from Wang et al. (2020) and Featherman and Pavlou (2003), capturing overall uncertainty and negative expectations related to device use. Privacy Risk (four items), adapted from Li et al. (2018) and Yang et al. (2017), measured concerns about data privacy and unauthorized use of personal information. Security Risk (four items), based on Wang et al. (2020) and Yang et al. (2017), assessed worries about hacking, insufficient security safeguards, and unauthorized system access.

Performance Risk (four items) from Wang et al. (2020) measured fears of device malfunction or failure. Time Risk (four items) evaluated the time required for learning, installation, troubleshooting, and maintenance. Financial Risk (four items), adapted from Wang et al. (2020) and Featherman and Pavlou (2003), captured concerns about high costs, ongoing monetary commitments, or potential financial fraud. Finally, Intention to Use (four items) was adapted from Wang et al. (2020) to assess users' willingness, likelihood, and expectation of using smart health-monitoring devices.

4. Results

4.1. Demographic Information Results

A total of 175 valid responses were collected and used for subsequent data analysis. Table 3 presents the demographic information of the respondents. In terms of gender, the sample consisted of 43.3% male and 54.4% female respondents, with a small proportion (2.2%) preferring not to disclose their gender. Regarding age distribution, the majority of respondents were between 26–33 years old (58.3%), followed by those aged 34–41 years

(23.3%) and 18–25 years (17.2%). Only 1.1% of respondents were in the 42–49 age group, indicating that most participants were young to middle-aged adults.

With respect to educational level, the largest group consisted of individuals with a high school education or below (63.3%), followed by those holding a bachelor's degree (20.6%), a master's degree (11.1%), and a 3-year college diploma (5%). No respondents reported holding a doctoral degree. For monthly individual income, more than half of the participants (58.9%) reported earning between 3,000,000 and 6,000,000 IDR, followed by 38.9% earning between 6,000,001 and 10,000,000 IDR, and 2.2% earning more than 10,000,000 IDR. Regarding employment status, the largest group of respondents were self-employed (57.8%), while 27.8% were employed full-time. Smaller proportions were unemployed (10.6%) or students (3.9%), and none selected the "other" option.

Table 3. Demographic information

Demographic		Frequency	Percent
Gender	Male	76	43.3 %
	Female	95	54.4%
	Prefer not to say	4	2.2%
Age	18 - 25	30	17.2 %
	26 - 33	102	58.3 %
	34 - 41	41	23.3 %
	42 - 49	2	1.1 %
Educational Level	High school or below	111	63.3%
	3-year college	9	5 %
	Bachelor's degree	36	20.6%
	Master's degree	19	11.1%
	3,000,000 - 6,000,000 IDR	103	58.9%
	6,000,001 - 10,000,000 IDR	68	38.9%
	More than 10,000,000 IDR	4	2.2%
Employment Status	Student	7	3.9%
	Employed full-time	49	27.8%
	Self-employed	100	57.8%
	Unemployed	19	10.6%

*Exchange rate: approximately 16,000 IDR per USD

4.2. Validity and Reliability Measurements

To assess the internal consistency and construct validity of the measurement model, several reliability and validity indicators were examined (Hair et al., 2019). Table 4 presents the standardized factor loadings, Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE) for each construct. All Cronbach's Alpha values exceeded the recommended minimum threshold of 0.70, indicating strong internal reliability across all constructs. The alpha values ranged from 0.870 (Security Risk) to 0.944 (Perceived Risk), confirming excellent reliability.

Convergent validity was also well supported. Following the guidelines of Hair et al. (2019), convergent validity is established when item loadings exceed 0.70, AVE values are greater than 0.50, and CR values exceed 0.70. The results show that all factor loadings were above the 0.70 threshold, demonstrating adequate indicator reliability. In addition, all constructs reported CR values between 0.911 and 0.960, and AVE values ranging from 0.719 to 0.857, all surpassing the recommended criteria.

Overall, these findings confirm that the measurement model exhibits strong reliability and convergent validity. The set of constructs covering perceived benefits, performance expectancy, effort expectancy, compatibility, image, risk dimensions, and intention to use demonstrates measurement adequacy and supports a multi-factor model suitable for further structural analysis.

