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MEDICAL PERSONNEL'S PERCEPTIONS OF THE IMPLEMENTATION OF ARTIFICIAL INTELLIGENCE AT HOSPITAL CONTEXT

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ABSTRACT: This study examines how medical personnel perceptions influence the acceptance of artificial intelligence in hospital services in the Cilegon area. It advances technology adoption literature by demonstrating that AI acceptance in healthcare is driven less by cognitive evaluation and more by capability-building mechanisms, particularly training and digital literacy, which mediate perception–behavior relationships. Using a PLS-SEM approach with survey data from 159 health workers, the findings show that training and digital literacy exert the strongest influence on AI acceptance, while cognitive, affective, and conative perceptions do not directly translate into adoption. Instead, affective and conative dimensions operate indirectly through capability development pathways. These results underscore the centrality of experiential and participatory learning in shaping technology readiness among healthcare professionals. The study implies that hospital digital transformation strategies should prioritize structured training and digital literacy enhancement to ensure effective and sustainable AI integration.

Keywords: Artificial Intelligence, Digital Literacy, Cognitive Perception, Affective Dimension, Conative Intention, Hospital Services

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INTRODUCTION

Artificial Intelligence (AI) has emerged as a transformative technological innovation and is playing an increasingly pivotal role in the modernization of healthcare services. Across hospitals worldwide, AI is utilized to support clinical processes such as patient triage, electronic medical record management, disease risk prediction, and workflow optimization. Its ability to process large volumes of data rapidly and accurately positions AI as a promising tool for enhancing the efficiency and quality of healthcare delivery. Rather than functioning as a replacement for medical professionals, AI is intended to operate as a decision-support system across both clinical and administrative contexts. However, ethical concerns, including patient data privacy, algorithmic transparency, and accountability for clinical outcomes—remain central to its implementation (Hansson & Fröding, 2024).

The acceptance of AI among healthcare professionals varies considerably. While some medical personnel welcome AI for its potential to reduce workload, accelerate service delivery, and improve decision-making accuracy, others demonstrate uncertainty or scepticism. This ambivalence suggests that AI adoption is influenced not only by technological sophistication but also by the perceptions and psychological readiness of healthcare workers as primary end-users (Kelly et al., 2022). Such complexity highlights the need for a more comprehensive understanding of the factors shaping medical professionals' attitudes and behaviours toward AI technologies.

Numerous studies have demonstrated AI's tangible contributions to improving healthcare efficiency. In hospital management, AI supports the forecasting of resource needs, operation scheduling, and the proactive identification of patient risk patterns. Clinically, AI assists with data-driven decision-making, including therapy recommendations, complication detection, and real-time patient monitoring. These advancements provide a substantive basis for examining medical personnel's perceptions of AI, particularly in relation to work efficiency, administrative burden reduction, and patient safety enhancement (Seeram & Kanade, 2024). However, technological achievements alone do not guarantee user acceptance. Understanding how perceptions are formed, and how they influence the implementation of AI in hospital settings remains essential.

To analyze technology acceptance by medical personnel, the Technology Acceptance Model (TAM) offers a relevant theoretical framework. TAM emphasizes two core constructs, perceived usefulness and perceived ease of use, which shape users' attitudes toward new technologies (Davis, 1989; Venkatesh & Bala, 2008). In the healthcare context, perceptions of AI's utility in improving work efficiency and its ease of integration into hospital systems are key determinants of acceptance. Moreover, ethical considerations such as data security and clarity of responsibility in AI-supported decisions contribute to the level of trust among medical personnel.

