

ADOPTION OF ARTIFICIAL INTELLIGENCE BY HEALTHCARE PROFESSIONALS: THE ROLE OF TECHNOLOGY ACCEPTANCE ON BEHAVIORAL INTENTION

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Abstract

This study aims to analyze the influence of Artificial Intelligence (AI) technology acceptance on behavioral intentions of healthcare workers in the context of pre-implementation at Primaya UKRIDA Hospital. Although AI offers benefits in improving efficiency, diagnostic accuracy, and clinical decision-making, its successful implementation depends on user acceptance. This study uses a quantitative approach with an integration of the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). The research variables include perceived usefulness, perceived ease of use, social influence, facilitating conditions, and technology anxiety on behavioral intentions. Data were collected through questionnaires to healthcare workers, namely doctors and nurses. The results showed that perceived usefulness, perceived ease of use, social influence, and facilitating conditions had a positive and significant effect on behavioral intentions, while technology anxiety had a negative effect. These findings indicate that perceived usefulness, ease of use, social support, and facility readiness increase AI adoption intentions, while technology anxiety is a barrier. This study emphasizes the importance of human resource readiness through digital literacy, training, and organizational support to support AI implementation in hospitals.

Keywords: *Artificial Intelligence, Technology Acceptance Model, Unified Theory of Acceptance and Use of Technology, behavioral intention* , health workers, hospitals.

Introduction

Advances in digital technology have driven major transformations in the healthcare sector, one of which is through the use of *Artificial Intelligence* (AI). AI has been applied in various healthcare services such as medical image analysis, *clinical decision support systems* (CDSS), disease prediction, automated medical record documentation, and chatbot-based telemedicine. This technology is considered capable of improving service efficiency, accelerating diagnosis, and supporting data-driven clinical decision-making (Biswas & Talukdar, 2024). The WHO positions healthcare digitalization, including the implementation of AI, as a crucial strategy for improving the quality and access of healthcare services (WHO, 2021). A study by Shaik et al. (2023) also shows that AI can support real-time patient monitoring, improve the accuracy of medical analysis, and accelerate the clinical decision-making process. Furthermore, *the Deloitte Global Health Care Outlook* (2024) reports that more than 60% of healthcare organizations have begun integrating AI into their service systems.

In Indonesia, digital transformation in healthcare continues to develop through the implementation of *Electronic Medical Records* (EMR), hospital information systems, telemedicine, and various other supporting technologies. Several hospitals are beginning to explore the use of AI in radiology, laboratories, anatomical pathology, medical documentation, CDSS, and robotic systems. However, the success of AI implementation depends not only on technological readiness but also on the readiness of human resources as primary users. Healthcare workers play a crucial role in determining the success of AI adoption, as user acceptance is a key factor in the implementation process of new technology.

Despite offering numerous benefits, the application of AI in healthcare still faces various challenges, such as concerns about the accuracy of AI results, patient data security, limited training, and the changing role of healthcare workers in medical services. Zhao et al. (2025) explain that social influence, facilitating conditions, and *technology anxiety* influence healthcare workers' intentions to use AI-CDSS. Meanwhile, Iskandar (2024) states that AI

acceptance is influenced by perceived usefulness *and* perceived ease of use . This suggests that psychological, social, and organizational factors play a crucial role in the success of AI implementation.

Primaya UKRIDA Hospital has implemented a digital-based service system through the use of a hospital information system and EMR, but AI technology has not been fully implemented in healthcare services. However, developments in healthcare technology indicate the potential use of AI in medical record management, CDSS, radiology and laboratory analysis, and clinical decision support in the future. Therefore, research is needed regarding the readiness and intentions of healthcare workers to accept AI before implementation. Swathi et al. (2025) showed that most healthcare workers have positive perceptions of AI, but there are still concerns regarding system errors, information security, and trust in AI recommendations. Zhao et al. (2025) also found that perceived benefits and organizational support influence intentions to use AI.

Based on previous research, most studies still focus on the acceptance of health information systems, EMRs, or healthcare workers' perceptions of AI in general. Research examining AI acceptance before implementation among healthcare workers in Indonesian hospitals is still limited, particularly regarding the influence of *perceived usefulness*, *perceived ease of use*, *social influence*, *facilitating conditions*, and *technology anxiety* on behavioral intention. Therefore, this study offers novelty by analyzing AI technology acceptance in the context of *pre-implementation acceptance* among doctors and nurses at Primaya UKRIDA Hospital using an integration of the TAM and UTAUT models.

This study aims to analyze the influence of these five variables on the behavioral intentions of healthcare workers. Theoretically, the results are expected to enrich research on AI acceptance in the pre-implementation phase. Practically, the results can be used by hospital management to design outreach, training, facility provision, and technical support that align with the readiness of potential users. For healthcare workers, this study provides an overview of the aspects that need to be prepared before using AI in services.