Table 4. Reliability and Validity Results

Constructs	**Items**	**Loadings**	**Cronbach's alpha**	**CR**	**AVE**
Perceived Benefits (PBN)	PBN1	0.915	0.936	0.954	0.839
	PBN2	0.926			
	PBN3	0.919			
	PBN4	0.904			
Performance Expectancy (PEC)	PEC1	0.877	0.892	0.925	0.756
	PEC2	0.888			
	PEC3	0.890			
	PEC4	0.820			
Effort Expectancy (EEC)	EEC1	0.854	0.906	0.930	0.728
	EEC2	0.794			
	EEC3	0.876			
	EEC4	0.866			
	EEC5	0.873			

Compatibility (CMB)	CMB1	0.913	0.887	0.922	0.747
	CMB2	0.864			
	CMB3	0.824			
	CMB4	0.853			
Image (IMG)	IMG1	0.876	0.891	0.925	0.754
	IMG2	0.854			
	IMG3	0.862			
	IMG4	0.882			
Perceived Risk (PRR)	PRR1	0.904	0.944	0.960	0.857
	PRR2	0.932			
	PRR3	0.934			
	PRR 4	0.932			
Privacy Risk (PVR)	PVR 1	0.905	0.901	0.931	0.771
	PVR 2	0.884			
	PVR 3	0.852			
	PVR4	0.870			
Security Risk (SCR)	SCR1	0.780	0.870	0.911	0.719
	SCR2	0.868			
	SCR3	0.858			
	SCR4	0.883			
Performance Risk (PMR)	PMR1	0.876	0.899	0.930	0.769
	PMR2	0.924			
	PMR3	0.860			
	PMR4	0.846			
Time Risk (TMR)	TMR1	0.864	0.904	0.932	0.776
	TMR2	0.875			
	TMR3	0.866			
	TMR4	0.916			
Financial Risk (FNR)	FNR1	0.916	0.911	0.937	0.789
	FNR2	0.915			
	FNR3	0.871			
	FNR4	0.850			
Intention to Use (ITU)	ITU1	0.903	0.929	0.949	0.825
	ITU2	0.866			
	ITU3	0.927			
	ITU4	0.934			

Notes: CR: Composite Reliability; AVE: Average Variance Extracted

4.3. Discriminant Validity (Fornell-Larcker criterion)

Discriminant validity was assessed using the Fornell-Larcker criterion to ensure that each construct in the model is empirically distinct from the others (Hair et al., 2019). According to this criterion, the square root of the AVE for each construct should exceed its correlations with all other constructs. As shown in Table 5, the diagonal values (presented in bold) are consistently higher than the inter-construct correlations in the corresponding rows and columns.

For example, the square root of AVE for key constructs such as Compatibility (0.864), Effort Expectancy (0.853), Perceived Benefits (0.916), Perceived Risk (0.926), and Intention to Use (0.908) all exceed their correlations with other constructs in the model. This pattern is similarly observed across the remaining variables, confirming that each construct shares more variance with its own indicators than with other constructs.These results indicate that the Fornell-Larcker criterion is satisfied, demonstrating adequate discriminant validity and confirming that the constructs are conceptually and statistically distinct from one another. If combined with HTMT analysis, the overall findings further reinforce the discriminant validity of the measurement model.

Table 5. Discriminant Validity (Fornell-Larcker criterion)

	CMB	EEC	FNR	IMG	ITU	PBN	PEC	PMR	PRR	PVR	SCR	TMR
CMB	**0.864**											
EEC	0.417	**0.858**										
FNR	0.480	0.421	**0.888**									
IMG	0.417	0.416	0.572	**0.868**								
ITU	0.570	0.635	0.675	0.582	**0.908**							
PBN	0.668	0.679	0.637	0.677	0.797	**0.916**						
PEC	0.406	0.430	0.533	0.439	0.584	0.705	**0.870**					
PMR	0.463	0.668	0.468	0.408	0.643	0.600	0.466	**0.877**				
PRR	0.486	0.626	0.728	0.555	0.830	0.744	0.592	0.702	**0.926**			
PVR	0.495	0.413	0.616	0.441	0.584	0.537	0.457	0.487	0.705	**0.878**		
SCR	0.420	0.337	0.394	0.430	0.614	0.452	0.313	0.437	0.590	0.433	**0.848**	
TMR	0.353	0.502	0.444	0.445	0.664	0.588	0.538	0.439	0.679	0.449	0.409	**0.881**

Notes: CMB: Compatibility; EEC: Effort Expectancy; FNR: Financial Risk; IMG: Image; ITU: Intention to Use; PBN: Perceived Benefits; PEC: Performance Expectancy; PMR: Performance Risk; PRR: Perceived Risk; PVR: Privacy Risk; SCR: Security Risk; TMR: Time Risk.