Despite AI's rapid growth, research on healthcare professionals' perceptions of AI in Indonesia remains limited. Existing studies predominantly focus on technical or managerial dimensions, while the attitudes and expectations of frontline medical staff have yet to be extensively explored. General practitioners, nurses, midwives, and allied health professionals are central to patient care and service delivery. Understanding their concerns, expectations, and readiness is therefore crucial for designing effective and sustainable AI implementation strategies. Without their active engagement and support, AI risks becoming a poorly integrated component of healthcare systems. Recent research on AI implementation in healthcare has expanded beyond traditional TAM constructs by incorporating psychological and organizational variables that better capture how clinicians interpret and interact with intelligent systems. Studies have begun to examine multidimensional perceptions, including cognition, affect, and conation, to understand how beliefs about AI's competence, emotional reactions such as trust or anxiety, and intention to use shape adoption outcomes. At the same time, emerging evidence highlights the importance of contextual enablers such as digital literacy programs, leadership support, and institutional readiness in strengthening acceptance among healthcare workers. While these studies mark an important shift toward a more holistic understanding of AI adoption, most have been conducted in high-income health systems. Research grounded in hospital settings in lower-middle-income countries remains sparse, leaving a gap in understanding how these multidimensional perceptions interact with organizational realities in contexts like Indonesia.

In light of these considerations, it can be concluded that although substantial clinical and operational evidence supports AI's effectiveness in healthcare, understanding medical personnel's perceptions remains a critical gap in the literature. Therefore, this study aims to

examine healthcare professionals' perceptions of AI implementation at Hospital In Cilegon Area, focusing on cognitive, affective, and conative dimensions, alongside organizational factors such as managerial support and digital literacy training.

THEORETICAL REVIEW

Artificial Intelligence (AI) in Healthcare Services

Artificial Intelligence (AI) has become a critical component in the transformation of modern healthcare systems. This technology supports clinical decision-making, streamlines administrative processes, and enhances hospital operational efficiency. AI contributes to patient data analysis, disease risk prediction, scheduling management, and real-time condition monitoring (Kumah, 2025). In Indonesia, the implementation of AI is still developing; however, its potential to improve service quality and reduce the workload of healthcare professionals is increasingly recognized.

Despite these benefits, the acceptance of AI among medical personnel remains uneven. While some practitioners embrace AI due to its perceived advantages, others express resistance stemming from concerns related to system accuracy, professional autonomy, and ethical issues such as data security. As a result, understanding healthcare professionals' perceptions is essential for designing effective AI implementation strategies. In this study, AI acceptance is defined as healthcare professionals' behavioral intention to use AI systems in their routine clinical and administrative work. This definition aligns with the Technology Acceptance Model (TAM) and its extensions, which conceptualize acceptance not as a broad attitudinal construct but as a user's intention to engage with a technology when required. Behavioral intention captures the degree to which medical personnel are willing, prepared, or motivated to incorporate AI-based tools into their workflow, reflecting a future-oriented readiness rather than actual usage behavior. By operationalizing acceptance in this way, the study ensures conceptual clarity and consistency with established technology adoption literature.

The cognitive dimension reflects a rational understanding of AI's functions, benefits, and potential risks (Koenig, 2024). Accordingly, the hypothesis posits that the higher the level of knowledge and comprehension healthcare professionals possess regarding AI (cognitive dimension), the greater their acceptance of AI implementation in healthcare services at Hospital.
H1: Cognition (X1) positively influences AI acceptance (Y).

The affective dimension includes emotional responses such as attitudes, trust, and feelings toward AI as a supportive technology (Venkatesh & Bala, 2008). The more positive the emotional disposition of healthcare professionals toward AI (affective dimension), the higher their acceptance of its implementation at Hospital.
H2: Affect (X2) positively influences AI acceptance (Y).

The conative dimension refers to behavioral intention or actual readiness to use AI (Ajzen, 1991). The stronger the intention and readiness of healthcare professionals to use AI (conative dimension), the greater their acceptance of AI implementation in healthcare services at Hospital.
H3: Conation (X3) positively influences AI acceptance (Y).

In social psychology, perception theory categorizes individual responses toward objects or technologies into three dimensions: cognitive (X1), affective (X2), and conative (X3). The cognitive dimension refers to knowledge and understanding of AI, including its utility and associated risks. The affective dimension encompasses emotional responses such as trust, concern, or enthusiasm. The conative dimension reflects behavioral intentions or readiness to adopt AI in professional practice. Together, these dimensions shape attitudes toward technology and influence actual behavior in the utilization of AI.