Theoretical Basis and Hypothesis

Artificial Intelligence

Artificial Intelligence (AI) is a computer-based technology designed to mimic human cognitive abilities in learning, information analysis, pattern recognition, prediction, and automated decision-making. The development of AI is driving digital transformation in the healthcare sector due to its ability to process large-scale data and provide support in medical services. Biswas and Talukdar (2024) explain that AI can assist in medical data processing, clinical documentation, and improve the effectiveness and efficiency of healthcare services. Shaik et al. (2023) state that AI, through machine learning technology, is capable of predicting patient conditions, real-time health monitoring, and supporting clinical decision-making. Dai et al. (2025) explain that AI works through computational algorithms capable of recognizing patterns and solving problems based on data. In the healthcare sector, AI applications include *Machine Learning*, *Natural Language Processing* (NLP), *Computer Vision*, and *Clinical Decision Support Systems* (CDSS). NLP is used to support electronic medical record management, automated medical documentation, and health chatbots (Biswas & Talukdar, 2024). *Computer vision* is utilized in the analysis of medical images such as radiology, CT scans, MRIs, and anatomical pathology to aid in disease detection (Nair et al., 2024). Furthermore, CDSS plays a role in providing data-driven clinical recommendations to support healthcare professionals' decisions (Zhao et al., 2025).

Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) is a theoretical framework used to explain individual behavior in accepting and using technology. This model was developed by Davis and is widely used in information technology acceptance research, including in the health sector. TAM explains that technology acceptance is influenced by user perceptions of benefits (*Perceived Usefulness*) and ease of use (*Perceived Ease of Use*), which then form behavioral intentions . Alsyof et al. (2022) explain that TAM is used to predict technology acceptance based on user beliefs about the benefits and ease of use of technology. Rahimi et al. (2024) state that TAM is widely used in health technology research because it is able to explain factors that influence the intention of health workers to adopt technology. Zhao et al. (2025) show that perceived benefits and ease of use influence the intention of health workers to use AI-based systems. Therefore, TAM is used in this study as a theoretical basis to explain the relationship between *Perceived Usefulness*, *Perceived Ease of Use*, and *Behavioral Intention* in AI acceptance at Primaya Hospital UKRIDA.

Perceived Usefulness

Perceived Usefulness is a construct in TAM that describes an individual's level of belief that the use of technology can improve effectiveness, productivity, and work quality. This construct indicates the extent to which healthcare workers believe technology can provide benefits in supporting medical services. Alsyouf et al. (2022) stated that the perceived benefits of digital health technology are an important factor influencing user intentions to adopt the technology. In this study, *Perceived Usefulness* is defined as the level of healthcare workers' belief that AI has the potential to provide benefits in supporting healthcare services at Primaya UKRIDA Hospital. This variable is measured through four indicators: the ability of AI to improve work effectiveness, healthcare productivity, speed of work completion, and quality of service and clinical decision-making.

Perceived Ease of Use

Perceived Ease of Use is a construct in TAM that describes The level of individual confidence that a technology can be used easily without requiring excessive effort. This concept relates to the user's ability to understand, learn, and operate the technology. Alsyouf et al. (2022) explain that *Perceived Ease of Use* relates to the user's perception of the ease of implementing a technology in the work process. Luo et al. (2024) state that ease of use is an important factor in the successful implementation of a health information system because less complex technology is more easily accepted by users. Park et al. (2025) found that perceived ease of use has a positive effect on the intention to use digital health technology. In this study, *Perceived Ease of Use* is defined as the level of confidence of healthcare workers that AI can be understood, learned, and used easily when implemented at Primaya UKRIDA Hospital. This variable is measured through four indicators: AI is easy to understand, easy to learn, easy to operate, and easy to use in daily healthcare activities.

Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT) is a theoretical framework used to explain the acceptance and use of technology based on individual, social, and organizational factors. This model was developed by Venkatesh et al. through the integration of several previous technology acceptance theories, such as TAM, TPB, and IDT. Venkatesh et al. (2022) explained that UTAUT is able to explain the relationship between factors that influence the intention and behavior of technology use. Dwivedi et al. (2021) stated that UTAUT is a comprehensive model because it combines various concepts that influence technology acceptance. Yang et al. (2024) explained that UTAUT remains relevant for analyzing modern digital technologies, including AI, because it is able to explain the influence of social factors and organizational support on technology acceptance. Zhao et al. (2025) found that Social Influence and *Facilitating Conditions* influence the intention of healthcare workers to use AI-CDSS. Therefore, this study uses *the Social Influence* and *Facilitating Conditions* aspects of UTAUT to explain the influence of the social environment and organizational support on the Behavioral Intention of health workers in accepting AI, and adds *the Technology Anxiety variable* to describe psychological factors that can influence technology acceptance.