4.4. Discriminant validity Heterotrait-Monotrait ratio of correlations (HTMT)

Additionally, Table 6 presents the HTMT ratios for all construct pairs. The results show that all HTMT values fall below the recommended threshold of 0.90, indicating strong discriminant validity across the model. The highest HTMT values were observed between Perceived Risk (PRR) and Intention to Use (ITU) (HTMT = 0.883), and between Perceived Benefits (PBN) and Intention to Use (ITU) (HTMT = 0.849), which still remain safely below the 0.90 criterion.

Other construct pairs such as Effort Expectancy-Performance Risk (HTMT = 0.751) and PBN-Effort Expectancy (HTMT = 0.747) also showed relatively higher associations but did not exceed the threshold. Since none of the HTMT ratios surpassed even the more liberal cut-off of 0.95, the results collectively support adequate discriminant validity within the measurement model.

These findings, together with the satisfactory AVE, CR, and factor loading results, confirm that the constructs in the model are empirically distinct while acknowledging that some relationships, particularly those involving perceived risk and intention to use reflect meaningful theoretical linkages.

Table 6. Discriminant validity Heterotrait-Monotrait ratio of correlations (HTMT)

	CMB	**EEC**	**FNR**	**IMG**	**ITU**	**PBN**	**PEC**	**PMR**	**PRR**	**PVR**	**SCR**	**TMR**
CMB												
EEC	0.465											
FNR	0.529	0.465										
IMG	0.469	0.466	0.629									
ITU	0.619	0.701	0.731	0.633								
PBN	0.732	0.747	0.689	0.739	0.849							
PEC	0.451	0.485	0.590	0.486	0.632	0.771						
PMR	0.511	0.751	0.516	0.460	0.699	0.652	0.517					
PRR	0.525	0.688	0.783	0.602	0.883	0.790	0.644	0.761				
PVR	0.551	0.465	0.678	0.493	0.633	0.585	0.509	0.541	0.763			
SCR	0.475	0.385	0.431	0.484	0.681	0.493	0.346	0.488	0.643	0.485		
TMR	0.392	0.558	0.484	0.493	0.718	0.639	0.604	0.480	0.727	0.493	0.456	

Notes: CMB: Compatibility; EEC: Effort Expectancy; FNR: Financial Risk; IMG: Image; ITU: Intention to Use; PBN: Perceived Benefits; PEC: Performance Expectancy; PMR: Performance Risk; PRR: Perceived Risk; PVR: Privacy Risk; SCR: Security Risk; TMR: Time Risk.

4.3. Structural Model

The structural model was evaluated using key model fit and explanatory power indicators. Model fit was first assessed using the Standardized Root Mean Square Residual (SRMR) and the Normed Fit Index (NFI). The SRMR value of 0.054 is below the recommended threshold of 0.08, indicating an acceptable level of model fit. Additionally, the NFI value of 0.719 exceeds the commonly cited cut-off of 0.70 (Hair et al., 2019), further supporting the adequacy of the model fit.

The explanatory power of the model was assessed through the coefficient of determination (R^2). The R^2 value for Perceived Benefits (PBN) was 0.820, indicating that performance expectancy, effort expectancy, compatibility, and image collectively explain 82.0% of the variance in perceived benefits, representing substantial explanatory power (Hair et al., 2014). Similarly, Perceived Risk (PRR) reported an R^2 value of 0.835, demonstrating that financial risk, privacy risk, security risk, performance risk, and time risk account for 83.5% of the variance in perceived risk, also reflecting strong explanatory strength. Finally, the R^2 value for Intention to Use (ITU) was 0.784, indicating that perceived benefits and perceived risk together explain 78.4% of the variance in the intention to use Korean digital health devices. A summary of the model fit indices and R^2 values is presented in Table 7.