Cognitive understanding drives motivation to engage in new technology training (Koenig, 2024). Thus, the higher the knowledge and comprehension that healthcare professionals possess

regarding AI (cognitive dimension), the greater their participation in training and digital literacy development at Hospital.
H4: Cognition (X1) positively influences training and digital literacy (M).

A positive attitude toward technology increases participation in digital training programs (Venkatesh & Bala, 2008). The more positive the emotional disposition of healthcare workers toward Artificial Intelligence (affective dimension), the higher their participation in training and digital literacy development related to AI at Hospital. H5: Affective (X2) positively influences training and digital literacy (M). Behavioral intention encourages active participation in technology competency development (Ajzen, 1991). The stronger the intention and readiness of health workers to use Artificial Intelligence (conative dimension), the greater their involvement in AI-related digital literacy training and development at Hospital. H6: Conative (X3) positively influences digital literacy and training (M).

The Technology Acceptance Model (TAM), introduced by Davis (1989) and expanded by Venkatesh & Bala (2008), posits that technology acceptance is primarily influenced by two key constructs: perceived usefulness and perceived ease of use. In the hospital context, healthcare professionals' perceptions of AI's utility for enhancing work efficiency and its ease of integration into existing systems are critical determinants of acceptance. TAM also highlights the role of organizational interventions, such as training programs, in shaping positive attitudes toward technology adoption. Digital literacy refers to the ability to understand, access, and effectively utilize AI technologies (Tang et al., 2021). It encompasses not only technical proficiency but also the capacity to critically engage with digital tools in clinical and administrative settings. Thus, the higher the level of training and digital literacy among healthcare professionals, the greater their acceptance of AI implementation at Hospital.
H7: Training and digital literacy (M) positively influence AI acceptance (Y).

Digital literacy training plays a pivotal role in bridging the gap between perception and actual technology use. Effective training programs enhance understanding, reduce resistance, and strengthen healthcare professionals' confidence in adopting AI technologies. Digital literacy also acts as a conduit between perception and behavioral engagement, strengthening the pathway from knowledge and attitudes to technology acceptance (Venkatesh & Bala, 2008). Training and digital literacy mediate the influence of healthcare professionals' knowledge and understanding of AI (cognitive dimension) on their acceptance of AI implementation at Hospital.
H8: Training and digital literacy (M) mediate the effect of cognition (X1) on AI acceptance (Y).

Training can support the translation of attitudes into actual technology use (Kumah, 2025). Thus, training and digital literacy mediate the influence of healthcare professionals' emotional attitudes toward AI (affective dimension) on AI acceptance.
H9: Training and digital literacy (M) mediate the effect of affect (X2) on AI acceptance (Y).

Digital literacy also strengthens the transition from intention to actual AI use (Ajzen, 1991). Therefore, training and digital literacy mediate the influence of healthcare professionals' readiness to use AI (conative dimension) on AI acceptance.
H10: Training and digital literacy (M) mediate the effect of conation (X3) on AI acceptance (Y).

Figure 1 illustrates the conceptual relationships between healthcare professionals' perceptions of Artificial Intelligence (AI), digital literacy training, and AI acceptance within the healthcare services of Hospital at Cilegon Area. Perception is categorized into three dimensions: cognitive (knowledge of AI functions, benefits, and risks), affective (emotional attitudes such as trust or concern), and conative (intention and readiness to use AI). These three dimensions are hypothesized to exert both direct effects on AI acceptance (H1–H3) and indirect effects through digital literacy and training as a mediating variable (H4–H10).

Digital literacy training functions as a critical bridge between perception and actual technology adoption. Healthcare professionals with more favorable perceptions are more likely to engage in training and digital literacy development, which subsequently strengthens their acceptance of AI. Overall, the model identifies two primary pathways: (1) the direct influence of perception on AI acceptance, and (2) the indirect influence mediated by digital literacy. This

structure provides a comprehensive analytical framework for understanding the key factors that determine the successful adoption of AI within hospital settings.