Social Influence

Social Influence is a construct in *the Unified Theory of Acceptance and Use of Technology (UTAUT)* that explains the extent to which individuals perceive that significant others influence their decisions to use a technology. This factor indicates that technology acceptance is influenced not only by personal perceptions but also by social support from colleagues, leaders, and the organizational environment. Venkatesh et al. (2022) explain that *Social Influence* relates to the influence of significant others on an individual's decision to use technology. Yang et al. (2024) state that social factors are an important component in digital technology acceptance because individuals tend to consider the views and behaviors of others before adopting technology. Zhao et al. (2025) found that *Social Influence* influences healthcare workers' intentions to use *Artificial Intelligence-Based Clinical Decision Support Systems (AI-CDSS)*, especially when there is support from colleagues and the organization. This variable is measured through indicators of peer support, leadership encouragement, hospital policies that support AI, and work environment support for AI implementation.

Facilitating Conditions

Facilitating Conditions is a construct in UTAUT that explains the extent to which individuals believe that their organization has provided the resources, facilities, infrastructure, and support necessary to use a technology. Adequate supporting conditions can increase user readiness to accept and utilize technology. Venkatesh et al. (2020) explain that *Facilitating Conditions* include the availability of resources, knowledge, technical assistance, and the suitability of the technology for the system being used. Yang et al. (2024) state that institutional support is a crucial

factor because users need facilities and organizational assistance for technology to be used effectively. Zhao et al. (2025) show that the availability of facilities, training, and organizational support influence the acceptance of AI-CDSS technology by healthcare workers. This variable is measured through indicators of the availability of technological facilities, support for hospital systems and policies, training on AI use, and technological infrastructure readiness.

Technology Anxiety

Technology anxiety is a psychological condition characterized by feelings of anxiety, fear, or discomfort experienced by individuals when confronted with new technology. High levels of anxiety can hinder technology acceptance because users feel less confident in their ability to operate the system. Meuter et al. (2003) explain that technology anxiety is a feeling of fear or worry that arises when individuals use or consider using new technology. Dwivedi et al. (2021) state that technology anxiety is a negative emotional response due to uncertainty about technology that can reduce usage intentions. Zhao et al. (2025) explain that in the use of AI-CDSS, technology anxiety can arise due to concerns about system errors, patient data security, and trust in AI recommendations. This variable is measured through indicators of concern about AI system errors, patient data security and confidentiality, dependence on technology, and trust in AI results or recommendations.

Behavioral Intention

Behavioral Intention is a concept in technology acceptance theory that describes an individual's level of intention, desire, and readiness to use a technology. This concept is an important predictor of actual technology use behavior because the higher a person's intention, the more likely the technology is to be used. Venkatesh et al. (2020) explain that Behavioral Intention indicates the extent to which a person has a plan and willingness to use a particular technology in their activities. Zhao et al. (2025) explain that Behavioral Intention describes the tendency of healthcare workers to accept and use AI-CDSS in their work. Winoto Tj. and Wahyoedi (2025) state that individual intention is an important predictor in shaping actual behavior because a positive attitude toward a technology can increase the tendency to use it. This variable is measured through indicators of intention to use AI, desire to use AI continuously, willingness to accept AI in work, and tendency to use AI in daily medical service activities.

Table 1 Research hypothesis

Hypothesis	The relationship is tested	Direction
H1	<i>Perceived usefulness on behavioral intention</i>	Positive
H2	<i>Perceived ease of use on behavioral intention</i>	Positive
H3	<i>Social influence on behavioral intention</i>	Positive
H4	<i>Facilitating conditions on behavioral intention</i>	Positive
H5	<i>Technology anxiety on behavioral intention</i>	Negative

Source: Data processed by researchers (2026)

Research methods

Types and Approaches of Research

This study used a quantitative explanatory approach with a cross-sectional design conducted at Primaya UKRIDA Hospital in 2026. The study population consisted of 177 healthcare workers including 20 general practitioners, 61 specialist physicians, and 96 nurses. Sampling was conducted using a purposive sampling technique with the criteria of respondents being active healthcare workers at Primaya UKRIDA Hospital, having an understanding of digital systems or health information systems, and being willing to complete the questionnaire completely.

Variables and data collection

Primary data were obtained through a questionnaire with a Likert scale of 1 to 5. The questionnaire measured five independent variables and one dependent variable. Operational definitions and measurement aspects are presented in Table 2.

