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ORIGINAL RESEARCH

Beyond Technology: Social Support, Risk, and Economic Value in Physicians' Telemedicine Adoption in Indonesia

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Abstract

Objectives: Adoption of technology by physicians is critical to improving healthcare delivery. This study examines the direct impact of economic value, perceived risk, and social support on the actual use of technology by physicians in Indonesia. The authors extend the traditional technology acceptance model (TAM) by focusing on actual use rather than intention. It also tests self-efficacy as a moderating factor.
Methods: A cross-sectional survey was conducted with 244 physicians. The proposed model integrates core TAM constructs with self-efficacy as a moderator. The relationships were tested using partial least squares structural equation modeling.
Results: The model shows that economic value and social support positively influence physicians' actual use, while perceived risk has a negative effect. Self-efficacy strengthens the impact of social support but does not moderate the effects of economic value or perceived risk. These findings underline the critical role of peer and superior support in driving real usage behavior when physicians feel confident.
Conclusion: This study contributes novel evidence by directly measuring actual use, which is less explored in TAM research. The findings highlight the need to strengthen supportive environments and build physicians' confidence to boost technology adoption. Future research should test this model across broader healthcare contexts and over time.

Plain Language Summary

Telemedicine can help physicians in Indonesia deliver better care, but using it in daily practice depends on more than just the availability of technology. The authors explored what drives physicians to move from intention to actual use. Clear economic value and strong social support from colleagues or supervisors encourage adoption, while concerns about digital risk can hinder use. Confidence in their ability also helps physicians turn support into real action. These findings suggest that hospitals should focus on providing training, reducing perceived risks, and creating supportive environments to help physicians successfully adopt telemedicine.

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The expansion of telemedicine services has continued beyond the COVID-19 pandemic. Yet its routine use remains inconsistent across user groups.[1] In the period 2024–2025, the emergence of new telemedicine startups,[2] stricter data privacy regulations,[3] and growing economic concerns have shaped telemedicine decisions when adopting digital health services.[4]

Despite technological advances, many physicians remain cautious due to professional risks such as diagnostic limitations, data privacy concerns, and potential legal implications.[4,5] Economic considerations also influence physicians' willingness to adopt telemedicine, as they weigh whether online consultations fairly compensate their time and expertise. Moreover, institutional and peer support plays a critical role in shaping physicians' confidence and motivation to engage in telemedicine.[1,6] These trends highlight the need to examine how social, economic, risk-related, and psychological factors interact to drive physicians' actual use of telemedicine platforms in daily practice.

While the Jaminan Kesehatan Nasional has been widely applied to explain technology adoption in healthcare,[4,7,8] most empirical studies have focused on patients as end-users, leaving the perspective of physicians relatively underexplored.[4,7,9,10] Prior research has primarily emphasized perceived usefulness and ease of use as key predictors of acceptance, yet has overlooked how external factors such as social support, perceived risk, and economic value shape physicians' decisions to integrate telemedicine into their clinical routines.[9,11] In addition, although self-efficacy has been investigated among patients, its role in influencing physicians' confidence to deliver quality remote care remains insufficiently examined.[8,12]

In Indonesia, the adoption of telemedicine has continued to expand since the COVID-19 pandemic, driven by both government initiatives and private sector innovations. Various telemedicine platforms have emerged to address healthcare access disparities, particularly in remote and underserved regions.[13] However, despite increasing availability, the integration of telemedicine into physicians' daily practice remains inconsistent.[13,14] Many physicians still prefer conventional face-to-face consultations due to concerns about diagnostic accuracy, patient trust, and regulatory uncertainties related to medical liability and data protection. In addition, disparities in digital infrastructure and uneven institutional support often hinder physicians' willingness to deliver care remotely. Financial aspects also come into play, as not all physicians perceive telemedicine consultations as equally rewarding or sustainable compared to traditional practice. These contextual challenges highlight the pressing need to investigate the factors that shape physicians' readiness and confidence to engage with telemedicine in the Indonesian healthcare system.[13,15]

This gap is particularly relevant in emerging economies, where healthcare professionals face unique challenges in balancing new digital workflows with conventional medical practice, especially from Indonesian physicians' evidence.

