Patient Perceptions and Trust in Artificial Intelligence for Radiology Services: Evidence from Indriati Solo Baru Hospital

Devanti Octavia Ellyamurti
Universitas Pelita Harapan; Tangerang, Indonesia
E-Mail: devantiellyamurty@gmail.com

Radityo Fajar Arianto
Universitas Pelita Harapan; Tangerang, Indonesia
E-Mail: radityo.arianto@uph.edu

Submitted:
OCTOBER 2025

Accepted:
DECEMBER 2025

ABSTRACT

Artificial Intelligence (AI) has emerged as a transformative innovation in radiology, offering faster and more accurate diagnostic capabilities. However, patient acceptance and trust remain critical challenges that influence its successful implementation. This study aims to analyze the factors influencing patients' perceptions and trust in the use of AI in radiology services at Indriati Hospital Solo Baru. This study uses a quantitative survey design with a cross-sectional approach and involves 153 respondents who underwent AI-based MRI examinations. Data was collected using a Likert-scale questionnaire with purposive sampling and analyzed using the Partial Least Squares-Structural Equation Modelling (PLS-SEM) method. The analysis results show that trust, efficiency, and being informed have a positive influence on perceived usefulness and perceived ease of use. Additionally, perceived usefulness and perceived ease of use increase the intention to use AI in radiology. The variables of transparency, data security, and privacy were also proven to strengthen the influence of trust on the intention to use AI in radiology. This finding confirms that benefits, convenience, trust, and assurances of transparency and data security significantly influence patient acceptance of AI.

Keywords: *Artificial Intelligence, Data Security, Radiology, Technology Acceptance Model, Transparency, Trust.*

ABSTRAK

Kecerdasan Buatan (Artificial Intelligence/AI) kini menjadi inovasi penting dalam bidang radiologi karena kemampuannya memberikan hasil diagnosis yang lebih cepat, akurat, dan efisien. Meskipun demikian, tingkat penerimaan dan kepercayaan pasien masih menjadi tantangan yang menentukan keberhasilan penerapan teknologi ini. Penelitian ini bertujuan untuk mengidentifikasi faktor-faktor yang memengaruhi persepsi serta kepercayaan pasien terhadap penggunaan AI dalam layanan radiologi di Rumah Sakit Indriati Solo Baru. Metode penelitian yang digunakan adalah survei kuantitatif dengan pendekatan cross-sectionaL,, melibatkan 153 responden yang menjalani pemeriksaan MRI berbasis AI. Pengumpulan data dilakukan menggunakan kuesioner skala Likert melalui teknik purposive sampling, kemudian dianalisis dengan metode Partial Least Squares-Structural Equation Modelling (PLS-SEM). Hasil penelitian menunjukkan bahwa kepercayaan, efisiensi, dan keterinformasian secara signifikan berpengaruh positif terhadap persepsi kegunaan dan kemudahan penggunaan AI. Selanjutnya, kedua persepsi tersebut mendorong meningkatnya niat pasien untuk menggunakan AI dalam radiologi. Selain itu, variabel transparansi, keamanan data, dan privasi terbukti memperkuat hubungan antara kepercayaan dan niat penggunaan AI. Temuan ini menegaskan bahwa persepsi terhadap manfaat, kemudahan, kepercayaan, serta adanya

JIMKES

Jurnal Ilmiah Manajemen Kesatuan
Vol. 13 No. 6, 2025
pp. 5547-5560
IBI Kesatuan
ISSN 2337 – 7860
E-ISSN 2721 – 169X
DOI: 10.37641/jimkes.v13i6.4315

jaminan transparansi dan perlindungan data menjadi faktor utama yang menentukan penerimaan pasien terhadap teknologi AI dalam layanan radiologi.

***Kata kunci**: Kecerdasan Buatan, Keamanan Data, Radiologi, Technology Acceptance Model, Transparansi, Kepercayaan.*

INTRODUCTION

Artificial Intelligence (AI) is a technological innovation that has been rapidly developing since the industrial revolution. It is capable of analyzing data through self-correction, reasoning, and learning (Thaariq et al., 2024). In healthcare, particularly radiology, AI has offered various advantages, including the production of more detailed images, the acceleration of examination processes, the improvement of diagnostic accuracy, and an increase of service efficiency, all of which have led to an increase of patient comfort (Trenggono & Bachtiar, 2023). This technology is not a replacement for the role of specialists; rather, it functions as a tool that can decrease diagnostic errors and workload (Krishna et al., 2025). Research conducted by Chen et al. (2024) demonstrated that the utilization of AI can decrease the time required for radiology reading by as much as 61.72%.

Various radiologists hold different opinions regarding the implementation of AI in radiology. Becker et al. (2022) conducted a study that found 75.7% of radiologists agreed that AI is advantageous, although some rejected its implementation. The outcome suggests a difference in acceptability, particularly in terms of its impact on clinical practice. Additionally, a study conducted by Zanardo et al. (2024) indicated that the workload of radiologists was influenced by AI in a variety of ways, with 4% experiencing a decrease, 48% experiencing an increase, and 46% experiencing no significant change in their workload. These results suggest that there are persistent uncertainties regarding the extent to which AI can effectively reduce job tasks or influence doctor-patient interactions.

The positive impact of AI applications has been established through many different types of medical imaging modalities. Although Magnetic Resonance Imaging (MRI) typically required long processing times, the utilization of Machine Learning (ML) has the potential to improve image quality and decrease acquisition time (Rahmania et al., 2024). The integration of AI with Virtual/Augmented Reality (VR/AR) has the potential to enhance data visualization and improve image analysis, thereby reducing the risk of inaccurate diagnosis (Najjar, 2023). Additionally, research conducted by Sun et al., (2025) in Beijing demonstrated that AI can expedite the detection of rib fractures in chest trauma cases, thereby enhancing diagnostic efficiency and minimizing the potential of medical errors and legal repercussions, such as malpractice litigation.

The clinical benefits of AI are increasingly evident, yet patient perspectives on its implementation remain limited. AI directly influences prognosis and treatment across emergency and non-emergency settings (Ongena et al., 2020). Within the Consumer Health Information Technology (CHIT) framework, patient acceptance depends on trust, efficiency, and being informed factors aligned with perceived usefulness and ease of use in the TAM model (Zhang et al., 2021). Trust reflects confidence in diagnostic accuracy and data security, requiring strong privacy and transparency safeguards. Efficiency refers to AI's ability to accelerate examinations and enhance image quality, as shown by Baghdadi et al. (2024) in stroke, trauma, and cancer cases, where AI reduced delays in diagnosis. Being informed captures patient expectations that AI can comprehensively detect diseases and predict future health risks (Clements et al., 2022; Glenning & Gualtieri, 2025; Miyosi, 2025).