Table 2 Operational definitions and measurement aspects

Variables	Indicator
<i>Perceived Usefulness</i> (PU)	1. Work effectiveness
	2. Productivity of health services
	3. Speed of work completion
	4. Quality of care and clinical decision making
<i>Perceived Ease of Use</i> (PEOU)	1. Ease of understanding AI
	2. Ease of learning AI
	3. Ease of operating AI
	4. Ease of using AI in healthcare activities
<i>Social Influence</i> (SI)	1. Co-worker support
	2. Influence of leaders/superiors
	3. Hospital policy support
	4. Work environment support
<i>Facilitating Conditions</i> (FC)	1. Availability of technology facilities
	2. System and organizational support
	3. Availability of AI training
	4. Technology infrastructure readiness
<i>Technology Anxiety</i> (TA)	1. Concerns about AI system errors
	2. Concerns about patient data security
	3. Concerns about technology dependency
	4. Trust in AI results or recommendations
<i>Behavioral Intention</i> (BI)	1. Intention to use AI
	2. Willingness to use AI when available
	3. The desire to use AI sustainably
	4. AI usage recommendations

Data analysis techniques

Data were analyzed using *Partial Least Squares Structural Equation Modeling* (PLS-SEM) through the SmartPLS version 3 application with evaluation of the measurement model and structural model. The measurement model was conducted to test the validity and reliability of the construct through convergent validity using *outer loading* and *Average Variance Extracted* (AVE), discriminant validity using the Fornell–Larcker criteria and Heterotrait–Monotrait Ratio (HTMT), and reliability using Cronbach's alpha and *composite reliability* (Hair et al., 2022). A construct is declared to meet convergent validity if the outer loading value is > 0.70 and $AVE \geq 0.50$, while reliability is met if the Cronbach's alpha and composite reliability values ≥ 0.70 . Discriminant validity testing is carried out by comparing the square root of AVE with the correlation between constructs using the Fornell–Larcker criteria and ensuring the HTMT value is < 0.90 .

The structural model was evaluated using R^2 , adjusted R^2 , Q^2 , f^2 , and path coefficients. The R^2 and adjusted R^2 values were used to assess the model's ability to explain endogenous variables, Q^2 to measure the model's predictive relevance, and f^2 to determine the magnitude of the influence of each predictor variable. Hypothesis testing was conducted using the bootstrapping method with significance criteria of a t-statistic > 1.96 and a p-value < 0.05 (Hair et al., 2022).

Research result

Respondent characteristics

This study involved 150 respondents who met the research criteria and provided complete data. Respondent characteristics included profession, gender, age, highest level of education, length of service, work unit, knowledge of Artificial Intelligence (AI), and experience using AI. The distribution of respondent characteristics based on these aspects is presented in Table 3.

Table 3 Respondent characteristics

Characteristics	Category	n	%
Profession	Nurse	83	55.3
	Medical specialist	53	35.3
	General practitioners	14	9.3
Gender	Woman	92	61.3
	Man	58	38.7
Age	< 25 years	27	18.0
	25–30 years	42	28.0
	31–40 years	33	22.0
	41–50 years	33	22.0
	> 50 years	15	10.0
last education	Specialist	52	34.7
	D3	50	33.3
	Profession	24	16.0
	S1	23	15.3
	S3	1	0.7
Years of service	< 1 year	20	13.3
	1–3 years	70	46.7
	4–6 years	60	40.0
Work unit	Inpatient	49	32.7
	Polyclinic	66	44.0
	Emergency Room	18	12.0
	ICU	17	11.3
Getting to Know AI	Yes	138	92.0
	No	12	8.0
Ever used AI?	Yes	86	57.3
	No	64	42.7

Based on professional characteristics, the respondents were dominated by nurses (83 people) (55.3%), followed by specialist doctors (53 people) (35.3%) and general practitioners (14 people) (9.3%). Based on gender, the majority of respondents were female (92 people) (61.3%). The largest age group was in the 25–30 years range (42 people) (28.0%), while based on the last education, the most respondents had specialist education (52 people) (34.7%) and D3 (50 people) (33.3%). Based on length of service, the most respondents had 1–3 years of work experience (70 people) (46.7%). Based on work units, the most respondents came from polyclinics (66 people) (44.0%), followed by inpatients (49 people) (32.7%). The most respondents were familiar with AI (138 people) (92.0%), and 86 people (57.3%) of them had used AI.

Convergent validity and reliability

Table 4 Outer Loading

Item	Public Works	PE	SI	FC	TA	BI
1	0.883	0.883	0.914	0.883	0.886	0.848
2	0.891	0.908	0.892	0.897	0.903	0.889
3	0.914	0.842	0.911	0.901	0.926	0.885
4	0.884	0.903	0.869	0.886	0.916	0.857
5	0.881	0.895	0.884	0.891	0.920	0.847
6	0.917	0.919	0.899	0.890	0.922	0.852
7	0.910	0.910	0.908	0.874	0.905	0.847
8	0.910	0.911	0.906	0.887	0.915	0.886

All items had an outer loading above 0.70. Therefore, all items in this research questionnaire passed the validity test.