Indonesia's healthcare system is characterized by a mixed public–private provision model, with over half of hospitals operated by private entities, reflecting a diverse and complex structure.[16,17] The country employs a substantial but unevenly distributed healthcare workforce, which poses challenges to equitable service delivery, especially in rural and remote regions. Indonesia has implemented a national social health insurance scheme (Jaminan Kesehatan Nasional) that covers approximately 73% of the population and aims to enhance financial protection and access to care.[16,18] Nevertheless, disparities in healthcare utilization persist due to factors such as differential insurance coverage (including subsidized versus contributory schemes), reimbursement limitations, and variations in healthcare quality across facilities, necessitating ongoing policy attention to optimize the system's efficiency and equity.[16]

To address this gap, the authors developed and analyzed an extended TAM framework by incorporating social support, perceived risk, economic value, and self-efficacy to explain physicians' actual use of telemedicine.[4,8,12] The model proposes that social support might encourage physicians' confidence to use telemedicine, while perceived risk could deter its adoption due to concerns over diagnostic accuracy and legal responsibility.[8] Economic value is expected to positively influence physicians' motivation by highlighting the financial and time efficiency benefits of remote consultations.[9,12] Furthermore, the moderating role of self-efficacy in translating these factors into actual behavioral outcomes is evaluated.[19] This framework aims to advance the understanding of physicians' technology adoption behavior by capturing the interplay of contextual and cognitive factors that drive their engagement with telemedicine services.

The proposed model includes six hypotheses (H1–H6), each reflecting a direct or moderated path among the core constructs. H1–H3 examine the direct effects of social support, perceived risk, and economic value on physicians' actual use of telemedicine.[8,12,20–23] Hypotheses H4–H6 specify the moderating role of self-efficacy in these relationships, testing whether physicians' confidence in their ability to deliver remote care strengthens or weakens the influence of social support, perceived risk, and economic value on their actual use of telemedicine services.[19,24,25] All hypothesized relationships are theoretically grounded in extensions of the TAM and social cognitive theory (Figure 1), and are empirically tested using structural equation modeling, with detailed results presented in the following sections.

Methods

Research Design and Sampling Method

This study employed a cross-sectional survey analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM),[26] which is well-suited for modeling complex latent constructs. Data were collected through an online survey distributed via an appropriate platform such as Google Forms to ensure ease of access and wide reach.