Patients' involvement in the development of AI in radiology is crucial to ensure that the technology aligns with their needs and expectations. While some patients show readiness to adopt AI, others express concerns that highlight the need for better education and communication. However, little is known about how patients perceive and assess AI-based radiology services, especially in Indonesia, where empirical evidence on patient-centered AI adoption remains limited.

The growing use of AI in radiology raises important questions regarding how patients view its diagnostic role, what shapes their trust, and how these perceptions influence acceptance of AI-assisted services. Most existing studies focus on clinical or technical aspects, leaving a gap in understanding patients' attitudes and acceptance, particularly within the Indonesian healthcare context. To address this gap, this study examines patient attitudes toward AI in radiology, identifies key factors influencing trust and acceptance, and provides insights to support patient-centered and ethically responsible AI implementation. By exploring perceptions, trust determinants, and the roles of usefulness, efficiency, and transparency, this research aims to build a clearer foundation for effective and human-centered integration of AI in radiological practice.

LITERATURE REVIEW & HYPOTHESIS DEVELOPMENT

The Effect of Trust on Perceived Usefulness and Perceived Ease of Use

The adoption of Artificial Intelligence (AI) in radiology is rapidly growing to meet increasing medical imaging demands, yet it brings challenges for radiologists such as high workloads, diagnostic errors, and burnout, while AI is widely regarded as a decision-support tool that enhances, rather than replaces, diagnostic efficiency and accuracy (Najjar, 2023; Liu et al., 2024; Nensa, 2025). Acceptance varies regionally: only 33.5% of 1,427 radiologists in the ACR survey use AI and most rate its performance inconsistent, whereas the ESR survey showed just 13.3% acceptance, in contrast to more positive attitudes among Chinese radiology residents (Allen et al., 2021; Huisman et al., 2021; Chen et al., 2023). Technically, AI in radiology relies on conventional machine learning with radiologist-defined features and deep learning with automatic feature extraction, delivering benefits such as improved image quality, faster diagnosis, and reduced radiation exposure (Zhang et al., 2021; Cheng et al., 2021; Chauhan et al., 2022; Obuchowicz et al., 2025). The Technology Acceptance Model (TAM) provides the primary theoretical lens, emphasizing Perceived Usefulness (PU), the degree to which AI improves diagnostic accuracy, workflow efficiency, and workload reduction, and Perceived Ease of Use (PEOU), which stresses system transparency and user-friendliness (Zhang et al., 2021; Wicaksono, 2022; Kitts, 2023; Lee et al., 2025). Additional influencing factors include individual aspects (prior experience, openness) and system aspects (data security, reliability), while key barriers remain lack of trust, awareness, being informed, as well as concerns over efficiency, transparency, and data privacy, underscoring that successful AI adoption in radiology ultimately depends on technological capabilities combined with favourable patient and clinician perceptions, trust, efficiency, transparency, and adequate information provision (Ongena et al., 2020; Park et al., 2022; Eltawil et al., 2023; Nciki et al., 2025).

Trust is a pivotal determinant in the adoption of AI in radiology, as patients who perceive AI as reliable, accountable, and transparent are significantly more likely to view it as both useful (PU) and easy to use (PEOU), in line with the core constructs of TAM (Davis, 1989; Wicaksono, 2022; Johansson & Engström, 2024). Empirical evidence consistently supports this link: higher trust strongly correlates with greater perceived usability and benefit, patients' knowledge and risk–benefit assessments enhance trust and subsequently PU, while trust fundamentally shapes stakeholders' evaluation of AI's clinical advantages (Borondy Kitts, 2023; Bergquist et al., 2024; Alipanahzadeh et al., 2025). Trust also positively influences PEOU, with greater transparency in AI increasing trust and perceived ease of operation, and patient trust reinforcing confidence in using AI without technical difficulty (Moy et al., 2024; Glenning and Gualtieri, 2025; Shabankareh et al., 2025). Furthermore, effective human–AI collaboration improves efficiency and reduces workload, thereby boosting both PU and PEOU, whereas ethical and safety considerations strengthen trust and indirectly support perceptions of usability (Brady & Neri, 2020; Najjar, 2023; Chen et al., 2024).

H1: Trust has a significant effect on perceived usefulness.
H2: Trust has a significant effect on perceived ease of use.

The Effect of Efficiency on Perceived Usefulness and Perceived Ease of Use

Efficiency is a critical factor in the adoption of artificial intelligence (AI) in radiology, as it directly affects diagnostic accuracy, image quality, and the speed of analysis. High efficiency allows AI systems to process medical images rapidly while maintaining reliability, which in turn shapes patient perceptions of usefulness and ease of use. According to Haan et al. (2019) and Zhang et al. (2021), patients tend to perceive AI as more beneficial and user-friendly when the technology demonstrates fast, accurate, and consistent performance.

Efficiency enhances Perceived Usefulness (PU) by providing tangible benefits such as quicker diagnosis, reduced waiting times, and improved clinical outcomes. Studies by Chen et al. (2024) and Sun et al. (2025) highlight that AI-assisted radiology reduces radiologists' workload and accelerates image interpretation, leading patients and practitioners to recognize the practical advantages of AI systems. Similarly, Moy et al. (2024) and Glenning and Gualtieri (2025) report that patients associate high operational efficiency with higher confidence in the technology's utility, which reinforces the perception that AI is beneficial in healthcare delivery. Efficiency also impacts Perceived Ease of Use (PEOU). Systems that provide fast, accurate, and streamlined processes are perceived as easier to operate, requiring less effort from users to obtain meaningful outcomes (Haan et al., 2019; Zhang et al., 2021). The reduction of complexity and time in diagnostic procedures not only improves user experience but also strengthens patients' willingness to engage with AI technology.

H3: Efficiency has a significant effect on perceived usefulness.
H4: Efficiency has a significant effect on perceived ease of use.

The Effect of Being Informed on Perceived Usefulness and Perceived Ease of Use

Being informed about the capabilities, limitations, and functionality of Artificial Intelligence (AI) in radiology plays a crucial role in shaping patient perceptions of its usefulness and ease of use. Patients who receive comprehensive, clear, and accurate information are more likely to recognize the benefits of AI, including its predictive accuracy, diagnostic efficiency, and ability to support clinical decision-making (Baghdadi et al., 2024).