Table 5 Convergent validity and reliability

Construct	AVE	Cronbach's alpha	Composite reliability
Public Works	0.8079	0.9660	0.9711
PE	0.8043	0.9652	0.9705
SI	0.8065	0.9657	0.9709
FC	0.7895	0.9619	0.9677
TA	0.8312	0.9710	0.9752
BI	0.7466	0.9514	0.9593

Source: SmartPLS output, 2026.

All constructs had AVE values above 0.50. Cronbach's alpha and *composite reliability values* for all constructs were also above 0.70, indicating that all variables had good reliability and met the criteria for further analysis.

Discriminant validity

Table 6 Fornell–Larcker Criteria

Construct	BI	FC	PE	Public Works	SI	TA
BI	0.8640					
FC	0.6064	0.8885				
PE	0.4661	0.2280	0.8968			
Public Works	0.5962	0.3474	0.1713	0.8989		
SI	0.5187	0.2438	0.0943	0.1775	0.8980	
TA	−0.4216	−0.1905	0.0103	−0.1550	−0.2188	0.9117

Source: SmartPLS output, 2026. The diagonal shows the square root of AVE.

Table 7 HTMT test results

Construct	BI	FC	PE	Public Works	SI
FC	0.6336				
PE	0.4834	0.2359			
Public Works	0.6183	0.3581	0.1742		
SI	0.5389	0.2503	0.1057	0.1847	
TA	0.4375	0.1943	0.0469	0.1596	0.2217

Source: SmartPLS output, 2026.

All HTMT values were below 0.90, indicating that each construct had good discriminant validity. These results indicate that all constructs in this study can be empirically distinguished and meet the criteria for proceeding to the structural model analysis stage.

Model explanation capability

Table 8 Explanatory power and predictive relevance

Endogenous variables	Adjusted R ²	Q ²
Behavioral intention	0.7858	0.585

Source: SmartPLS output, 2026.

Based on the table, the adjusted R² value of 0.7858 indicates the model's explanatory power of 78.58%, while the remaining 21.42% is explained by factors outside the research model. This value indicates that the model has strong explanatory power. Furthermore, the Q² value of 0.585 (>0) indicates that the model has predictive relevance for Behavioral Intention in this study.

Effect size and hypothesis testing**Table 9 Effect size of each predictor**

Predictor	f ²	Category
<i>Perceived usefulness</i>	0.5021	Big
<i>Perceived ease of use</i>	0.4433	Big
<i>Social influence</i>	0.3952	Big
<i>Facilitating conditions</i>	0.3344	Currently
<i>Technology anxiety</i>	0.2760	Currently

Source: SmartPLS output, 2026. f² limits: 0.02 small; 0.15 medium; 0.35 large.

The effect size (f²) value shows that *Perceived Usefulness* has the largest influence on *Behavioral Intention* with a value of 0.5021, followed by *Perceived Ease of Use* at 0.4433 and *Social Influence* at 0.3952. These three variables are included in the large effect category. Meanwhile, *Facilitating Conditions* with a value of 0.3344 and *Technology Anxiety* at 0.2760 are included in the medium effect category. These results indicate that all predictors contribute to the model's ability to explain variations in Behavioral Intention.

Table 10 Results of hypothesis testing

Track	β	Mean	Elementary School	t	p	Results
H1 PU → BI	0.3486	0.3482	0.0492	7,0869	< 0.001	Accepted
H2 PE → BI	0.3138	0.3092	0.0430	7,2911	< 0.001	Accepted
H3 SI → BI	0.3013	0.3056	0.0382	7,8871	< 0.001	Accepted
H4 FC → BI	0.2929	0.2939	0.0413	7,0845	< 0.001	Accepted
H5 TA → BI	-0.2491	-0.2432	0.0395	6,2990	< 0.001	Accepted

Source: SmartPLS output, 2026. β = original sample; mean = bootstrap sample mean; SD = bootstrap standard deviation. The p-value in the original output is listed as 0.0000.

The results of the hypothesis testing indicate that all relationships between variables in the model meet the significance criteria with a p-value <0.05. The variables *Perceived Usefulness*, *Perceived Ease of Use*, *Social Influence*, and *Facilitating Conditions* have a positive influence on *Behavioral Intention*, while *Technology Anxiety* shows a negative relationship. This indicates that increasing perceptions of usefulness, ease of use, social support, and supporting conditions can increase the intention to use AI, while anxiety about technology has the potential to be a barrier to AI acceptance.