Table 7. Model fit and coefficient determination

Fit Measurement	
SRMR	0.054
NFI	0.719
R^2 (Perceived Benefits)	0.820
R^2 (Perceived Risk)	0.835
R^2 (Intention to Use)	0.784

Notes: SRMR: Standardized Root Mean Square Residual; NFI: Normed Fit Index.

4.4. Hypothesis Testing Result

The structural model was assessed to examine the hypothesized relationships among the constructs. Table 8 summarizes the path coefficients, t-values, and significance levels for all hypothesized paths. Results show that all four antecedents of perceived benefits, performance expectancy, effort expectancy, compatibility and image had significant positive effects on the Perceived Benefits (PBN) construct. Performance expectancy (H1: $\beta = 0.335$, $t = 9.120$, $p < 0.001$), effort expectancy (H2: $\beta = 0.296$, $t = 7.708$, $p < 0.001$), compatibility (H3: $\beta = 0.290$, $t = 9.293$, $p < 0.001$), and image (H4: $\beta = 0.286$, $t = 7.360$, $p < 0.001$) were all supported, indicating that each dimension significantly strengthens overall perceived benefits.

Similarly, all five hypothesized antecedents to perceived risk (PRR) were statistically significant. Privacy risk (H5: $\beta = 0.198$, $t = 4.642$, $p < 0.001$), security risk (H6: $\beta = 0.155$, $t = 4.054$, $p < 0.001$), performance risk (H7: $\beta = 0.281$, $t = 7.005$, $p < 0.001$), time risk (H8: $\beta = 0.273$, $t = 7.733$, $p < 0.001$) and financial risk (H9: $\beta = 0.292$, $t = 6.356$, $p < 0.001$) all exerted significant positive effects on perceived risk.

Regarding the final structural paths, both Perceived Benefits (PBN) and Perceived Risk (PRR) significantly predicted Intention to Use (ITU) Korean digital health-monitoring devices. Perceived benefits showed a strong positive effect (H10: $\beta = 0.403$, $t = 6.398$, $p < 0.001$), indicating that higher perceived benefits increase intention to use. Perceived risk exhibited an even stronger positive effect (H11: $\beta = 0.530$, $t = 8.321$, $p < 0.001$), suggesting that consumers who are more aware of potential risks also demonstrate a heightened intention to use the devices. Overall, all eleven hypotheses (H1–H11) were supported, confirming the significance of both benefit-related and risk-related antecedents in shaping consumer adoption intention.

Table 8. Hypothesis Testing Results

Hypothesis	Paths	Coefficient (*β*)	*t*	Results
H1	PEC → PBN	0.335	9.120***	Supported
H2	EEC → PBN	0.296	7.708***	Supported
H3	CMB → PBN	0.290	9.293***	Supported
H4	IMG → PBN	0.286	7.360***	Supported
H5	PVR → PRR	0.198	4.642***	Supported
H6	SCR → PRR	0.155	4.054***	Supported
H7	PMR → PRR	0.281	7.005***	Supported
H8	TMR → PRR	0.273	7.733***	Supported
H9	FNR → PRR	0.292	6.356***	Supported
H10	PBN → ITU	0.403	6.398***	Supported
H11	PRR → ITU	0.530	8.321***	Supported

Notes: CMB: Compatibility; EEC: Effort Expectancy; FNR: Financial Risk; IMG: Image; ITU: Intention to Use; PBN: Perceived Benefits; PEC: Performance Expectancy; PMR: Performance Risk; PRR: Perceived Risk; PVR: Privacy Risk; SCR: Security Risk; TMR: Time Risk; *** $p < 0.001$

5. Discussion

The purpose of this study was to examine how perceived benefits and perceived risks driven by performance expectancy, effort expectancy, compatibility, image, and the various risk dimensions influence Indonesian consumers' intention to adopt Korean smart health-monitoring devices. The findings provide strong empirical support for all hypothesized relationships and contribute to a clearer understanding of how individuals in an emerging-market healthcare environment evaluate foreign digital health technologies.

All four benefit dimensions significantly enhanced the perceived benefits construct. performance expectancy ($\beta = 0.335$), effort expectancy ($\beta = 0.296$), compatibility ($\beta = 0.290$), and image ($\beta = 0.286$) each exerted meaningful positive effects.