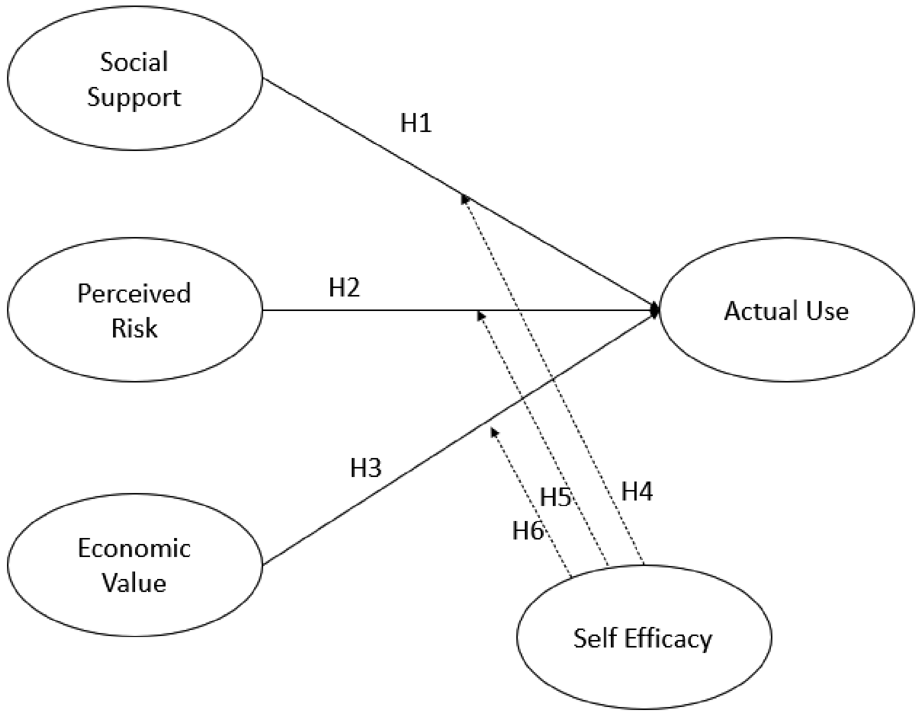

Fig. 1. The proposed research model includes six hypotheses (H1–H6): H1–H3 examine the direct effects of social support, perceived risk, and economic value on physicians' actual use of telemedicine; H4–H6 assess the moderating role of self-efficacy in these relationships. See text for greater detail.

A stratified sampling method was used to select 300 respondents, with equal representation of age groups: 50% of participants were above the median age, and 50% were below it. Out of the total distributed questionnaires, 244 valid responses were returned and included in the final analysis. Following this, the refined online survey was distributed to 300 physicians using a purposive sampling strategy, resulting in 244 complete and eligible responses from licensed physicians, yielding a valid response rate of 81.3%. Participants included general practitioners and specialists with prior experience in telemedicine, recruited through national medical associations, hospital networks, and a central telemedicine platform.

Measurement

The constructs were adapted from established frameworks such as actual use, perceived risk and economic,[27–29] social support[12,30,31] and self-efficacy,[32,33] ensuring content and convergent validity among constructs and indicators. Therefore, factors like social support, self-efficacy, perceived digital risk, and economic value were measured using five-point Likert scales, while actual use was captured through frequency-based items. The measurement instruments for this study were adapted and contextualized to fit the specific focus of our research model. Five latent constructs were assessed using self-reported items grouped as follows: (1) four items measuring social support, (2) four items assessing perceived risk, (3) four items evaluating economic value, (4) four items measuring actual use of the system, and (5) four items assessing self-efficacy as a moderating variable.

Respondents reported engaging with multiple telemedicine modalities that reflect the evolving digital healthcare landscape in Indonesia. The most frequently cited forms of use included video consultations, which enable real-time interaction and clinical assessment; telephone-based consultations, often utilized for follow-up care or quick medical advice; and chat-based applications, providing asynchronous communication that allows patients to send questions and receive guidance at their convenience. These modalities capture the range of digital practices adopted by physicians and highlight the heterogeneity of telemedicine delivery formats, each with distinct implications for accessibility, efficiency, and perceived clinical value.

Responses were recorded using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The items were selected and adapted from established measurement scales validated in prior studies to ensure conceptual relevance and reliability within the context of this study. To ensure the instruments were culturally and contextually appropriate, a standardized multi-step adaptation procedure was carried out: initial translation and back-translation were conducted by bilingual experts in social sciences and consumer behavior; pre-testing was performed with a pilot group of 30 respondents to check item clarity, relevance, and local appropriateness; and minor wording revisions were made to enhance comprehension while preserving the conceptual integrity of each construct. This process ensured that the measurement instruments accurately captured the intended dimensions and were suitable for the target population.

Results and Discussion

Respondents' Profile

A total of 244 physicians participated in the survey, with 44.3% (n = 108) identified as male and 55.7% (n = 136) as female. The majority (76.2%, n = 186) were classified as Millennials (born between 1981 and 1996), while 23.8% (n = 58) were non-Millennials (born before 1981). Regarding professional background, 61.5% (n = 150) were general practitioners and 38.5% (n = 94) were specialists. These distributions indicate a diverse respondent pool in terms of gender, age, and professional role, which strengthens the validity of the study's conclusions on telemedicine adoption behavior. The detailed demographic characteristics of the respondents are presented in Table 1.