Discussion**The influence of perceived usefulness on behavioral intention**

The results support H1 that *Perceived Usefulness* has a positive and significant effect on *Behavioral Intention* with a path coefficient of 0.3486, a t-statistic of 7.0869, and a p-value <0.001. The f² value of 0.5021 indicates that this variable has the largest effect size in the model. These findings indicate that the higher the healthcare workers' perception of the benefits of AI, the higher their intention to use AI. The benefits considered include support for healthcare services, accelerated information processing, increased productivity, and support in clinical decision-making.

These results align with the TAM concept, which places perceived usefulness as a crucial factor in shaping technology adoption intentions. Cahyawan and Mahyuni (2020) demonstrated that perceived usefulness plays a role in physicians' acceptance of EMR technology. Zhao et al. (2025) also discussed the relationship between performance improvement expectations and AI-CDSS adoption intentions. In this study, hospital management can communicate the benefits of AI through application examples relevant to healthcare workers' work to help users understand the technology's value before implementation.

The influence of perceived ease of use on behavioral intention

Hypothesis 2 regarding the effect of *Perceived Ease of Use* on *Behavioral Intention* is declared accepted. The test results show an original sample value of 0.3138, a T-statistic of 7.2911 (>1.96), and a p-value of 0.0000 (<0.05), so it can be concluded that *Perceived Ease of Use* has a positive and significant effect on *Behavioral Intention* to use *Artificial Intelligence* among healthcare workers at Primaya UKRIDA Hospital. This finding indicates that the easier AI is to understand, learn, and use, the higher the intention of healthcare workers to accept and utilize the technology in healthcare services. Ease of use is an important aspect because healthcare workers need technology

that can support their work without adding complexity to the service process. The results of this study indicate that ease of use is a crucial factor in the acceptance of health technology. Cahyawan and Mahyuni (2021) explain that *Perceived Ease of Use* is a factor influencing physicians' acceptance of *Electronic Medical Records*. Yang et al. (2025) also demonstrated through a meta-analysis that *Perceived Ease of Use* has a positive relationship with *Behavioral Intention* in technology acceptance by healthcare professionals. Furthermore, Victorya et al. (2024) demonstrated that acceptance of digital healthcare services is related to system quality and user experience. Therefore, AI systems that are easy to understand and use can improve user comfort and support healthcare professionals' readiness to adopt the technology.

The influence of social influence on behavioral intention

Hypothesis 3 regarding the effect of *Social Influence* on Behavioral Intention is declared accepted. The test results show an original sample value of 0.3013, a T-statistic of 7.8871 (>1.96), and a p-value of 0.0000 (<0.05). Based on these results, it can be concluded that *Social Influence* has a positive and significant effect on Behavioral Intention to use *Artificial Intelligence* among healthcare workers at Primaya UKRIDA Hospital. This finding indicates that the stronger the social support from the work environment, the higher the healthcare workers' intention to accept and use AI. Social influences in this study include support from colleagues, leaders, hospital management, and organizational culture that can shape user confidence in the implementation of new technologies.

The results of this study align with those of Zhao et al. (2025), who demonstrated that *social influence* positively influences physicians' willingness to adopt AI. This study explains that decisions to use AI are influenced by the professional environment, including support and experience from colleagues and the organization. It also demonstrates that *social influence* is a crucial factor in the adoption of healthcare technology. These findings suggest that social and institutional support can help reduce user uncertainty and increase healthcare workers' readiness to accept AI implementation in the hospital environment.

The influence of facilitating conditions on behavioral intention

Hypothesis 4 regarding the effect of *Facilitating Conditions* on Behavioral Intention is declared accepted. The test results show an original sample value of 0.2929, a T-statistic of 7.0845 (>1.96), and a p-value of 0.0000 (<0.05). These results indicate that *Facilitating Conditions* have a positive and significant effect on Behavioral Intention to use *Artificial Intelligence* among healthcare workers at Primaya UKRIDA Hospital. This finding indicates that the better the supporting conditions available, the higher the readiness of healthcare workers to accept AI. These supporting conditions include the availability of technological facilities, infrastructure, networks, training, user guides, and technical support that assist the process of using AI.

The results of this study indicate that AI acceptance is influenced not only by individual perceptions but also by the organization's readiness to provide a supportive environment. Zhao et al. (2025) explain that *Facilitating Conditions* relate to user confidence in the availability of technical and organizational support in the use of technological systems. Furthermore, Josephine et al. (2023) show that digital services and the competence of healthcare workers are important aspects in supporting the successful implementation of health technology. These findings confirm that facility readiness, user capabilities, training, and organizational support are crucial in building AI acceptance in the hospital environment.