These results align with major technology-adoption theories such as UTAUT and the Diffusion of Innovation Theory, which emphasize that perceived usefulness, ease of use, lifestyle fit, and social value shape positive evaluations of new technologies. Performance expectancy and compatibility were particularly influential, suggesting that Indonesian consumers place considerable importance on the functional usefulness of Korean digital health devices and their ability to integrate naturally into daily routines. Contrary to some previous research (e.g., Wang et al., 2020), this study also found strong effects for effort expectancy and image, indicating that ease of learning and social prestige play substantial roles in forming positive benefit perceptions.

This highlights the growing social acceptance and desirability of advanced Korean health technologies in Indonesia's digitally evolving consumer market. Regarding risk perceptions, all five dimensions, privacy ($\beta = 0.198$), security ($\beta = 0.155$), performance ($\beta = 0.292$), time ($\beta = 0.273$), and financial risk ($\beta = 0.281$) significantly increased overall perceived risk. These findings indicate that Indonesian consumers hold notable concerns when evaluating foreign digital health devices, particularly those that collect sensitive health information. Consistent with earlier studies (Featherman & Pavlou, 2003; Li et al., 2018; Yang et al., 2017), privacy and security risks remain central, reflecting widely held fears of data misuse or unauthorized access.

Performance and time risks were also significant, suggesting concerns about device malfunction, accuracy, and the time required for setup, troubleshooting, and maintenance. In contrast to Wang et al. (2020), who reported a relatively weaker influence of financial risk for smart home technologies, this study found that financial concerns play a substantial role in shaping risk perceptions. This result reflects Indonesia's emerging-market context, where affordability, maintenance costs, and perceived value-for-money are critical considerations when evaluating foreign digital health innovations.

Both perceived benefits (β = 0.403, p < 0.001) and perceived risk (β = 0.530, p < 0.001) significantly predicted intention to use Korean smart health-monitoring devices. From a Net Valence Model perspective, the positive PRR–ITU relationship reflects heightened risk awareness and involvement in health-related decision-making rather than a direct facilitation of adoption (Featherman & Pavlou, 2003; Li et al., 2016). The positive effect of perceived benefits aligns with theoretical expectations, when consumers view a device as useful, convenient, and beneficial for health management, they are more willing to adopt it. The finding that perceived risk also had a significant and even stronger positive effect represents a noteworthy contribution. Prior research suggests that perceived risk does not uniformly deter technology adoption, as risk awareness may coexist with strong usage intentions when perceived value or benefits are sufficiently high (Featherman & Pavlou, 2003; Li et al., 2016; Xie et al., 2021).

Although risk is typically assumed to reduce adoption intention, this study suggests a more complex psychological process. Users who are more aware of the risks may simultaneously perceive the device as more advanced, impactful, or medically important, leading to heightened involvement and consideration rather than avoidance. This pattern aligns with emerging evidence in high-value or high-stakes health technologies, where perceived risks do not necessarily prevent adoption if users believe the potential health benefits outweigh concerns.

Overall, the results emphasize that Indonesian consumers evaluate Korean digital health devices through a combination of benefit-driven motivations and risk-related considerations. Unlike many traditional technology contexts where benefits dominate decision-making, the healthcare context appears to evoke a more nuanced cost–benefit assessment, in which risks play a prominent and sometimes motivating role in shaping adoption intention.

6. Implications and Conclusion

6.1. Theoretical Implications

This study offers several contributions to the existing body of knowledge on digital health adoption, particularly in cross-border healthcare technology contexts. First, by applying the Net Value Model within the Indonesian market and focusing on Korean digital health devices, the study extends technology adoption theories to an understudied international and emerging-market context. While prior research has largely examined domestic users or generalized digital health settings, this study highlights how users in developing healthcare ecosystems evaluate foreign health technologies by weighing both perceived benefits and perceived risks.

Second, the significant effects of compatibility, effort expectancy, image, and performance expectancy on perceived benefits reinforce the multidimensional nature of perceived value. These findings align with prior UTAUT and innovation adoption-based studies but expand them by demonstrating that social image and lifestyle fit are equally important in cross-cultural device adoption.