Studies indicate that knowledge positively influences perceived usefulness. When patients understand how AI can assist radiologists in analyzing images and improving diagnostic outcomes, they are more likely to perceive the technology as advantageous (Olayeye et al., 2025). Stroud et al. (2025) further highlight that transparent information about AI systems, including their capabilities and constraints, strengthens patients' confidence in the technology, reinforcing the perception that it adds meaningful value to healthcare delivery. Being informed also enhances Perceived Ease of Use (PEOU). Patients with a clear understanding of AI processes experience lower cognitive load and uncertainty, making interactions with AI systems feel more straightforward and accessible (Baghdadi et al., 2024; Olayeye et al., 2025). Providing guidance, explanations, or educational resources regarding AI functionality reduces apprehension and technical barriers, thereby increasing willingness to engage with AI technologies in clinical settings (Ongena et al., 2020; Stroud et al., 2025).

H5: Being informed has a significant effect on perceived usefulness.
H6: Being informed has a significant effect on perceived ease of use.

The Effect of Perceived Usefulness and Perceived Ease of Use on Intention to Use

Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) are central constructs in the Technology Acceptance Model (TAM), influencing users' intention to adopt new technologies (Davis, 1989; Wicaksono, 2022). In the context of AI-based radiology, patients are more likely to accept and intend to use AI systems when they perceive these systems as both beneficial and user-friendly (Johansson & Engström, 2024; Moy et al., 2024). Perceived usefulness refers to the degree to which a patient believes that using AI improves healthcare outcomes, such as diagnostic accuracy, speed of image interpretation, and overall clinical decision-making efficiency. Studies show that when patients recognize these benefits, their intention to use AI significantly increases (Alipanahzadeh et al., 2025). For example, Chen et al. (2024) and Sun et al. (2025) highlight that AI-assisted radiology reduces radiologists' workload and enhances diagnostic efficiency, which patients perceive as valuable, thereby strengthening their willingness to engage with the technology.

Perceived ease of use, on the other hand, reflects the extent to which patients believe that AI systems are simple and straightforward to interact with. Higher PEOU reduces cognitive effort and technical barriers, increasing user confidence and the likelihood of adoption (Borondy Kitts, 2023; Moy et al., 2024). When patients perceive AI as intuitive and accessible, they are more motivated to use it, even if they initially have limited experience with such technology. Studies by Ongena et al. (2020) and Baghdadi et al. (2024) further emphasize that clear interfaces and user guidance enhance PEOU, thereby supporting patients' intention to adopt AI-based radiology tools.

H7: Perceived usefulness has a significant effect on intention to use AI in radiology.
H8: Perceived ease of use has a significant effect on intention to use AI in radiology.

The Moderating Effect of Transparency and Data Security and Privacy

Transparency and data security are essential contextual factors influencing the acceptance of AI in radiology. From a theoretical standpoint, the extended Technology Acceptance Model (TAM) and trust-based technology frameworks posit that transparency and security shape how users transform trust into behavioral intention. Transparency in the decision-making processes, data sources, and evaluation mechanisms of AI is essential for improving trust and influencing the intention to use (Hemphill et al., 2023). When patients are informed about how AI analyzes radiological data and generates diagnostic outputs, they perceive greater accountability and reliability, which strengthen the link between trust and intention to use AI (Brady & Neri, 2020; Kitts, 2023).

Empirical studies further confirm that AI transparency significantly influences trust in healthcare applications (Shabankareh et al., 2025). A critical concern in the implementation of AI is the protection of patient personal information. Trust and intention to use are both enhanced by having an awareness of safety regarding data security and privacy (Hasani et al., 2022; Kitts, 2023). Transparency and data protection not only represent ethical imperatives but also serve as moderating mechanisms. High transparency and strong privacy assurance amplify the effect of trust on patients' intention to use AI, whereas low levels of either factor may weaken this relationship. Therefore, this study proposes that transparency and data security moderate the influence of trust on the intention to use AI in radiology.

H9: Transparency moderates the influence of trust on the intention to use AI in radiology.
H10: Data security and privacy moderate the influence of trust on the intention to use AI in radiology.

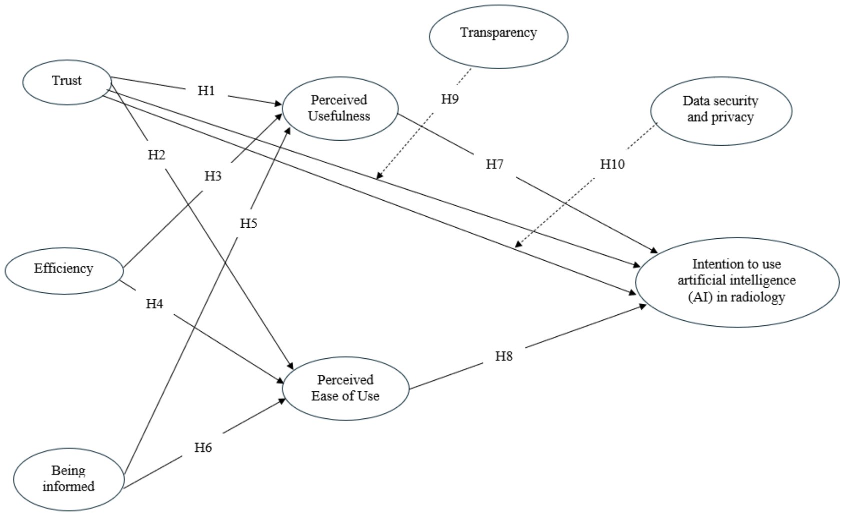

Figure 1. Conceptual Framework

Figure 1 illustrates ten research hypotheses that will be empirically validated with data from patients who participate in AI-based radiology diagnostic procedures at Indriati Solo Baru Hospital. Three independent variables represent the conceptual framework: trust, efficiency, and being informed. Furthermore, the intention to use AI in radiology will be predicted by two moderating variables, namely transparency and data security and privacy.

RESEARCH METHODS

This research used a cross-sectional survey design and a quantitative approach to analyze the factors that influence patient acceptance of AI in radiology. This design is appropriate when researchers need to test complicated relationships, including moderation effects, as it is able to measure latent constructs. As a consequence, the use of the quantitative approach guarantees that this study will be objective and will be able to make a statistical generalization from the sample to the population.

The sample was chosen through purposive sampling based on the following criteria: participants must be 18–65 years old, have no communication disorders, and be willing to participate. The research population consisted of patients who participated in AI-based MRI examinations at Indriati Solo Baru Hospital. The G*Power® software power analysis was employed to determine the minimum sample size, which was 153 respondents. A structured questionnaire was employed to collect primary data, which was based on a Likert scale with five points that was adapted from previous studies (Bougie & Sekaran, 2016; Subhaktiyasa, 2024). The variables of the study consisted of three independent variables: trust, efficiency, and being informed; two moderating variables: transparency and data security and privacy; and one dependent variable: intention to use AI in radiology.

Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS software version 4.1.1.4 was employed to test the measurement and structural models, and Importance-Performance Map Analysis (IPMA) was employed to enhance the interpretation of the results (Sarstedt et al., 2023; Ringle, 2024). PLS-SEM was chosen over the covariance-based SEM because it is appropriate for predictive and explorative analysis in complex models with moderators that are analyzed using small to medium sample sizes. The procedure we present is robust to non-normal sampling distributions and emphasizes the maximization of explained variance (R^2) of endogenous constructs. The instrument's reliability and validity were evaluated using indicator reliability, Cronbach's alpha, composite reliability, and Average Variance Extracted (AVE) (Hair et al., 2022).

RESULTS

Table 1 presents the demographic characteristics of the respondents, including gender, age, education, and occupation, which provide an overview of the sample composition used in examining patients' intention to use AI in radiology.

Table 1. Demographic Data

Demographic Respondents	Characteristic	Total (n)	Percentage (%)
Gender	Male	80	52.3
	Female	73	47.7
Age	18-25 years	31	20.3
	26-35 years	54	35.3
	36-45 years	44	28.8
	46-55 years	13	8.5
	56-65 years	11	7.2
Education	Senior high school	18	11.8
	Diploma	25	16.3
	Bachelor's degree	75	49
	Master's degree	35	22.9
Occupation	Corporate employee	55	35.9
	Government employee	42	27.5
	Self employed	30	19.6
	Retired	13	8.5
	Housewife	13	8.5

Table 1 presents the demographic data from 153 respondents. The majority of respondents were aged 26-35 years (35.3%) and were male (52.3%). The highest education level was mostly a bachelor's degree (49%), and the majority of respondents were corporate employees (35.9%).

Table 2. Reliability and Validity Test

Variable	Indicator	Outer Loadings	Cronbach's Alpha	Composite Reliability (rho_a)	Composite Reliability (rho_c)	Average Variance Extracted (AVE)
Trust	T1	0.821	0.897	0.912	0.928	0.763
	T2	0.899				
	T3	0.920				
	T4	0.852				
Efficiency	E1	0.866	0.883	0.892	0.928	0.811
	E2	0.907				
	E3	0.928				
Being Informed	BI1	0.932	0.843	0.844	0.927	0.865
	BI2	0.928				
Transparency	TR1	0.863	0.838	0.854	0.902	0.754
	TR2	0.890				
	TR3	0.852				
Data Security and Privacy	DSP1	0.918	0.933	0.957	0.952	0.831
	DSP2	0.936				
	DSP3	0.885				
	DSP4	0.907				
Perceived Usefulness	PU1	0.920	0.812	0.812	0.914	0.842
	PU2	0.915				
Perceived Ease of Use	PEOU1	0.900	0.901	0.902	0.938	0.835
	PEOU2	0.935				
	PEOU3	0.907				
Intention to Use AI in Radiology	ITUAI1	0.834	0.790	0.791	0.877	0.705
	ITUAI2	0.876				
	ITUAI3	0.807				

The first step in PLS-SEM analysis is to evaluate the reliability of the indicators in the outer model by analyzing outer loadings. The instrument test results indicate that all indicators have a loading value greater than 0.708, which indicates they are all valid (Hair et al., 2019). The second step involves an analysis of internal consistency. Based on Table 2, A construct is considered reliable if the Cronbach's alpha value exceeds 0.7 and the composite reliability ranges within the range of 0.7-0.95 (Hair et al., 2022). Thereafter, the convergent validity is evaluated using the Average Variance Extracted (AVE). Table 2 indicates that all constructs have an AVE of 0.50 or greater, indicating that they are capable of explaining at least 50% of the variance in their indicators, thereby obtaining the convergent validity requirement (Sarstedt et al., 2022).

Table 3. HTMT Ratio Test

Variable	T	E	BI	PU	PEOU	ITUAI	TR	T	TRP X T
Efficiency	0.753								
Being Informed	0.637	0.770							
Perceived Usefulness	0.724	0.773	0.743						
Perceived Ease of Use	0.687	0.747	0.719	0.660					
Intention to Use AI in Radiology	0.684	0.705	0.628	0.791	0.782				
Transparency	0.143	0.315	0.263	0.348	0.343	0.485			
Data Security and Privacy	0.172	0.49	0.261	0.211	0.377	0.417	0.284		
Transparency x Trust	0.076	0.116	0.162	0.097	0.085	0.132	0.114	0.020	
Data Security and Privacy x Trust	0.072	0.048	0.147	0.099	0.024	0.034	0.025	0.066	0.463

The Heterotrait-Monotrait (HTMT) ratio is used to analyze discriminant validity in the final step of the outer model analysis. A construct is considered valid if its HTMT value is less than 0.90 (Henseler et al., 2015; Sarstedt et al., 2022). According to Table 3, the discriminant validity has been satisfied, as all HTMT values are below the threshold. Consequently, this research has established the accuracy and reliability of all indicators in measuring their respective constructs.

Table 4. Hypothesis Test

Hypothesis	Standard Deviation	T-Statistics	P-Values	Result
Trust → Perceived Usefulness	0.112	2.522	0.006	Supported
Trust → Perceived Ease of Use	0.092	2.901	0.002	Supported
Efficiency → Perceived Usefulness	0.117	2.532	0.006	Supported
Efficiency → Perceived Ease of Use	0.082	3.653	0.000	Supported
Being informed → Perceived Usefulness	0.093	2.760	0.003	Supported
Being informed → Perceived Ease of Use	0.088	3.159	0.001	Supported
Perceived usefulness → Intention to Use Artificial Intelligence in Radiology	0.084	3.267	0.001	Supported
Perceived ease of use → Intention to Use Artificial Intelligence in Radiology	0.080	3.097	0.001	Supported
Transparency x Trust → Intention to Use Artificial Intelligence in Radiology	0.042	2.776	0.003	Supported
Data security and privacy x Trust → Intention to Use Artificial Intelligence in Radiology	0.042	2.281	0.011	Supported

According to the inner model analysis in Table 4, conducted using the bootstrapping method, all structural paths in this study exhibited a p-value < 0.05, indicating that all hypotheses were accepted. The variables trust, efficiency, and being informed have been proven to have a positive and significant impact on perceived usefulness and perceived ease of use. Perceived ease of use and perceived usefulness also had a positive impact on the intention to use AI in radiology. The results of the moderation tests indicated that the influence of trust on intent to use was enhanced by transparency, data security, and privacy. The results of this research establish that all constructs in the research model make a substantial contribution, both directly and moderating roles.