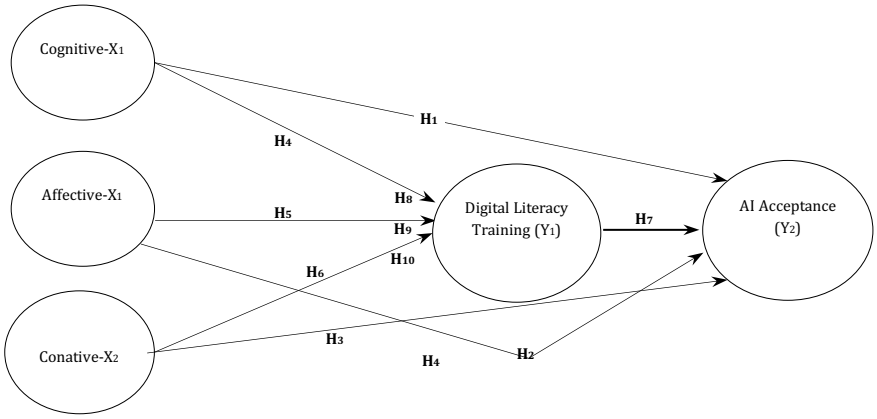


Figure 1. Conceptual Framework

RESEARCH METHOD

This study employed a cross-sectional survey design with a quantitative approach to examine the factors influencing healthcare professionals' perceptions and acceptance of Artificial Intelligence (AI) implementation in healthcare services at General Hospital In Cilegon Area. The study population consisted of physicians, nurses, midwives, and allied health personnel who were actively working and directly interacting with technology-based service systems.

A purposive sampling technique was applied based on the following criteria: (1) a minimum of one year of professional experience and (2) willingness to participate. Power analysis using G*Power indicated a minimum required sample size of 153 respondents, as in Table 1.

Table 1. Demographic Data

s	Frequency (n)	Percentage (%)
Age of Respondents		
< 25 years	18	11.8%
25–35 years	62	40.5%
36–45 years	45	29.4%
46–55 years	20	13.1%
> 55 years	8	5.2%
Gender		
Male	68	44.4%
Female	85	55.6%
Education		
Diploma	39	25.5%
Bachelor's (S1)	84	54.9%
Master's (S2)	26	17.0%
Doctoral (S3)	4	2.6%
Professional Role		
General Practitioners	28	18.3%
Specialist Physicians	17	11.1%
Nurses	72	47.1%
Midwives	21	13.7%
Allied Health Personnel	15	9.8%

Data were collected using a structured questionnaire with a five-point Likert scale, adapted from prior studies (Bougie & Sekaran, 2016; Subhaktiyasa, 2024). The independent variables

consisted of healthcare professionals' perceptions of AI, cognitive, affective, and conative. The mediating variable was digital literacy and training, and the dependent variable was AI acceptance.

Table 1 presents the demographic profile of healthcare professionals at General Hospital In Cilegon Area. Most respondents were between 25 and 45 years old, representing the age group most actively engaged in clinical practice. Female participants accounted for 55.6%, while male participants represented 44.4%, reflecting national workforce patterns. Regarding educational attainment, the majority held a Bachelor's degree (54.9%), followed by Diploma holders (25.5%), Master's degree graduates (17.0%), and a small proportion with Doctoral qualifications (2.6%). This distribution suggests a solid academic foundation conducive to understanding and adopting technological innovations such as Artificial Intelligence (AI). Professionally, nurses formed the largest group (47.1%), followed by general practitioners, midwives, specialist physicians, and allied health personnel.

Instrument validity and reliability were assessed using Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE) (Hair et al., 2022). Partial Least Squares Structural Equation Modeling (PLS-SEM) was conducted using SmartPLS version 4.1.1.5. Partial Least Squares Structural Equation Modeling (PLS-SEM) was selected over covariance-based SEM because the primary objective of this study is prediction and theory development rather than theory confirmation. PLS-SEM is well suited for exploratory models that include multiple latent variables, complex relationships, and mediating effects, particularly when constructs are newly adapted or when measurement models may not yet be fully established.