Outer Model PLS-SEM

In PLS-SEM, the measurement model, commonly referred to as the outer model, specifies how latent variables are measured by their observed indicators. Before assessing the structural (inner) model, it is essential to evaluate the reliability and validity of the outer model to ensure that the constructs are measured consistently and accurately.[26]

Each indicator should have a factor loading (λ) greater than 0.70 to demonstrate that it adequately reflects the associated latent construct. The internal consistency reliability (ICR) for all constructs, assessed through both Cronbach's alpha and Composite Reliability (CR), exceeded the recommended threshold of 0.70, indicating satisfactory consistency among the indicators. Convergent validity was also supported, as all constructs achieved average variance extracted (AVE) values greater than 0.50, confirming that each construct explains more than half of the variance in its indicators. In addition, discriminant validity was established using the Fornell–Larcker criterion, which showed that the square root of each construct's AVE was higher than its correlations with other constructs, indicating that the latent variables are distinct and measure separate concepts as intended.[26,34] The overall results of the outer model can be seen in Table 2.

Table 1. Demographic profile of respondents

Variable	Respondent group	Frequency (n)	Percentage (%)
Gender	Male	108	44.3%
	Female	136	55.7%
Age	Millennial	186	76.2%
	Non-Millennial	58	23.8%
Education	General Practitioner	150	61.5%
	Specialist	94	38.5%

Millennial: born between 1981 and 1996; non-millennial: born earlier than 1981.

Overall, the results of the outer model assessment indicate that all measurement indicators and constructs in this study are statistically acceptable. All factor loadings meet or exceed the recommended thresholds, ICR (CR) values are above 0.70, and the AVE values surpass 0.50 for all constructs. The measurement results demonstrate that the social support construct is robustly measured by four indicators, with factor loadings ranging from 0.841 to 0.921. Specifically, recommendations from seniors or mentors (λ = 0.921) and colleagues (λ = 0.904) emerged as the strongest contributors, while encouragement from family (λ = 0.841) and support from supervisors (λ = 0.879) also showed substantial loadings. The construct achieved an AVE of 0.786, Cronbach's alpha of 0.909, and a CR of 0.936, indicating that the items consistently and reliably capture the intended dimension of social support.

The self-efficacy constructs likewise demonstrated excellent measurement properties, with all four indicators showing strong factor loadings between 0.903 and 0.920. Items related to physicians' confidence in operating telemedicine systems, resolving technical problems, making accurate clinical decisions, and performing routine activities all loaded well above the minimum threshold. The AVE for self-efficacy was 0.830, with Cronbach's alpha and CR values of 0.932 and 0.951, respectively, confirming high internal consistency and convergent validity.

Similarly, perceived digital risk, economic value, and actual use constructs were all statistically supported. Perceived digital risk showed factor loadings ranging from 0.876 to 0.926, with an AVE of 0.793, Cronbach's alpha of 0.917, and CR of 0.939. Economic value was measured with loadings between 0.855 and 0.940, achieving an AVE of 0.830, alpha of 0.931, and CR of 0.951. Finally, actual use demonstrated factor loadings from 0.829 to 0.885, with an AVE of 0.735, Cronbach's alpha of 0.880, and CR of 0.917. These results confirm that all constructs fulfill the recommended statistical criteria, providing a solid foundation for the structural model analysis. Table 2 shows the overall results of the outer model PLS-SEM in this study.