Table 5. Performance and Importance Assessment Results

Indicator	Importance	Performance	Variable	Importance	Performance
T1	0.077	70.752	Trust	0.349	69.634
T2	0.098	70.098			
T3	0.114	70.098			
T4	0.108	67.647			
E1	0.053	62.527	Efficiency	0.156	68.199
E2	0.056	69.935			
E3	0.063	72.059			
BI1	0.076	62.745	Being Informed	0.139	63.753
BI2	0.074	64.706			
PU1	0.152	71.078	Perceived Usefulness	0.275	70.584
PU2	0.148	70.098			
PEOU1	0.088	75.000	Perceived Ease of Use	0.247	75.304
PEOU2	0.093	76.797			
PEOU3	0.089	74.020			
TR1	-0.081	58.170	Transparency	-0.214	55.190
TR2	-0.095	58.388			
TR3	-0.070	47.712			
DSP1	0.049	67.102	Data Security and Privacy	0.147	65.312
DSP2	0.045	66.449			
DSP3	0.037	63.834			
DSP4	0.031	62.092			
Mean	0.057	66.728	Mean	0.157	66.853

Table 5 presents the IPMA results for the Intention to Use AI in Radiology construct, which indicate an average importance value of 0.157 and a performance value of 66.853. At the indicator level, the average importance value is 0.057, and the performance value is 66.728. Four quadrants are formed by vertical and horizontal lines that represent these two values, facilitating the identification of variables and indicators that are performing well and those that require development. The quadrant's position of each variable and indicator can be used to inform recommendations for enhancing the factors that influence AI use in radiology from a patient perspective, as well as to assist management in determining implementation priorities and performance improvement strategies.

In Figure 2, the IPMA analysis shows that the indicators T1, T2, T3, T4, E3, PU1, PU2, PEOU1, PEOU2, and PEOU3 are categorized as high importance–high performance in the upper-right quadrant. PU1 records the highest importance value at 0.152. According to TAM theory, which emphasizes perceived usefulness as the primary predictor of technology acceptance, this value reflects patients' confidence that AI improves image quality and thereby enhances diagnostic accuracy. The performance value of 76.797 for PEOU2 further indicates that the user-friendliness of AI substantially increases examination efficiency and diagnostic precision. Meanwhile, the indicators BI1 and BI2 are positioned in the lower-right quadrant, categorized as high importance–low performance. This suggests that while patients acknowledge AI's potential to predict future disease and support comprehensive examinations, its current performance in these areas remains limited. These findings highlight a strategic opportunity to build greater patient trust and strengthen acceptance by improving AI's predictive and comprehensive analytical capabilities.

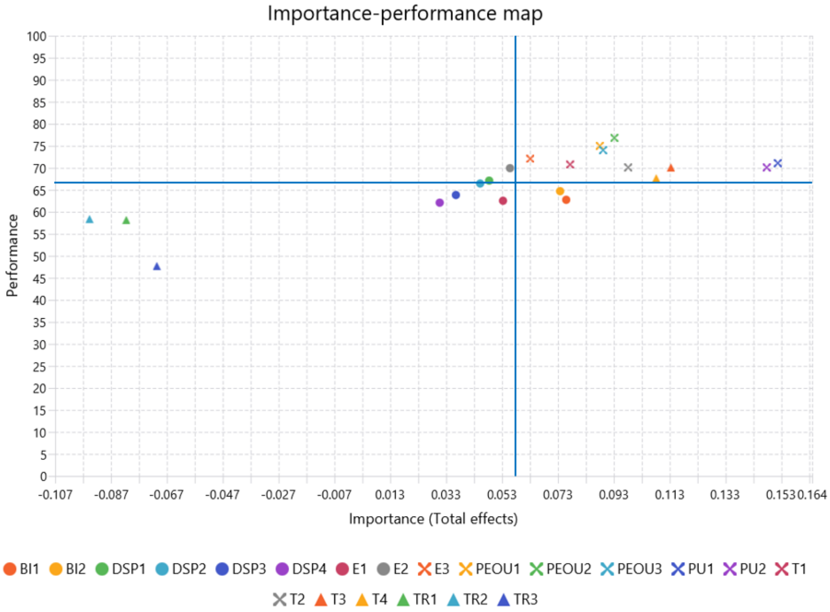

Figure 2. IPMA Indicator

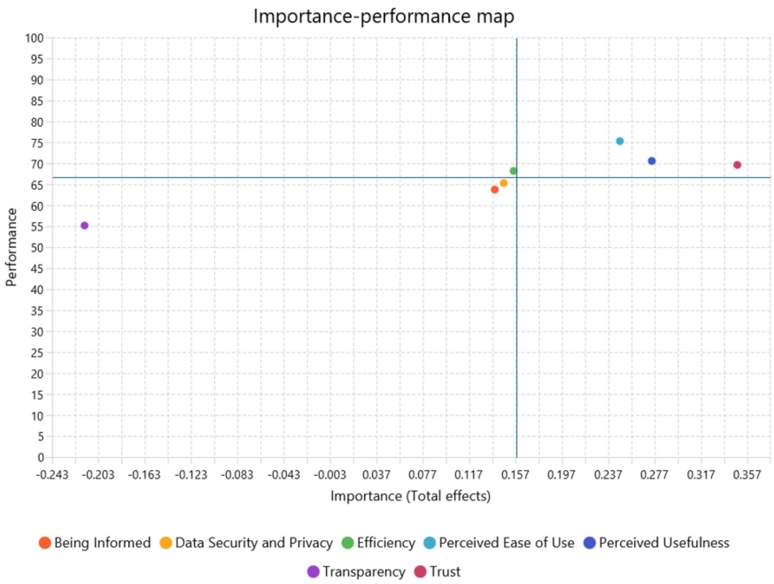

Figure 3. IPMA Construct

In Figure 3, the IPMA analysis categorizes trust, perceived usefulness, and perceived ease of use as high importance–high performance variables. This indicates that patients regard these factors as significant, perceive them as effective, and consider them highly influential in their intention to use AI in radiology examinations. In contrast, transparency, data security, and privacy, and being informed fall into the low importance–low performance category, suggesting that patients assign them relatively low priority. This trend likely reflects patients' limited understanding of the importance of transparency, data protection, and privacy, alongside their stronger emphasis on efficiency, accuracy, and user-friendliness. To strengthen the perception and significance of these variables, it is essential to provide more comprehensive education highlighting the risks and benefits of AI while also improving transparency, security, and data privacy.