RESULTS

Outer Model

The results of data analysis using SmartPLS indicated in Table 2 that all constructs in the measurement model achieved satisfactory validity and reliability. All indicator outer loadings exceeded the recommended minimum threshold of 0.70, confirming that each item effectively represents its respective latent construct. Several indicators, including X1.3 (0.832), X1.4 (0.824), and M1.3 (0.841), exhibited particularly strong factor loadings, indicating their substantial contribution to construct measurement, as summarized in Table 2.

Table 2. Results of Reliability and Validity Testing

Variable	Indicators	Outer Loadings	Cronbach's Alpha	rho_a	rho_c	AVE
Cognitive	X1.1	0.713	0.780	0.742	0.742	0.742
	X1.2	0.787				
	X1.3	0.832				
	X1.4	0.824				
Affective	X2.1	0.734	0.723	0.705	0.789	0.659
	X2.2	0.866				
	X2.3	0.724				
Conative	X3.1	0.749	0.701	0.796	0.746	0.795
	X3.2	0.708				
	X3.4	0.751				
Digital Literacy &Training	M1.1	0.704	0.747	0.780	0.839	0.670
	M1.2	0.735				
	M1.3	0.841				
	M1.5	0.819				
AI Acceptance	Y1.1	0.722	0.742	0.750	0.839	0.867
	Y1.2	0.832				
	Y1.3	0.779				
	Y1.4	0.768				

Source: Adapted Smartpls 4 Output (2026)

In terms of internal consistency reliability, all constructs achieved Cronbach's Alpha values above 0.70, with the highest scores observed for the Cognitive construct (0.780) and AI Acceptance (0.742). The Composite Reliability (CR) values ranged from 0.742 to 0.867, indicating high internal consistency across constructs. Furthermore, the Average Variance Extracted (AVE) values for all constructs were above the 0.50 threshold, confirming that convergent validity was satisfactorily met. The AI Acceptance construct recorded the highest AVE value at 0.867, suggesting that its indicators are highly representative of the underlying latent variable.

The results of the discriminant validity test showed that inter-construct correlations ranged from moderate to high (see Table 3). The highest was identified between digital literacy and AI acceptance (0.846), followed by the correlation between conative perception and digital literacy (0.515). Although these values remain within acceptable thresholds, their magnitude underscores the importance of cautious interpretation to ensure that the constructs remain conceptually distinct.

Table 3. Discriminant Validity

Constructs	Affective	AI Acceptance	Cognitive	Conative
Affective				
AI Acceptance	0.573			
Cognitive	0.603	0.467		
Conative	0.603	0.713	0.507	
Digital Literacy	0.623	0.846	0.506	0.515

Source: Adapted Smartpls 4 Output (2026)

The correlations between affective perception and AI acceptance (0.573), as well as between cognitive perception and AI acceptance (0.467), indicated an adequate level of differentiation among the constructs. Overall, discriminant validity can be considered satisfactory; however, the relatively close relationships among certain variables highlight the need for careful confirmation that each construct uniquely captures its intended theoretical dimension within the model.

Inner Model

Structural model (inner model) evaluation was conducted after confirming that the measurement model (outer model) met all required validity and reliability criteria. This stage of analysis involved assessing the coefficient of determination (R-square), effect size (f-square), and the statistical significance of the research hypotheses. Together, these analyses provide a comprehensive view of the model's predictive strength and clarify the extent to which each variable contributes to explaining variance in the endogenous constructs.

Table 4. R Square

Path	R-square	R-square adjusted
AI	0.467	0.452
LAT&LD	0.413	0.402

Source: Adapted Smartpls 4 Output (2026)

The PLS-SEM results showed that the AI acceptance construct achieved an R-square value of 0.467, with an adjusted R-square of 0.452. This demonstrates that approximately 46.7% of the variance in AI acceptance is accounted for by healthcare professionals' perceptions and digital literacy. Similarly, the digital literacy and training construct recorded an R-square of 0.413 and an adjusted R-square of 0.402, suggesting that 41.3% of its variance is explained by cognitive, affective, and conative perceptions. Both values fall within the moderate explanatory category, indicating that the model possesses sufficient predictive capability and is well-suited for identifying key determinants of healthcare professionals' readiness and acceptance of AI technology within hospital settings. Furthermore, the effect size (f^2) in Table 5. shows that the digital literacy and training variable has the strongest influence on AI acceptance, with an f^2 value of 0.323, placing it within the moderate-to-strong effect range.