The results of the discriminant validity assessment using the Fornell–Larcker criterion (Table 3) indicate that each construct's square root of AVE (shown on the diagonal) is higher than its correlations with other constructs (off-diagonal values). For example, the square root of AVE for actual use is 0.857, which is greater than its correlations with economic value (0.571), self-efficacy (0.549), and social support (0.559). Similarly, economic

Table 2. Overall results of outer model PLS-SEM

Construct	Code	Items	Factor loading	AVE	Cronbach's alpha	Composite reliability (rho_c)	Notes
Social Support	SS 1	The family encourages telemedicine use	0.841	0.786	0.909	0.936	Statistically supported
	SS 2	Senior/mentor recommendations	0.921				
	SS 3	Colleagues' recommendations	0.904				
	SS 4	The supervisor supports telemedicine use	0.879				
Self-Efficacy	SE 1	Able to operate systems effectively	0.903	0.830	0.932	0.951	Statistically supported
	SE 2	Capable of resolving technical issues	0.917				
	SE 3	Confident in making accurate clinical decisions during virtual consultations	0.904				
	SE 4	Trusting their own ability in routine activities	0.92				
Perceived Digital Risk	PR 1	Legal protection concerns	0.881	0.793	0.917	0.939	Statistically supported
	PR 2	Data leakage concerns	0.876				
	PR 3	Diagnostic error risk	0.878				
	PR 4	Technical disruption impact	0.926				
Economic Value	EV 1	Reduce operational costs	0.855	0.83	0.931	0.951	Statistically supported
	EV 2	Enables serving more patients	0.94				
	EV 3	Saves time on administrative tasks	0.932				
	EV 4	Adds economic value	0.914				
Actual Use	AU 1	Routinely uses telemedicine weekly	0.829	0.735	0.88	0.917	Statistically supported
	AU 2	Significant practice time on telemedicine	0.885				
	AU 3	Uses telemedicine for chronic patient monitoring	0.882				
	AU 4	Consultation duration comparable to in-person	0.831				

AU: actual use; AVE: average variance extracted; EV: economic value; PLS-SEM; Partial Least Squares Structural Equation Modeling; PR: perceived digital risk; SE: self-efficacy; SS: social support.

Table 3. Fornell–Larcker results

	Actual use	Economic value	Perceived risk	Self-efficacy	Social support
Actual use	0.857				
Economic value	0.571	0.911			
Perceived risk	–0.136	–0.170	0.892		
Self-efficacy	0.549	0.749	–0.092	0.91	
Social support	0.559	0.589	–0.012	0.656	0.887

value has a square root of AVE of 0.911, exceeding its correlations with actual use (0.571), self-efficacy (0.749), and social support (0.589).

Perceived risk shows a square root of AVE of 0.892, which is substantially higher than its negative correlations with other constructs, such as actual use (–0.136) and economic value (–0.170). Self-efficacy demonstrates strong discriminant validity as well, with a square root of AVE of 0.910 that surpasses its correlations with economic value (0.749), actual use (0.549), and social support (0.656). Social support has a square root of AVE of 0.887, which is greater than its correlations with other constructs. Overall, these results confirm that each construct is empirically distinct from the others, fulfilling the Fornell–Larcker criterion for discriminant validity. This supports the adequacy of the measurement model and strengthens confidence in the structural relationships examined in the subsequent analysis.

Inner Model PLS-SEM

In PLS-SEM, the inner model refers to the structural model that specifies the hypothesized relationships among latent constructs. To ensure its adequacy, the inner model must be evaluated by examining the R-squared values for predictive accuracy and the Variance Inflation Factor (VIF) to detect any multicollinearity issues. Once these assessments meet acceptable standards, hypothesis testing is conducted to determine the significance and strength of the structural paths.[35] Table 4 shows the results of VIF in the study.