DISCUSSION

Demographic analysis indicates that most respondents were male (52.3%) and aged 26–35 years (35.3%), suggesting that younger individuals are generally more receptive to AI in radiology due to its perceived efficiency and accuracy (Glenning & Gualtieri, 2025). Older patients, however, tend to prioritize accountability and trust. Gender differences were also observed: males exhibited higher trust in AI as a diagnostic support tool, while females were more sceptical, fearing potential replacement of human expertise (Young et al., 2021). Most respondents held a bachelor's degree (49%) and worked as corporate employees (35.9%), consistent with prior research indicating that higher education promotes acceptance of new technologies, including AI-based radiology systems (Miró Catalina et al., 2023; Busch et al., 2025).

Trust was found to play a critical role in shaping both perceived usefulness and perceived ease of use. Patients who trust AI perceive it as more beneficial and user-friendly, as they view it as an assistive rather than substitutive tool for radiologists (Kitts, 2023). This aligns with Bergquist et al. (2024), who emphasize that reliable AI enhances efficiency and accelerates diagnostic processes. Conversely, concerns regarding transparency and accuracy reduce perceptions of AI's benefits (Baghdadi et al., 2024; Glenning & Gualtieri, 2025; Suhara, 2025). These findings support H1 and H2 and underscore the importance of open communication, patient education, and robust data security to foster trust.

Efficiency significantly influenced PU and PEOU. Respondents agreed that AI improves diagnostic accuracy and patient comfort by reducing examination times, minimizing waiting periods, and producing higher-quality images (Eman & Alanazi, 2023; Mahedi et al., 2024). High perceived efficiency reduces technical complexity and enhances satisfaction, reinforcing the theoretical foundation of TAM (Davis, 1989; Toker et al., 2025). Therefore, H3 and H4 are supported, indicating that efficient AI-driven procedures increase both perceived benefits and usability.

Being informed also positively affects PU and PEOU. Patients who received clear, comprehensive information about AI's diagnostic functions, predictive capabilities, and clinical benefits evaluated the technology more favorably (Zhang et al., 2021). Awareness allows patients to recognize AI as a tool that assists medical professionals and improves service efficiency. Transparent communication regarding AI's performance fosters understanding and comfort, aligning with findings from Baghdadi et al. (2024). These results support H5 and H6, highlighting the importance of education and information provision.

PU and PEOU directly influenced patients' intention to use AI. Recognition of tangible benefits, such as improved accuracy, faster procedures, and higher service quality, increased willingness to adopt AI (Ongena et al., 2020; Baghdadi et al., 2024). Ease of use further enhances trust by improving both workflow and patient experience (Chen et al., 2023; Zhang et al., 2021). Transparency, data security, and privacy protections reinforced trust and intention to use AI (Budiherwanto, 2025; Alipanahzadeh et al., 2025; Yadav et al., 2023). Clear explanations of AI processes reduce the "black box" perception, while strong data protection ensures ethical handling of patient information, demonstrating that secure and transparent systems significantly strengthen adoption. These findings confirm H7 and H8 and validate the applicability of TAM in healthcare technology adoption (Davis, 1989; Zhang et al., 2021).

Additionally, H9 and H10 are supported, highlighting the moderating role of trust. Transparency positively influences patients' intention to use AI when trust is high, and similarly, strong data security and privacy measures enhance intention under high trust. These findings align with Alipanahzadeh et al. (2025) and Yadav et al. (2023), who emphasized that transparent communication and robust data protection strengthen confidence and willingness to adopt AI. Clear explanations of AI processes help reduce the "black box" perception, while secure management of personal and medical data ensures ethical compliance and fosters adoption. Theoretically, this study reinforces TAM's relevance in radiology, while emphasizing trust, efficiency, and being informed as critical antecedents of PU and PEOU. Practically, the results suggest strategies for patient education, system transparency, and robust data governance to facilitate AI adoption. Positive perceptions of usefulness, ease of use, trust, efficiency, and informed awareness collectively support broader implementation of AI in clinical radiology.

CONCLUSION

The findings reveal that the application of the Technology Acceptance Model (TAM) to AI utilization in radiology deepens the understanding of determinants influencing patient acceptance. The results demonstrate that patients' intention to adopt AI in radiology is positively shaped by trust, efficiency, and being informed through their impact on perceived usefulness and ease of use. In addition, moderating variables such as transparency, data security, and privacy amplify the effect of trust on patients' willingness to use AI. This study underscores the importance of ethical and legal frameworks, as well as transparent communication, in fostering patient confidence toward AI-based radiology services. Consequently, the research not only validates TAM's applicability among active technology users but also expands its scope to encompass patients as passive users, an area that remains underexplored in existing literature.

This research has limitations, despite its theoretical and practical contributions. The results were limited in generalizability, and longitudinal analysis of patient perceptions was not possible due to the cross-sectional design implemented in a single hospital. Additionally, the measurements of the moderating variables were exclusively dependent on patient perceptions, without any verification of institutional policies or relevant legal regulations. Hence, future studies are recommended to adopt longitudinal or mixed-method designs, include analyses of relevant policies and regulations, and engage a broader range of healthcare institutions across diverse regions to strengthen the validity of results. Such an approach would contribute to a deeper and more contextual understanding of patient acceptance, thereby supporting the safe, effective, and patient-oriented integration of AI in radiology.

REFERENCES

[1] Alipanahzadeh, H., Eikefjord, E., Korbmacher, M., & Alipanahzadeh, H. (2025). *Exploring the impact of patients' risk-benefit and knowledge perceptions on trust and intention to use AI based medical imaging tools in radiology*. Retrieved in May 20, 2025 from https://ssrn.com/abstract=5266350

[2] Allen, B., Agarwal, S., Coombs, L., Wald, C., & Dreyer, K. (2021). 2020 ACR data science institute artificial intelligence survey. *Journal of the American College of Radiology*, *18*(8), 1153–1159.

[3] Baghdadi, L. R., Mobeirek, A. A., Alhudaithi, D. R., Albenmousa, F. A., Alhadlaq, L. S., Alaql, M. S., & Alhamlan, S. A. (2024). Patients' attitudes toward the use of artificial intelligence as a diagnostic tool in radiology in Saudi Arabia: Cross-sectional study. *JMIR Human Factors, 11*(1), 5310-2322.

[4] Becker, C. D., Kotter, E., Fournier, L., & Martí-Bonmatí, L. (2022). Current practical experience with artificial intelligence in clinical radiology: A survey of the European Society of Radiology. *Insights into Imaging*, *13*(1), 107-120.

[5] Bergquist, M., Rolandsson, B., Gryska, E., Laesser, M., Hoefling, N., Heckemann, R., Schneiderman, J. F., & Björkman-Burtscher, I. M. (2024). Trust and stakeholder perspectives on the implementation of AI tools in clinical radiology. *European Radiology*, *34*(1), 338–347.

