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An analysis of the unified theory of acceptance and use of technology (UTAUT) to the adoption of electronic medical records in hospital settings

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ABSTRACT: Electronic Medical Records (EMRs) are increasingly recognized as vital tools for enhancing the efficiency, accuracy, and quality of healthcare delivery. Despite regulatory mandates in Indonesia, the adoption of EMRs remains uneven, particularly in rural healthcare settings. This study applied the Unified Theory of Acceptance and apply of Technology (UTAUT) to investigate the behavioral intention of healthcare professionals working in private hospitals to use electronic medical records. A quantitative, cross-sectional design was implemented involving 90 participants selected through purposive sampling in an Indonesian hospital. The study's data were gathered between October 2024 and January 2025 using a validated 18-item UTAUT-based questionnaire. Data analysis was conducted with SPSS and SmartPLS software. Results indicated that all four UTAUT construct – Performance Expectancy (β = 0.200, p = 0.016), Effort Expectancy (β = 0.353, $p < 0.001$), Social Influence (β = 0.291, $p < 0.001$), and Facilitating Conditions (β = 0.262, p = 0.008 – had statistically significant positive effects on Behavioral Intention. The model demonstrated moderate explanatory power (R^2 = 0.655) and strong predictive relevance (Q^2 = 0.512). These results validate the UTAUT model's suitability in this context and provide practical insights for strengthening EMR implementation strategies. Future research should consider longitudinal approaches and multi-site comparisons to enhance generalizability and policy relevance.

KEYWORDS: Behavioral intention; electronic medical records; hospital pharmacy; pharmacy informatics; UTAUT.

INTRODUCTION

Digital technology's growing incorporation into healthcare systems has revolutionized the management of administrative and clinical procedures [1]. Electronic Medical Records (EMRs) represent a core component of this digital transformation, thereby enabling efficient documentation, retrieval, and sharing of patient health information across various care settings. EMRs have been shown to help improve care coordination, enhance decision-making, and reduce medical errors compared to the traditional paper-based records [2]. Many countries have been accelerating the EMR adoption, as reflected in the Third Global Survey on electronic health by the United Nation's World Health Organization (WHO), which reported that 46% of member states had implemented national EMR systems by 2015 [3]. In Indonesia, regulatory frameworks such as Ministry of Health Regulation No. 18/2022 mandate the implementation of integrated health information systems to improve service quality and continuity of care [4].

Despite these policy efforts, the adoption of EMRs in several developing countries, including Indonesia, remains challenging [5]. Healthcare institutions face a combination of infrastructural and organizational barriers, e.g., inadequate digital infrastructure, limited technical support, poor data interoperability, and user resistance [6]. Moreover, concerns regarding patient privacy and data security further complicate EMR implementation, notably in settings with weak governance frameworks [7]. Crucially, the success of EMR

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adoption depends on the behavioral intention of healthcare providers – individuals who ultimately determine whether such technologies are accepted and meaningfully used in clinical practice.

To understand and predict user acceptance, the Unified Theory of Acceptance and Use of Technology (UTAUT) has emerged as a robust model. Originally developed by Venkatesh et al. (2003), UTAUT incorporates components from eight previous models and asserts that users' intention and behavior (BI) about technology use are directly influenced by Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) [8]. Numerous health informatics scenarios have validated this approach [9], including research on the use of EMRs in various settings.

The UTAUT framework was selected for this study because it provides a more comprehensive and integrative approach compared to other acceptance models such as the Technology Acceptance Model (TAM), the Technology–Organization–Environment (TOE) framework, and the Human–Organization–Technology Fit (HOT-Fit) model. Unlike TAM, which primarily focuses on perceived usefulness and ease of use, UTAUT encompasses additional sociotechnical factors—namely social influence and facilitating conditions—that are highly relevant in hospital settings where hierarchical culture and resource constraints shape technology adoption. Compared with TOE, which emphasizes organizational readiness and external pressures, UTAUT directly captures user-level behavioral intentions that determine actual system utilization [10]. Moreover, unlike HOT-Fit, which concentrates on post-implementation evaluation, UTAUT is explicitly designed to predict pre-adoption behavior and user acceptance dynamics. These multidimensional advantages make UTAUT particularly suitable for examining the behavioral intentions of healthcare professionals in developing-country contexts, where social norms, institutional support, and perceived effort strongly influence the success of electronic medical record adoption.