Therefore, the inner model continues with the R-squared and model assessment analysis. The R-squared value of 0.425 (as shown in Figure 2) indicates that the predictors in the model collectively explain 42.5% of the variance in actual use. The adjusted R-squared of 0.408 confirms that this explanatory power remains substantial even after accounting for the number of predictors in the model. The model fit indices indicate an acceptable fit, with the SRMR value for both the saturated and estimated models at 0.064, which is below the recommended threshold of 0.08. Additionally, the chi-square, d_ULS, d_G, and NFI values support the overall fit of the structural model, with an NFI of 0.855 suggesting a satisfactory level of model–data correspondence.[35,36]

Table 4. Results of VIF in the study

Relationship	VIF results	Interpretation
Economic Value → Actual Use	2.747	No Multicollinearity
Perceived Risk → Actual Use	1.309	No Multicollinearity
Social Support → Actual Use	2.017	No Multicollinearity
Self-Efficacy × Economic Value → Actual Use	1.905	No Multicollinearity
Self-Efficacy × Perceived Risk → Actual Use	1.33	No Multicollinearity
Self-Efficacy × Social Support → Actual Use	1.697	No Multicollinearity

VIF:Variance Inflation Factor.

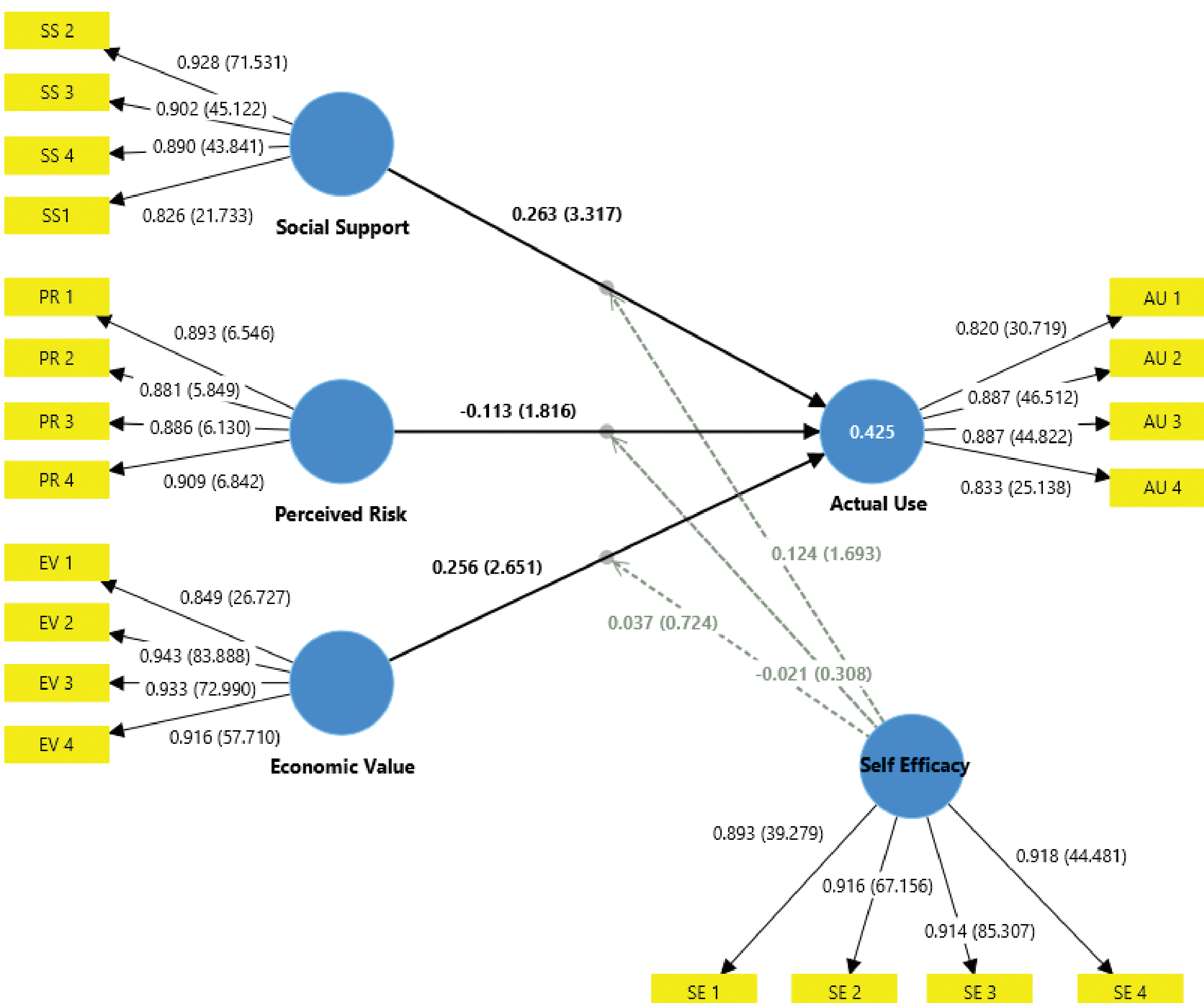

Fig. 2. Structural model of social support, perceived risk, economic value, and self-efficacy to explain physicians' actual use of telemedicine. AU: actual use; PR: perceived digital risk; SE: self-efficacy; SS: social support.

After ensuring that the measurement model and model fit criteria were satisfactorily met, the structural relationships hypothesized in this study were tested to examine factors influencing physicians' actual use of telemedicine (as shown in Table 5 and Figure 2). The results show that economic value has a significant positive effect on actual use (β = 0.256, p = 0.004). This indicates that physicians perceive telemedicine as a tool that adds tangible economic benefits, such as reducing operational costs and enabling them to serve more patients efficiently.[21,37] The previous studies highlighted that perceived economic and performance advantages are key drivers for technology adoption in healthcare settings.[21,37]

Perceived digital risk was found to have a significant negative effect on actual use (β = −0.113, p = 0.035), indicating that concerns about legal protection, data security, and potential technical failures continue to act as barriers for physicians when integrating telemedicine into daily practice. This result is consistent with previous studies who emphasized that perceived risks and privacy concerns can dampen physicians' willingness to rely on new health information technologies.[22,38] Despite technological advancements, this persistent risk perception underlines the importance of providing robust legal frameworks and technical support to mitigate these barriers.[22,38]