Tabel 5. F Square

Constructs	AI	LAT&LD
Affective	0.009	0.053
AI		
Cognitive	0.009	0.012
Conative	0.006	0.300
LAT&LD	0.323	

Source: Adapted Smartpls 4 Output (2026)

This finding indicates that improvements in digital literacy and training substantially enhance healthcare professionals' acceptance of AI implementation. The conative variable also demonstrates a considerable contribution to digital literacy and training ($f^2 = 0.300$), suggesting that intention and readiness to use AI are key drivers motivating professionals to engage in training and strengthen their digital competencies. In contrast, the effects of cognitive perception ($f^2 = 0.012$) and affective perception ($f^2 = 0.053$) on digital literacy and training fall within the small effect category, although both still provide measurable contributions. For direct effects on AI acceptance, the influence of affective ($f^2 = 0.009$), cognitive ($f^2 = 0.009$), and conative ($f^2 = 0.006$) perceptions also remains within the small effect range. These results indicate that while perceptions of AI are relevant, their most substantial impact on AI acceptance occurs indirectly through enhanced digital literacy and training. Collectively, these findings highlight the strategic role of digital literacy as the central mechanism connecting perception to actual technology acceptance within hospital environments.

Following the verification that both the measurement model (outer model) and structural model (inner model) satisfied the established reliability and validity criteria, the analysis proceeded to the hypothesis testing stage. This phase assessed the statistical significance of both direct and indirect effects among the constructs. The results presented in this section provide empirical verification of the hypothesized causal relationships linking exogenous variables, the mediating variable, and the endogenous variable, thereby supporting the theoretical framework that underpins the study.

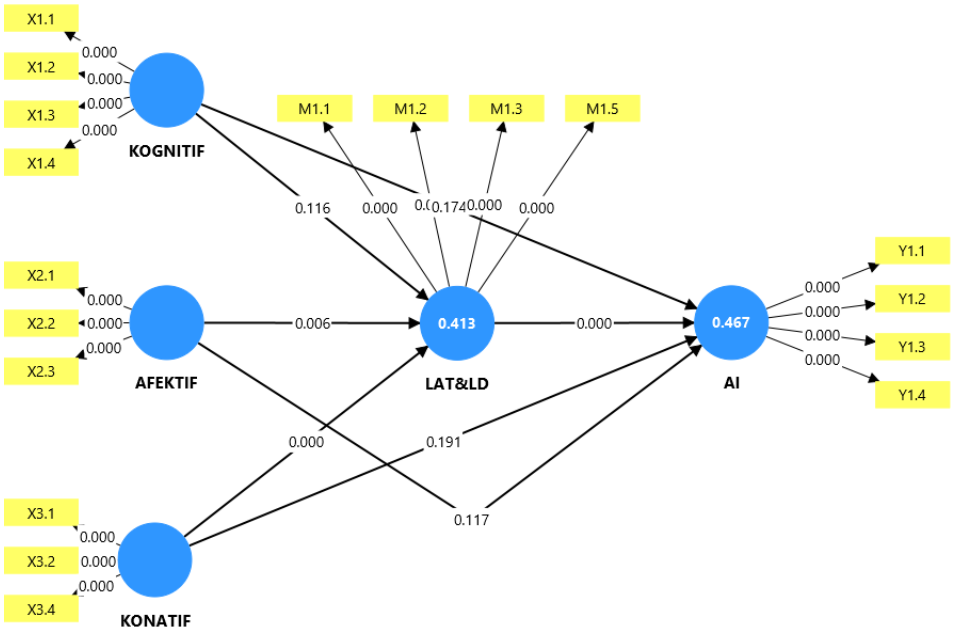


Figure 2. Inner Model
Source: Adapted Smartpls 4 Output (2026)