However, research applying UTAUT to EMR adoption in Indonesian hospitals remains scarce, notably quantitative studies implementing structural equation modeling (SEM-PLS) to measure behavioral intention. Most local researches focus on descriptive analyses or simpler models like the Technology Acceptance Model (TAM), often ignoring cultural and infrastructural variables unique to developing nations [11]. In order to close this gap, this study uses the UTAUT framework and SmartPLS analysis to investigate behavioral aspects influencing EMR use at PKU Muhammadiyah Gamping Hospital, a rural hospital in the Special Region of Yogyakarta. With a validated questionnaire and a robust sample of 90 healthcare professionals, the study mainly aims to evaluate the impact of the PE, EE, FC, and SI components on behavioral intention to use EMRs.

▪ MATERIALS AND METHODS

Study design and participants

This study used an observational, quantitative, cross-sectional design to investigate behavioral intention toward EMR usage among healthcare professionals, guided by the UTAUT method. Cross-sectional approach, which is appropriate for testing theoretical models in organizational behavior research, was selected to capture the perceptions of healthcare professionals at one particular moment in time [12]. Practically, the research was conducted at the PKU Muhammadiyah Gamping Hospital, a prominent secondary care facility located in Sleman Regency, Special Region of Yogyakarta, Indonesia. It was selected due to its ongoing implementation of EMR systems and the diversity of healthcare professionals involved in the digital documentation. The data collection period spanned from October 2024 to January 2025, ensuring sufficient time to engage with all the participants from different departments and shifts.

The study's participants included all clinical and nonclinical healthcare professionals who were actively utilizing the hospital's EMR system. Using a 95% confidence level and a 10% margin of error, the Lemeshow-Lwanga method was used to calculate the sample size, which is suitable for populations of unknown or huge sizes [13]. This computation indicated that a minimum sample size of 78 individuals was needed, and a final sample of 90 participants was chosen to boost statistical power and take potential non-response into consideration. A purposive sampling technique was applied, targeting healthcare personnel with at least one year of experience using the EMR system, ensuring familiarity with the technology and its implementation challenges. Inclusion criteria were: (1) healthcare professionals (e.g., physicians, nurses, pharmacists, medical record officers) who had used the EMR for at least one year at PKU Muhammadiyah Gamping Hospital, and (2) those who provided informed consent. Exclusion criteria included incomplete questionnaire responses and withdrawal from participation before data collection was completed.

Research instruments

A structured questionnaire based on the UTAUT paradigm, which was first created for this study, was used to gather data [8]. The instrument included 18 items, covering four independent variables – PE, EE, SI, and FC – as well as the dependent variable, BI. This questionnaire was adapted from the validated versions in existing studies and then translated into Bahasa Indonesia using the forward-backward translation method to ensure cultural and linguistic appropriateness [14]. Each construct was further measured using items rated on a 5-point Likert scale, with 1 denoting "strongly disagree" and 5 denoting "strongly agree". This scale's ease of use and dependability in assessing attitudinal dimensions have led to its widespread use in health IT adoption studies [15].

Prior to data collection, instrument validity was tested using Pearson correlation, items with a correlation coefficient (r) higher than the threshold at $p<0.05$ considered valid. Furthermore, Cronbach's Alpha [16] was used to evaluate internal consistency dependability; an α of 0.60 or higher was considered appropriate for exploratory research. The pilot test involved 20 respondents from a different but comparable healthcare facility.

Data collection and analysis

The data collection process involved three methods: (1) structured questionnaires, which served as the primary data source; (2) direct observations, where the researcher observed how EMRs were used in clinical settings to understand contextual factors; and (3) brief semi-structured interviews, conducted informally to clarify participant responses or gather additional insight on system usage and user challenges. Both SPSS version 26 and SmartPLS version 4 were used to enter and analyze the collected data. Descriptive statistics, including frequencies, percentages, and measures of central tendency, were performed using SPSS to characterize the respondents' demographic traits.