The influence of technology anxiety on behavioral intention

Hypothesis 5 regarding the effect of *Technology Anxiety* on Behavioral Intention is declared accepted. The test results show an original sample value of -0.2491, a T-statistic of 6.2990 (>1.96), and a p-value of 0.0000 (<0.05). Based on these results, it can be concluded that *Technology Anxiety* has a negative and significant effect on Behavioral Intention to use *Artificial Intelligence* among healthcare workers at Primaya UKRIDA Hospital. This finding indicates that the higher the level of anxiety about AI, the lower the healthcare workers' intention to use the technology. This anxiety is related to concerns about system errors, data security, trust in AI results, and changes in the role of healthcare workers due to the use of technology.

The results of this study align with Zhao et al. (2025) who showed that technology anxiety negatively impacts doctors' willingness to adopt AI. Anxiety about technology can arise from a lack of understanding, limited experience, and concerns about the risks of error, bias, ethics, and data privacy. Furthermore, Tj et al. (2025) showed that the quality of human resources is a crucial factor in supporting hospital performance. These findings suggest that improving digital literacy, training, and technical assistance can help healthcare workers understand the function of AI as a service-supporting technology, thereby reducing psychological barriers in the AI acceptance process.

Conclusion and Suggestions

Conclusion

Based on the results of research on the influence of acceptance of *Artificial Intelligence technology* on the *Behavioral Intention* of health workers at Primaya UKRIDA Hospital, it can be concluded that:

1. *Perceived Usefulness* (X1) has a positive and significant effect on *Behavioral Intention* (Y). The higher the healthcare worker's perception of the benefits of AI, the higher the intention to use AI in healthcare services.
2. *Perceived Ease of Use* (X2) has a positive and significant effect on *Behavioral Intention* (Y). The ease of understanding, learning, and using AI increases healthcare workers' acceptance of the technology.
3. *Social Influence* (X3) has a positive and significant effect on *Behavioral Intention* (Y). Support from colleagues, leaders, and the organizational environment can increase the intention to use AI.
4. *Facilitating Conditions* (X4) has a positive and significant effect on *Behavioral Intention* (Y). The availability of facilities, infrastructure, training, and technical support supports the readiness of healthcare workers in using AI.
5. *Technology Anxiety* (X5) has a negative and significant effect on *Behavioral Intention* (Y). The higher the anxiety towards AI, the lower the intention of healthcare workers to use the technology.

Suggestion

1. For UKRIDA Primaya Hospital, it is necessary to improve the understanding and readiness of healthcare workers through outreach, training, AI simulations, and the provision of adequate facilities and technical support.
2. For healthcare workers, improving digital literacy and understanding the benefits and risks of AI is essential so that technology can be utilized to support services while maintaining professionalism, ethics, and patient safety.
3. For further researchers, it is recommended to add other variables such as trust, perceived risk, privacy concern, digital literacy, organizational readiness, and perceived security, as well as consider moderating variables such as age, profession, work experience, and experience using digital technology.

REFERENCES

- Alsyouf, A., Lutfi, A., Al-Bsheish, M., Jarrar, M., Al-Mugheed, K., Almaiah, M.A., & Alsyouf, A. (2022). Exposure detection applications acceptance: The case of COVID-19. *International Journal of Environmental Research and Public Health* , 19(12), 7307. <https://doi.org/10.3390/ijerph19127307>
- Biswas, S., & Talukdar, B. (2024). Intelligent clinical documentation: Harnessing generative AI for patient-centric clinical note generation. *Journal of Healthcare Informatics Research* , 8(1), 45–60. <https://doi.org/10.1007/s41666-024-00145-2>
- Cahyawan, AK, & Mahyuni, LP (2021). Implementation of electronic medical records in hospitals: A model to understand physician acceptance of new technology. *Indonesian Journal of Health Information Systems* , 7(2), 112–123.
- Dai, Y., Chen, X., Wang, Z., & Li, H. (2025). Attitudes of healthcare professionals toward artificial intelligence in healthcare: A cross-sectional survey study. *BMC Medical Informatics and Decision Making* , 25(1), 78–91. <https://doi.org/10.1186/s12911-025-02456-7>
- Deloitte. (2024). *2024 Global Health Care Outlook: AI and digital transformation in healthcare* . Deloitte Insights. <https://www2.deloitte.com/global/en/pages/life-sciences-and-healthcare/articles/global-health-care-sector-outlook.html>
- Dwivedi, Y.K., Hughes, L., Rana, N.P., Slade, E.L., & Williams, M.D. (2021). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management* , 57, 101994. <https://doi.org/10.1016/j.ijinfomgt.2019.08.002>
- Hair, J.F., Hult, G.T.M., Ringle, C.M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). Sage Publications.
- Ingle, A., Patil, S., & Sharma, R. (2024). Artificial intelligence applications in clinical decision support systems: A systematic review. *Healthcare Analytics* , 6, 100245. <https://doi.org/10.1016/j.health.2024.100245>
- Iskandar, M. (2024). Analysis of acceptance of artificial intelligence technology in health services using the TAM approach. *Journal of Health Information Technology* , 12(1), 55–67.