Based on the PLS-SEM analysis diagram, the conative construct demonstrates the strongest influence on digital literacy and training, with a path coefficient of 0.191. This is followed by the cognitive construct (0.116), while the affective construct exhibits an insignificant effect (–0.006). These findings indicate that healthcare professionals' intention and behavioural readiness to engage with AI contribute more substantially to the enhancement of digital literacy than their knowledge or emotional responses. Furthermore, digital literacy and training exert a positive influence on AI acceptance, as shown by a path coefficient of 0.117, suggesting that strengthening digital competencies plays a meaningful role in supporting AI adoption within hospital settings. The model's explanatory power is moderate, with R^2 values of 0.413 for digital literacy and training and 0.467 for AI acceptance. These values indicate that the model is sufficiently robust for explaining how perception, readiness, and digital capacity interact in the context of AI-driven digital transformation. Overall, the findings suggest that strategies aimed at improving digital literacy, particularly those that target motivation and behavioural readiness, are more effective than approaches relying solely on cognitive understanding or affective attitudes. The detailed hypothesis testing results are presented in the following table 6.

Table 6. Hypothesis Testing Results

Hipotesis/direct	Path	*t*-statistic	*p*-value	Result
H1	Cognitive →AI	0.938	0.174	Not Supported
H2	Affective → AI	1.190	0.117	Not Supported
H3	Conative → AI	0.875	0.191	Not Supported
H4	Cognitive → Lat&LD	1.193	0.116	Not Supported
H5	Affective → Lat&LD	2.508	0.006	Supported
H6	Conative → Lat&LD	6.899	0.000	Supported
H7	Lat&LD → AI	7.322	0.000	Supported
	Hypothesis/indirect	t statistic	p value	Result
H8	Cognitive → Lat&LD → AI	1.205	0.114	Not Supported
H9	Affective → Lat&LD → AI	2.422	0.008	Supported
H10	Conative → Lat&LD → AI	4.550	0.000	Supported

Source: Adapted Smartpls 4 Output (2026)

DISCUSSION

The results of hypothesis testing for H1 indicate that the cognitive construct has a positive but non-significant direct effect on AI acceptance, suggesting that healthcare professionals' conceptual understanding of AI is insufficient to directly influence adoption in hospitals in Cilegon. This finding implies that cognitive aspects alone do not independently shape acceptance attitudes, aligning with the Technology Acceptance Model (TAM), which posits that perceived usefulness and ease of use require reinforcement from affective and conative components. Roveta et al. (2023) emphasize that cognitive understanding must be supported by hands-on experience, while Kumah (2025) highlights the necessity of adaptive learning systems. Natali et al. (2025) further warn that AI integration may lead to skill decline without continuous contextual understanding, and Castello et al. (2022) identify digital literacy as a critical bridge between knowledge and acceptance. Collectively, these studies confirm that cognitive factors require mediation to produce meaningful effects.

Similarly, H2 results show that affective constructs exhibit a positive but non-significant direct effect on AI acceptance, indicating that emotional attitudes alone are insufficient to drive adoption. While theoretically supported by the Affective Neuroscience Approach and TAM, affective influence typically operates through perceived usefulness and ease of use. Montag et al. (2024) demonstrate that emotions such as curiosity and enthusiasm shape attitudes but do not consistently lead to adoption, while Alrashed et al. (2023) find that trust in AI depends more on clinical experience and perceived safety. Natali et al. (2025) highlight emotional resistance as a barrier without adequate support, and Castello et al. (2023) emphasize the necessity of digital literacy to translate affective responses into adoption behavior.

For H3, the conative construct also shows a positive but non-significant direct effect on AI acceptance, indicating that behavioral intention and readiness alone do not sufficiently drive

adoption. Zhang et al. (2024) argue that intention is shaped by system effectiveness and institutional support, while Kumah (2025) and Roveta et al. (2023) emphasize the importance of experiential training and organizational intervention. Castello et al. (2022) further note that motivation must be supported by digital literacy and perceived benefits, reinforcing that conative effects become meaningful only when mediated.