Meanwhile, the study used SmartPLS to implement the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach for inferential analysis. This method is suitable for predictive modeling and theory development, particularly when the data distribution assumptions are not met and the sample size is moderate [17]. The inner model evaluation included several components, including: (a) R^2 (Coefficient of Determination) was used to assess how well the independent variables explain variance in the dependent variable. The corresponding values of 0.67, 0.33, and 0.19 were deemed significant, moderate, and weak; (b) The blindfolding process was used to calculate Q-square (Predictive Relevance), which measures the predictive ability of the model. Q^2 values above zero represents meaningful predictive relevance; and (c) The significance of the proposed correlations between constructs was tested using path coefficients and bootstrapping (5,000 resamples). At a 95% confidence level, a path was deemed statistically significant if the t-statistics were greater than 1.96 and the p-values were less than 0.05. This analysis approach aligns with standards recommended for theory-driven studies in healthcare technology adoption [18].

Ethical approvals

This research was approved ethically by the Research and Training Division of PKU Muhammadiyah Gamping Hospital, as documented in Ethical Clearance Letter No. 188/KEP-PKU/X/2024.

▪ RESULTS

Respondent characteristics

The study involved 90 healthcare professionals working at PKU Muhammadiyah Gamping Hospital who had used the EMR system for at least one year. The demographic profile was evaluated to describe the distribution of participants based on age, gender, professional role, and years of experience. Analysis of age distribution, as shown in Table 1, revealed that the greatest percentage of those surveyed (57.8%) were between the ages of 31 and 40, then those between the ages of 21 and 30 (38.9%), and a small fraction (3.3%) above 40 years. This demographic spread reflects a relatively young workforce, a main factor that may contribute to greater adaptability toward digital technologies, as suggested by prior studies indicating that younger employees are more likely to adopt health information systems. Regarding gender, the sample was predominantly female, with 68.9% (n= 62) of respondents identifying as women and the remaining 31.1% (n=

28) as men. This aligns with national trends in Indonesian healthcare institutions, where nursing and allied health professions are often female-dominated.

Table 1. Respondent characteristics (n = 90).

Variable	Category	N (%)
Age	21–30 years-old	35 (38.9)
	31–40 years-old	52 (57.8)
	>40 years-old	3 (3.3)
Gender	Male	28 (31.1)
	Female	62 (68.9)
Profession	Nurse	70 (77.8)
	Physician	2 (2.2)
	Midwife	1 (1.1)
	Pharmacist	9 (10.0)
	Medical Record Staff	8 (8.9)
Years of Service	1–8 years	49 (54.5)
	9–16 years	38 (42.2)
	> 16 years	3 (3.3)

With respect to professional roles, the majority of the study participants were nurses (77.8%), followed by pharmacists (10%), medical record officers (8.9%), physicians (2.2%), and midwives (1.1%). The dominance of nursing staff in the sample reflects their central role in daily patient data documentation using EMR systems. The inclusion of a range of professions ensures the study captures diverse user experiences across clinical and administrative functions. Regarding work experience, over half of the participants (54.5%) had worked in hospitals for one to eight years, while 42.2% had worked for 9–16 years, and a smaller group (3.3%) had more than 17 years of experience. These data suggest a mature workforce that has had sufficient time to become familiar with institutional workflows, including EMR systems.

Validity and reliability

Prior to conducting a full-scale analysis, the study instruments' concept validity and internal consistency reliability were thoroughly evaluated. Using Pearson correlation tests, all 18 questionnaire items demonstrated correlation coefficients (r-values) exceeding the critical threshold value of 0.444 at a 5% significance level, indicating good item validity. These study findings confirm that each item was appropriately correlated with its construct, guaranteeing precise depiction of the intended theoretical ideas. The questionnaire validity results for this study are shown in Table 2 below.

Table 2. Results of this study's validity questionnaire.