Third, the strong influence of financial, performance, time, privacy, and security risks on perceived risk provides empirical support for the multidimensionality of perceived risk frameworks in the healthcare domain. Importantly, the larger effect of perceived risk on adoption intention compared to perceived benefits challenges the traditional assumption that value perceptions are the primary driver of technology acceptance. Instead, it highlights the heightened sensitivity of healthcare consumers to uncertainty and data-related vulnerabilities.

Finally, this study contributes theoretically by demonstrating that digital health adoption in emerging markets is shaped not only by functional evaluations but also by contextual, cultural, and cross-border trust factors, highlighting the need to re-evaluate traditional technology acceptance models when applied to international digital health ecosystems.

6.2. Managerial Implications

This study provides several practical insights for Korean digital health device manufacturers, policymakers, and Indonesian healthcare operators seeking to expand smart healthcare adoption. First, the strong influence of perceived benefits suggests that companies should clearly communicate functional advantages such as accuracy, ease of use, and lifestyle compatibility when marketing digital health devices in Indonesia. User education campaigns, localized demonstrations, and partnerships with Indonesian clinics or hospitals can increase device familiarity and perceived value.

Second, although perceived risk was found to be positively associated with adoption intention, this result does not imply that higher risk promotes adoption. Rather, it reflects users' heightened awareness and evaluation of potential concerns. Accordingly, organizations must prioritize risk reduction strategies.

Third, enhancing trust and credibility is essential for foreign-produced health devices. Collaborations with Indonesian healthcare professionals, endorsements from local medical associations, and user instructions written in Indonesian can help reduce cultural and informational barriers.

Fourth, companies should invest in localized customer support, ensuring users have access to real-time troubleshooting and guidance. This is especially important for minimizing time-related and performance risks associated with unfamiliar technology.

Overall, these findings suggest that Korean digital health manufacturers must adopt a dual strategy in Indonesia, increase perceived benefits through usability and convenience while simultaneously lowering perceived risks through transparency, affordability, and localized support.

6.3. Limitation and Future Studies

This study examined Indonesian consumers' adoption intention toward Korean digital health devices by applying the Net Value Model, which conceptualizes adoption decisions as a balance between perceived benefits and perceived risks. Using PLS-SEM analysis on data from 175 Indonesian respondents, the study found that all benefit-related constructs significantly enhanced perceived benefits, whereas all risk-related constructs significantly contributed to perceived risk. Both perceived benefits and perceived risks strongly predicted intention to use Korean digital health devices, with perceived risks exerting a stronger influence. These findings highlight the importance of addressing consumer concerns in markets where healthcare uncertainty, digital literacy gaps, and trust in foreign technologies may affect adoption.

The study contributes to technology adoption literature by extending existing models to an international digital health context and demonstrating the dominant role of risk perceptions in health-related consumer decisions. Practically, the results provide actionable insights for Korean healthcare technology firms seeking to enhance market entry strategies and user confidence in Indonesia's rapidly evolving digital health ecosystem.

Despite meaningful contributions, this study has several limitations. First, the use of convenience sampling limits the generalizability of the findings across all Indonesian consumer segments. The sample may not fully represent older adults, rural populations, or individuals with limited digital familiarity. Second, the study relies on self-reported perceptions, which may be influenced by personal bias, limited product experience, or social desirability. Third, the research focuses solely on Korean digital health devices, which may limit the applicability of the findings to other foreign healthcare technologies.

Fourth, the model does not examine potential moderating variables such as age, health status, digital literacy, or trust that could influence the strength of benefit–risk effects. Finally, this study captures a cross-sectional perspective, preventing causal inference or analysis of changes in perceptions over time.

Future studies can build upon these findings in several ways. First, researchers may employ larger or stratified samples to compare different demographic groups and improve generalizability. Second, future research could incorporate moderating variables (e.g., health literacy, trust in foreign technology, prior experience, or cultural orientation) to better understand individual differences. Third, comparative studies across multiple countries or between Korean and non-Korean digital health devices could highlight cultural and technological differences in adoption behavior. Fourth, longitudinal designs could observe how perceived benefits, risks, and adoption intention evolve with ongoing experience or exposure to digital health technologies. Finally, qualitative or mixed-method research may provide deeper insights into consumer expectations, barriers, and contextual influences that are not captured through survey-based models.

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