The results for H4 indicate that cognitive factors do not significantly influence digital literacy and training, suggesting that knowledge alone does not drive learning engagement. This aligns with adult learning theory, where conceptual understanding must be complemented by motivation and organizational support. Zhang et al. (2024), Roveta et al. (2023), Castello et al. (2022), and Kumah (2025) collectively emphasize that effective digital literacy development depends on experiential learning, perceived relevance, and behavioral readiness.

In contrast, H5 and H6 show that affective and conative constructs significantly influence digital literacy and training, with conative factors emerging as the strongest driver. These findings align with behavioral frameworks, where emotional engagement enhances learning interest and behavioral intention reflects readiness to participate. Roveta et al. (2023), Zhang et al. (2024), Castello et al. (2022), and Kumah (2025) consistently highlight that motivation and emotional alignment are essential for successful digital learning outcomes.

The results for H7 demonstrate that digital literacy and training exert the strongest positive effect on AI acceptance, confirming their central role as mediating mechanisms. This aligns with competency-based models, where digital readiness determines successful technology adoption. Zhang et al. (2024), Roveta et al. (2023), Castello et al. (2022), and Kumah (2025) all emphasize that structured, context-specific training enhances confidence, reduces resistance, and facilitates meaningful interaction with AI systems.

Mediation analysis further supports this conclusion. While cognitive perception does not significantly influence AI acceptance through digital literacy, affective and conative constructs demonstrate significant indirect effects, confirming that emotional and behavioral factors shape acceptance only when translated into capability development. These findings align with Zhang et al. (2024), Roveta et al. (2023), Castello et al. (2022), and Kumah (2025), who consistently identify digital literacy as a critical bridge between perception and adoption.

CONCLUSION AND FURTHER STUDY

This study demonstrates that training and digital literacy are the primary determinants of AI acceptance among healthcare professionals in hospital settings, while cognitive, affective, and conative perceptions do not exert direct influence but operate indirectly through capability-building mechanisms. These findings indicate that emotional readiness and behavioral intention must be translated into practice through structured, context-specific training, positioning experiential learning as the central driver of AI integration in clinical environments. The model offers a useful foundation for multidimensional, perception-based adoption frameworks in healthcare, particularly by clarifying that technology acceptance is less about awareness and more about applied competence. However, several limitations should be acknowledged. The quantitative and cross-sectional design restricts deeper exploration of underlying psychological and organizational processes and limits the ability to capture changes over time. In addition, the study focuses primarily on individual-level perceptions and does not incorporate broader determinants such as institutional policies, managerial support, regulatory environments, and infrastructure readiness, thereby constraining the generalizability of the findings across diverse healthcare settings.

Building on these limitations, future research should adopt longitudinal designs to examine the evolution of perceptions, capabilities, and acceptance behaviors over time, as well as integrate qualitative or mixed-method approaches to capture contextual and organizational dynamics more comprehensively. Further investigation is also needed to incorporate multilevel factors, including leadership support, governance structures, and technological infrastructure, to develop a more systemic understanding of AI adoption in healthcare. From a managerial perspective, the findings suggest that hospitals should shift from technology-centric strategies toward capability-centric transformation by investing in continuous, participatory, and context-relevant training programs that strengthen digital literacy while also fostering confidence and trust in AI systems. Managers should also align training initiatives with clinical workflows, ensure institutional support mechanisms, and create learning environments that encourage

experimentation and feedback, thereby enabling healthcare professionals to translate knowledge and intention into sustained and effective AI utilization.

ETHICAL DISCLOSURE

This study was conducted in accordance with established ethical standards for research involving human participants. Ethical approval was obtained from the relevant institutional review board prior to data collection. All participants were informed about the purpose of the study, and their participation was voluntary. Informed consent was obtained from all respondents, and confidentiality as well as anonymity of the data were strictly maintained throughout the research process. No identifiable personal information was collected, and all procedures complied with applicable ethical guidelines for research in healthcare settings.

CONFLICT OF INTERESTS

The authors declare that there are no conflicts of interest related to this study. The research was conducted independently without any financial or commercial relationships that could be construed as a potential conflict of interest. All interpretations and conclusions presented in this study are solely those of the authors.

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