Constructs	Item	R-values	R-table	Description
Performance expectancy	PE1	0.967	0.444	Valid
	PE2	0.933		
	PE3	0.915		
	PE4	0.967		
Effort expectancy	EE1	0.795	0.444	Valid
	EE2	0.874		
	EE3	0.791		
	EE4	0.625		
Social influence	SI 1	0.873	0.444	Valid
	SI 2	0.85		
	SI 3	0.837		
Facilitating condition	FC 1	0.511	0.444	Valid
	FC 2	0.516		
	FC 3	0.857		
	FC 4	0.824		
Behavioral intention	BI 1	0.845	0.444	Valid
	BI 2	0.828		
	BI 3	0.756		

Cronbach's Alpha values were determined for each UTAUT model construct in order to assess reliability. The following were the outcomes: PE (0.96), EE (0.763), SI (0.762), FC (0.634), and BI (0.705). All these values surpassed the commonly accepted threshold of 0.60 for exploratory research, indicating high internal consistency across all these constructs.

R-square and Q-square

Prior to assessing the structural relationships, the measurement model was examined to ensure the reliability and validity of the latent constructs. All factor loadings exceeded the recommended threshold of 0.70, confirming indicator reliability. Internal consistency was supported as composite reliability (CR) values ranged from 0.78 to 0.94, exceeding the 0.70 benchmark. Convergent validity was verified through average variance extracted (AVE) values above 0.50 for all constructs, indicating that the indicators sufficiently explained their latent variables. Discriminant validity was established using both the Fornell–Larcker criterion and the Heterotrait–Monotrait ratio (HTMT), where the square root of each construct's AVE was higher than its correlations with other constructs and HTMT values remained below 0.85. These findings confirmed that the measurement model met the reliability and validity criteria, allowing subsequent interpretation of the structural model results, including path coefficients, R^2, and Q^2 values.

To evaluate the explanatory capacity and predictive significance of the structural model (inner model), as illustrated in figure 1, R-squared (R^2) and Q-squared (Q^2) values were calculated. Behavioral Intention's (BI) R^2 score was 0.655, which, according to Chin's (1998) categorization, indicates a moderate model fit (R^2 between 0.33 and 0.67) [19]. It suggests that the combination of all constructs accounts for 65.5% of BI variance, an acceptable result for studies examining human behavior in health informatics.

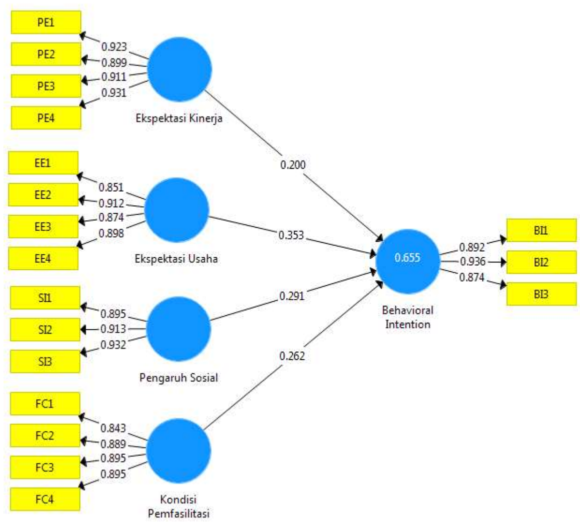

Figure 1. Structural model of the study.

In addition to R^2, Figure 2 illustrates how the predictive significance of the model was evaluated using Q-square (Q^2). The Q^2 value for BI was 0.512, which exceeds the threshold of 0.35 and is considered substantial, demonstrating the high out-of-sample predictive significance of the model . A $Q^2 > 0$ confirms that the model accurately predicts the endogenous construct beyond mere chance. These metrics support the UTAUT model's applicability in this situation by indicating that the structural model not only explains a sizable amount of the variance in the dependent variable but also has predictive power.

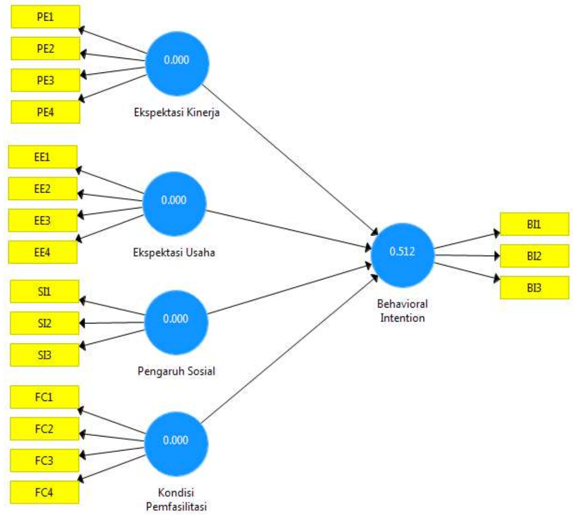

Figure 2. Predictive relevance of the study.