Furthermore, social support was the strongest predictor among the direct effects (β = 0.263, p < 0.001), reinforcing the view that professional encouragement from mentors, colleagues, and supervisors significantly motivates physicians to adopt telemedicine.[8,12] The previous studies demonstrated that physicians are more likely to adopt telemedicine systems when they perceive strong endorsement and encouragement from senior colleagues and department heads.[8] The support from peers and supervisors not only provides practical guidance but also reduces uncertainty and resistance by signaling professional approval of the new system.[7,28,39] Hence, social influence within hospitals can positively affect physicians' attitudes toward using health information technology, as professional networks create a sense of shared norms and collective confidence.[39] Such support mechanisms help overcome common barriers like lack of familiarity or perceived complexity by fostering a climate where adopting new tools becomes a professionally expected and supported behavior.[29] Taken together, these studies underline that in professionalized environments like hospitals, social and managerial encouragement is a powerful lever for accelerating technology uptake.

However, the moderating effects reveal more nuanced dynamics. The interactions between self-efficacy and both economic value (β = –0.021, p = 0.379) and perceived risk (β = 0.037, p = 0.234) were not statistically significant, indicating that self-efficacy does not strengthen or weaken the effect of these factors on actual use in this context. Interestingly, only the interaction between self-efficacy and social support was significant (β = 0.124, p = 0.045), suggesting that physicians with higher self-efficacy are more responsive to social influence when deciding to adopt telemedicine. In other words, when users feel confident in their ability to use the platform (high self-efficacy), they are more likely to be influenced by social factors such as recommendations or behaviors of important others (social influence) in their decision to actually engage in the use of the healthcare platform.[40] Self-efficacy enhances the effect of social influence because confident users are better able to translate social pressure or encouragement into actual use behavior. Overall, these findings highlight the fact that while individual confidence is crucial, its ability to moderate the impact of contextual factors may vary, which opens avenues for future studies to explore these dynamics in different healthcare contexts and professional cultures.[40]

Conclusion

This study involved 244 physicians in Indonesia and extends the TAM by testing self-efficacy as a moderating factor on actual use of technology. Unlike most TAM-based studies that focus only on intention to use, this research directly investigates actual use, which provides stronger and more practical evidence of real adoption behavior (a perspective still rarely studied in depth, especially in the context of healthcare professionals in developing countries).