- Luo, J., Ahmad, SF, Alyaemeni, A., Ou, Y., Irshad, M., Alyafi-Alzahri, R., Alsanie, G., & Unnisa, ST (2024). Role of perceived ease of use, usefulness, and financial strength on the adoption of health information systems: The moderating role of hospital size. *Humanities and Social Sciences Communications*, 11 , Article 516. <https://doi.org/10.1057/s41599-024-02976-9>
- Meuter, M.L., Ostrom, A.L., Bitner, M.J., & Roundtree, R. (2003). The influence of technology anxiety on consumer use and experiences with self-service technologies. *Journal of Business Research*, 56 (11), 899–906. [https://doi.org/10.1016/S0148-2963\(01\)00276-4](https://doi.org/10.1016/S0148-2963(01)00276-4)
- Nair, P., Joseph, T., & Menon, R. (2024). AI-powered medical imaging for disease diagnosis and detection: Current trends and future directions. *Radiology and Artificial Intelligence Journal* , 5(2), 88–101. <https://doi.org/10.1148/ryai.240021>
- Okonji, E.F., Adeoye, O.A., & Yusuf, A.M. (2024). Artificial intelligence in disease diagnosis and clinical decision-making: Implications for healthcare systems. *International Journal of Medical Informatics* , 184, 105327. <https://doi.org/10.1016/j.ijmedinf.2024.105327>
- Rahimi, B., Nadri, H., Afshar, H.L., & Timpka, T. (2024). A systematic review of the technology acceptance model in health informatics. *Applied Clinical Informatics* , 15(1), 102–118. <https://doi.org/10.1055/s-0043-1778124>
- Reddy, S. (2024). Generative AI in healthcare: Opportunities, challenges, and future implications. *npj Digital Medicine* , 7(1), 34–46. <https://doi.org/10.1038/s41746-024-01012-8>
- Shaik, T., Tao, X., Higgins, N., Li, Y., Gururajan, R., Zhou, X., & Acharya, U. R. (2023). Remote patient monitoring using artificial intelligence: Current state, applications, and challenges. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery* , 13(2), e1485. <https://doi.org/10.1002/widm.1485>
- Sugiyono. (2022). *Quantitative, qualitative, and R&D research methods* . Alfabeta.
- Swathi, P., Kumar, V., & Rajesh, M. (2025). Healthcare professionals' perception toward artificial intelligence adoption in hospitals. *Healthcare Technology Letters* , 12(1), 15–27. <https://doi.org/10.1049/htl2.12045>
- Venkatesh, V., Thong, J.Y.L., & Xu, X. (2020). Unified theory of acceptance and use of technology: A synthesis and the road ahead. *Journal of the Association for Information Systems* , 21(5), 328–376. <https://doi.org/10.17705/1jais.00628>
- Victorya, J., Winoto Tj, H., Tecocalu, M., & Wahyoedi, S. (2024). Service quality mediates the influence of trust on patient satisfaction in telemedicine applications. *Syntax Literate: Indonesian Scientific Journal*, 9 (5), 3102–3133. <https://doi.org/10.36418/syntax-literate.v9i5.15286>
- Winoto, H., Tecocalu, M., Colline, F., Desnelita, Y., Pasaribu, B., & Sucahyo, YG (2021). *Technology Acceptance Model to solve e-learning problems for teachers in schools* . In *Proceedings of the International Conference on Industrial Engineering and Operations Management (IEOM)*, Monterrey, Mexico . IEOM Society International.
- World Health Organization. (2021). *Global strategy on digital health 2020–2025* . World Health Organization. <https://www.who.int/publications/i/item/9789240020924>
- Yang, H., Lee, J., & Kim, S. (2024). Acceptance of digital health technology using UTAUT model among healthcare professionals. *Healthcare Informatics Research* , 30(1), 22–35. <https://doi.org/10.4258/hir.2024.30.1.22>
- Zhao, Y., Wang, J., Liu, H., & Chen, X. (2025). Analysis of clinical doctors' adoption willingness pathway for the artificial intelligence-based clinical decision support system (AI-CDSS). *BMC Health Services Research* , 25(1), 102–118. <https://doi.org/10.1186/s12913-025-11876-3>