Hypothesis testing

The study evaluated the relationships between the four UTAUT predictors and Behavioral Intention (BI) through bootstrapping analysis (5.000 samples) using SmartPLS 4.0. Using path coefficients (β), t-statistics, and p-values, each proposed path was examined for statistical significance; significance was established at $p < 0.05$ and $t > 1.96$. As shown in Figure 3, first of all, the hypothesis tested the influence of PE on BI. There was a significant positive relationship, as indicated by the path coefficient of $\beta = 0.200$, t-statistic of 2.411, and p-value of 0.016. It confirms the notion that healthcare professionals are more likely to use EMRs if they think the systems enhance productivity and job satisfaction, which is in line with previous research [8].

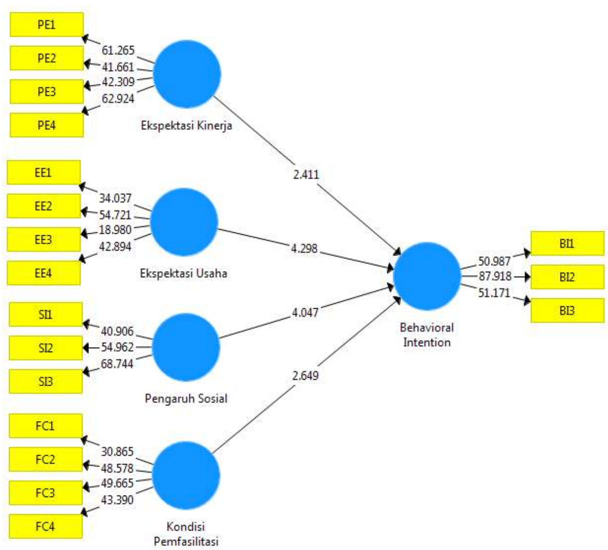

Figure 3. Hypothesis test.

The results of the second hypothesis' evaluation of EE showed a highly significant effect with a $\beta = 0.353$, a t-statistic of 4.298, and a p-value < 0.001. This implies that EMR acceptance is significantly influenced by perceived simplicity of use, a pattern also seen in recent health technology deployments in Indonesia and other developing nations [20]. Additionally, BI was statistically significantly impacted by the SI components ($\beta = 0.291$, $t = 4.047$, and $p < 0.001$). The results imply that peer behavior, management encouragement, and cultural norms within the hospital environment have a significant impact on how people intend to use EMRs. Similar outcomes have been found in healthcare contexts where social expectation aspects strongly influence technology adoption [21]. Meanwhile, the final hypothesis tested the influence of FC on BI. With $\beta = 0.262$, t

= 2.649, and p = 0.008, the result was statistically significant, indicating that adequate technical infrastructure and support services positively influence intentions of the EMR adoption. It highlights the importance of institutional readiness and system availability in stimulating sustainable EMR usage, in line with previous systematic review study. Table 3 represents the results of each construct of UTAUT to the BI.

Table 3. The results of UTAUT constructs to the BI.

Variabel	Real sample (O)	T-statistic (|O/STDEV|)	P-Values
PE → BI	0.200	2.411	0.016
EE → BI	0.353	4.298	0.000
SI → BI	0.291	4.047	0.000
FC → BI	0.262	2.649	0.008

Of all the study findings above, all these hypotheses were supported, showing that the UTAUT model is effective in explaining the behavioral intention to use EMRs among healthcare staff in this setting. These findings provide robust empirical evidence for targeted strategies aimed at enhancing EMR acceptance and integration in similar healthcare institutions.