Table 5. Summary of hypotheses testing results

Paths	Original sample	T-statistics	P-values	Results
H1: Economic Value → Actual Use	0.256	2.651	0.004	Supported
H2: Perceived Risk → Actual Use	-0.113	1.816	0.035	Supported
H3: Social Support → Actual Use	0.263	3.317	0.000	Supported
H4: Self-Efficacy × Economic Value → Actual Use	-0.021	0.308	0.379	Not Supported
H5: Self-Efficacy × Perceived Risk → Actual Use	0.037	0.724	0.234	Not Supported
H6: Self-Efficacy × Social Support → Actual Use	0.124	1.693	0.045	Supported

The results also imply that clear economic benefits and strong peer or superior support can encourage physicians to actually use technology, whereas high perceived risk discourages it. Furthermore, self-efficacy strengthens the relationship between social support and actual use but does not significantly moderate the effects of economic value or perceived risk. This highlights the fact that physicians' confidence plays a more important role in leveraging social support than in influencing economic or risk perceptions.

These findings support prior evidence that peer and superior support can play a critical role in driving technology adoption in healthcare organizations. Beyond these results, future research should explore additional factors that may influence technology adaptation, such as institutional support, organizational culture, or sociodemographic characteristics. Considering these broader dimensions will enrich the understanding of how healthcare professionals adopt telemedicine in diverse contexts.

Limitations

This study has some limitations. First, it focused only on physicians in Indonesia, which might limit the generalizability of the findings to other healthcare professionals or different healthcare systems. Second, this study used a cross-sectional design, so it does not capture changes in behavior or self-efficacy over time.

Despite these limitations, the novelty of this research lies in its direct focus on *actual use* rather than intention and its extension of the TAM by integrating self-efficacy as a moderator providing fresh insights into how individual confidence interacts with social factors to shape real usage behavior.

Going Forward

Future research should expand on these findings by including other potential moderating or mediating variables such as organizational culture, trust in digital systems, or the quality of training provided. Longitudinal or mixed-method designs could enrich understanding of how self-efficacy develops and how interventions can sustain or enhance it.

Finally, studies involving other healthcare professionals or broader regional contexts would help validate and strengthen the generalizability of this study's conclusions on actual technology use in healthcare practice. Moreover, this study did not examine other relevant factors, such as institutional support (e.g. organizational policies, infrastructure availability) or physicians' sociodemographic characteristics (e.g. age, gender, digital literacy), which may also shape telemedicine adoption. Future research should address these aspects, incorporate longitudinal or mixed-method designs, and expand the sample to broader regional and professional contexts.

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Conflicts of Interest

No competing interests exist among the authors. The authors declare that they have no financial or non-financial relationships or activities that could have influenced the results or interpretation of this research.

Contributors

Conceptualization: ES, HH, RN, and LN; Methodology: ES; Software: ES; Validation: ES; Formal Analysis: ES; Investigation: ES; Resources: ES; Data Curation: ES; Writing Original Draft Preparation: ES, HH, RN, and LN; Writing Review and Editing: ES; Visualization: ES; All authors, ES, HH, RN, and LN, have read and agreed to the published version of the manuscript.

Data Availability Statement (DAS), Data Sharing, Reproducibility, and Data Repositories

AI-assisted tools, including language refinement and grammar correction software (Grammerly, Quillbot), were used for improving linguistic clarity and formatting of the manuscript. No part of the analytical work, dataset processing, or result generation was performed using AI-generated content.

Application of AI-Generated Text or Related Technology

None used.

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