[6] Brady, A. P., & Neri, E. (2020). Artificial intelligence in radiology-ethical considerations. *Diagnostics*, *10*(4), 231-243.

[7] Budiherwanto, I. (2025). The influence of artificial intelligence and the technology acceptance model on sustainable financial governance. *Jurnal Ilmiah Manajemen Kesatuan*, *13*(3), 1791–1802.

[8] Busch, F., Hoffmann, L., Xu, L., Zhang, L. J., Hu, B., García-Juárez, I., ... & Zhang, S. (2025). Multinational attitudes toward AI in health care and diagnostics among hospital patients. *JAMA Network Open*, *8*(6), 4452-4452.

[9] Chauhan, D., Anyanwu, E., Goes, J., Besser, S. A., Anand, S., Madduri, R., Getty, N., Kelle, S., Kawaji, K., Mor-Avi, V., & Patel, A. R. (2022). Comparison of machine learning and deep learning for view identification from cardiac magnetic resonance images. *Clinical Imaging*, *82*(1), 121–126.

[10] Chen, M., Wang, Y., Wang, Q., Shi, J., Wang, H., Ye, Z., Xue, P., & Qiao, Y. (2024). Impact of human and artificial intelligence collaboration on workload reduction in medical image interpretation. *Npj Digital Medicine*, *7*(1), 349-360.

[11] Chen, Y., Wu, Z., Wang, P., Xie, L., Yan, M., Jiang, M., Yang, Z., Zheng, J., Zhang, J., & Zhu, J. (2023). Radiology residents' perceptions of artificial intelligence: Nationwide cross-sectional survey study. *Journal of Medical Internet Research*, *25*(1), 123-133.

[12] Cheng, P. M., Montagnon, E., Yamashita, R., Pan, I., Cadrin-Chênevert, A., Romero, F. P., Chartrand, G., Kadoury, S., & Tang, A. (2021). Deep learning: An update for radiologists. *Radiographics*, *41*(5), 1427–1445.

[13] Clements, W., Thong, L. P., Zia, A., Moriarty, H. K., & Goh, G. S. (2022). A prospective study assessing patient perception of the use of artificial intelligence in radiology. *Asia Pacific Journal of Health Management*, *17*(1), 861-875.

[14] Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly: Management Information Systems*, *13*(3), 319–339.

[15] Eltawil, F. A., Atalla, M., Boulos, E., Amirabadi, A., & Tyrrell, P. N. (2023). Analyzing barriers and enablers for the acceptance of artificial intelligence innovations into radiology practice: a scoping review. *Tomography*, *9*(4), 1443-1455.

[16] Eman, N., & Alanazi, A. T. (2023). Imaging in healthcare: A glance at the present and a glimpse into the future. *Cureus*, *15*(3), 1-13.

[17] Glenning, J., & Gualtieri, L. (2025). Patient perspectives on artificial intelligence in medical imaging. *Journal of Participatory Medicine*, *17*(1), 61-76.

[18] Haan, M., Ongena, Y. P., Hommes, S., Kwee, T. C., & Yakar, D. (2019). A qualitative study to understand patient perspective on the use of artificial intelligence in radiology. *Journal of the American College of Radiology*, *16*(10), 1416–1419.

[19] Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European business review*, *31*(1), 2-24.

[20] Hair, J. F., Tomas, G., Hult, M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM).* New York: SAGE Publications, Inc.

[21] Hasani, N., Morris, M. A., Rhamim, A., Summers, R. M., Jones, E., Siegel, E., & Saboury, B. (2022). Trustworthy artificial intelligence in medical imaging. *PET Clinics, 17*(1), 1-12.

[22] Hemphill, S., Jackson, K., Bradley, S., & Bhartia, B. (2023). The implementation of artificial intelligence in radiology: a narrative review of patient perspectives. *Future Healthcare Journal*, *10*(1), 63–68.

[23] Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135.

[24] Huisman, M., Ranschaert, E., Parker, W., Mastrodicasa, D., Koci, M., Pinto De Santos, D., Coppola, F., Morozov, S., Zins, M., Bohyn, C., Koç, U., Wu, J., Veean, S., Fleischmann, D., Leiner, T., & Willemink, M. J. (2021). An international survey on AI in radiology in 1,041 radiologists and radiology residents part 1: fear of replacement, knowledge, and attitude. *Eur Radiol*, *31*(9), 7058–7066.

[25] Johansson, J. V., & Engström, E. (2024). 'Humans think outside the pixels' – radiologists' perceptions of using artificial intelligence for breast cancer detection in mammography screening in a clinical setting. *Health Informatics Journal*, *30*(3), 1-12.

[26] Kitts, A. B. (2023). Patient perspectives on artificial intelligence in radiology. *Journal of the American College of Radiology*, *20*(9), 863-867.

[27] Krishna, NK, R., Anupama, R. S., & Shivaraj, K. (2025). Artificial Intelligence in Radiology: Augmentation, Not Replacement. *Cureus*, *17*(6), 1760-1770.

[28] Lee, A. T., Ramasamy, R. K., & Subbarao, A. (2025). Understanding psychosocial barriers to healthcare technology adoption: A review of TAM technology acceptance model and unified theory of acceptance and use of technology and UTAUT frameworks. *Healthcare (Basel)*, *13*(3), 250-261.

[29] Liu, H., Ding, N., Li, X., Chen, Y., Sun, H., Huang, Y., Liu, C., Ye, P., Jin, Z., Bao, H., & Xue, H. (2024). Artificial intelligence and radiologist burnout. *JAMA Network Open*, *7*(11), 48-60.

[30] Mahedi, R. A., Iqbal, H., Azmee, R., Azmee, M., Jakir, F., Nishan, M. A., Uddin, M. B., & Afrin, S. (2024). Current trends and future prospects of artificial intelligence in transforming radiology. *Journal of Current Health Sciences*, *4*(2), 95–104.

[31] Miró Catalina, Q., Femenia, J., Fuster-Casanovas, A., Marin-Gomez, F. X., Escalé-Besa, A., Solé-Casals, J., & Vidal-Alaball, J. (2023). Knowledge and perception of the Use of AI and its implementation in the field of radiology: Cross-sectional study. *Journal of Medical Internet Research*, *25*(1), 728-740.

[32] Miyosi, N. (2025). Use of AI in diagnostic imaging and future prospects. *JMA Journal*, *8*(1), 198–203.

[33] Moy, S., Irannejad, M., Jeanneret Manning, S., Farahani, M., Ahmed, Y., Gao, E., Prabhune, R., Lorenz, S., Mirza, R., & Klinger, C. (2024). Patient perspectives on the Use of artificial intelligence in health care: A scoping review. *Journal of Patient-Centered Research and Reviews*, *11*(1), 51–62.

[34] Najjar, R. (2023). Redefining radiology: A review of artificial intelligence integration in medical imaging. *Diagnostics*, *13*(17), 72-84.

[35] Nciki, A. I., Hlabangana, L. T., & Nciki, A. (2025). Perceptions and attitudes towards AI among trainee and qualified radiologists at selected South African training hospitals. *SA Journal of Radiology*, *29*(1), 41-55.

[36] Nensa, F. (2025). The future of radiology: The path towards multimodal AI and superdiagnostics. *European Journal of Radiology Artificial Intelligence*, *2*(1), 14-25.

[37] Obuchowicz, R., Lasek, J., Wodziński, M., Piórkowski, A., Strzelecki, M., & Nurzynska, K. (2025). Artificial intelligence-empowered radiology, current status and critical review. *Diagnostics*, *15*(3), 282-293.

[38] Olayeye, K., Owens-Charles, C. R., Choudhari, J., Parikh, E., & Liang, Z. J. (2025). Future perspectives in radiology: Artificial intelligence for responsible imaging (AIRI). *Cureus*, 32(1), 1-12.

[39] Ongena, Y. P., Haan, M., Yakar, D., & Kwee, T. C. (2020). Patients' views on the implementation of artificial intelligence in radiology: development and validation of a standardized questionnaire. *European Radiology*, *30*(2), 1033–1040.

[40] Park, I., Kim, D., Moon, J., Kim, S., Kang, Y., & Bae, S. (2022). Searching for new technology acceptance model under social context: Analyzing the determinants of acceptance of intelligent information technology in digital transformation and implications for the requisites of digital sustainability. *Sustainability (Switzerland)*, *14*(1), 579-590.

[41] Rahmania, S., Tandibali, H., & Putri, E. R. (2024). Aplikasi klinis AI dalam treatment planning radioterapi untuk brain tumor. *Progressive Physics Journal*, *5*(2), 458–468.

[42] Ringle, C. M., Wende, S., & Becker, J. M. (2022). *SmartPLS 4. Oststeinbek: SmartPLS*. Retrieved in June 30, 2025, from https://www.smartpls.com/

[43] Sarstedt, M., Hair, J. F., & Ringle, C. M. (2023). "PLS-SEM: indeed a silver bullet"–retrospective observations and recent advances. *Journal of Marketing Theory and Practice*, *31*(3), 261–275.

[44] Sarstedt, M., Hair, J. F., Pick, M., Liengaard, B. D., Radomir, L., & Ringle, C. M. (2022). Progress in partial least squares structural equation modeling use in marketing research in the last decade. *Psychology and Marketing*, *39*(5), 1035–1064.

[45] Sarstedt, M., Radomir, L., Moisescu, O. I., & Ringle, C. M. (2022). Latent class analysis in PLS-SEM: A review and recommendations for future applications. *Journal of Business Research*, *138*(1), 398–407.

[46] Sekaran, U., & Bougie, R. (2016). *Research methods for business: A skill building approach*. New Jersey: John Wiley & Sons.

[47] Shabankareh, M., Khamoushi Sahne, S. S., Nazarian, A., & Foroudi, P. (2025). The impact of AI perceived transparency on trust in AI recommendations in healthcare applications. *Asia-Pacific Journal of Business Administration*, 2(3), 1-13.

[48] Stroud, A. M., Minteer, S. A., Zhu, X., Ridgeway, J. L., Miller, J. E., & Barry, B. A. (2025). Patient information needs for transparent and trustworthy cardiovascular artificial intelligence: A qualitative study. *PLOS Digital Health*, *4*(4), 1-13.

[49] Subhaktiyasa, P. G. (2024). Menentukan populasi dan sampel: Pendekatan metodologi penelitian kuantitatif dan kualitatif. *Jurnal Ilmiah Profesi Pendidikan*, *9*(4), 2721–2731.

[50] Suhara, A. (2025). Human capital strategies to address artificial intelligence challenges in the contemporary work environment. *Jurnal Ilmiah Manajemen Kesatuan*, *13*(5), 3793–3802.

[51] Sun, L., Fan, Y., Shi, S., Sun, M., Ma, Y., Zhang, K., Zhang, F., Liu, H., Yu, T., Tong, H., & Yang, X. (2025). AI-assisted radiologists vs standard double reading for rib fracture detection on CT images: A real-world clinical study. *PLoS ONE*, *20*(1), 6732-6844.

[52] Thaariq, M. A., Baskara, M. D. M., Chaniago, R. A., Christin, D., & Ernawati, I. (2024). Systematic literature review: Analisis penerapan kecerdasan buatan dalam bidang kesehatan. *Prosiding Seminar Nasional Mahasiswa Bidang Ilmu Komputer dan Aplikasinya, 5*(1), 168-173.

[53] Toker, I., Jansen, S., & Lorenz, D. (2025). Impact of standardized reporting systems on patient experience in radiology. *Journal of Patient Experience*, *12*(1), 1-13.

[54] Trenggono, P. H., & Bachtiar, A. (2023). Peran artificial intelligence dalam pelayanan kesehatan: A systematic review. *Jurnal Ners Universitas Pahlawan*, *1*(1), 451-462.

[55] Wicaksono, R. (2022). *Teori dasar technology acceptance model*. Sidoarjo: CV. Seribu Bintang.

[56] Yadav, N., Pandey, S., Gupta, A., Dudani, P., Gupta, S., & Rangarajan, K. (2023). Data privacy in healthcare: In the era of artificial intelligence. *Indian Dermatology Online Journal*, *14*(6), 788–792.

[57] Young, A. T., Amara, D., Bhattacharya, A., & Wei, M. L. (2021). Patient and general public attitudes towards clinical artificial intelligence: a mixed methods systematic review. *The Lancet Digital Health*, *3*(9), 599-611.

[58] Zanardo, M., Visser, J. J., Colarieti, A., Cuocolo, R., Klontzas, M. E., Pinto dos Santos, D., & Sardanelli, F. (2024). Impact of AI on radiology: a EuroAIM/EuSoMII 2024 survey among members of the European society of radiology. *Insights into Imaging*, *15*(1), 18-30.

[59] Zhang, Z., Citardi, D., Wang, D., Genc, Y., Shan, J., & Fan, X. (2021). Patients' perceptions of using artificial intelligence (AI)-based technology to comprehend radiology imaging data. *Health Informatics Journal*, *27*(2), 11-21.