▪ DISCUSSION

Principal findings

This study investigated the behavioral intention to use EMRs among healthcare professionals at the PKU Muhammadiyah Gamping Hospital, Special Region of Yogyakarta, Indonesia, through the perspective of the UTAUT. The results showed that behavioral intention was significantly predicted by all four UTAUT elements such as: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Condition (FC), confirming the model's suitability for use in healthcare informatics.

The behavioral intention characteristics were first shown to be significantly positively impacted by the PE. This research shows that healthcare personnel are more likely to embrace and utilize the electronic system when they believe it will help them perform better on the job. It is consistent with the argument that perceived usefulness plays a key role in technology acceptance, especially in time-sensitive environments like hospitals [22]. According to earlier research, medical personnel are more inclined to use electronic medical records (EMRs) if they think they can increase productivity and patient safety [23], [24]. In the meantime, the best indicator of behavioral intention was the EE. This supports the idea that system usability is a key factor in acceptance. Systems perceived as user-friendly reduce cognitive load and resistance, thus promoting quicker learning and integration into routine tasks [25]. According to the TAM, attitudes toward usage are largely shaped by perceived ease of use, especially in settings with limited resources where digital literacy can vary greatly [26].

Additionally, SI significantly impacted behavioral intention. Peer support, supervisors, and institutional culture was found to encourage EMR adoption. This aligns with prior findings that social norms, especially in hierarchical healthcare environments, can substantially influence technology use behavior [27],[28], [29]. Social modeling and peer advocacy have been shown to reduce fear of new technologies and build user confidence. Lastly, FC significantly influenced behavioral intention. Respondents who perceived that the hospital had adequate infrastructure, e.g., reliable internet, supportive IT personnel, and functional hardware, were more willing to engage with the EMR system. These results highlight the significance of operational readiness with technical support in sustaining EMR usage, echoing literature that emphasizes the role of institutional support in post-implementation success [30], [31].

In comparison with previous studies, The findings align with the initial UTAUT paradigm put forth by Venkatesh et al. [32], which has been widely validated in healthcare contexts [33]. Multiple studies from Indonesia and other low-and middle-income countries (LMICs) confirm the model's predictive strength in health technology adoption, particularly in EMR and telemedicine contexts [34],[35]. The consistent significance of all four UTAUT predictors affirms the robustness of the model across diverse healthcare settings. Moreover, the strong influence of EE and SI found in this study reflects the operational realities of LMICs, where training gaps and hierarchical organizational structures are prevalent. Similar patterns were reported by Razak et al. [36] and D'Exelle et al. [37], highlighting the critical role of contextual adaptation when implementing health IT solutions in developing countries.

Strenghts and limitations of the study

This study's methodological rigor is a key strength. Using SmartPLS to apply structural equation modeling offered robust statistical validation, while the adapted and validated questionnaire ensured cultural relevance [38]. The sample size of 90 healthcare professionals, though modest, exceeded the minimum threshold for SEM and included diverse clinical roles, enhancing generalizability within the hospital setting. This study does have certain drawbacks, though. Initially, it used a cross-sectional design, which made it more difficult to determine causal linkages. Second, self-reported measures were used for data collection, which could add bias because of social desirability or misinterpretation of questionnaire items. Third, the study was confined to a single hospital, limiting external validity across different healthcare systems or regions. Future longitudinal or multi-site studies could address these limitations.

Impacts of the study

This study has several practical and theoretical implications. From a practical standpoint, the results can inform hospital administrators and policymakers in Indonesia and similar settings to focus on usability, peer influence, and infrastructure when designing EMR implementation strategies. Training programs should prioritize user-friendly system interfaces and ensure continuous technical support, particularly for users less familiar with digital systems [39]. From a theoretical perspective, the study supports the usefulness of UTAUT in health informatics and offers empirical data from a rural Indonesian context, which is not well examined in the literature. It also adds nuance to the role of social and infrastructural variables, offering a more grounded perspective for future adaptation of the UTAUT model in LMIC contexts.

Suggestions for future

Longitudinal designs should be explored in future studies to evaluate how behavioral intention and actual EMR usage evolve over time. Incorporating objective usage data from system logs could validate self-reported behavior [40]. Additionally, extending the study to multiple hospitals or incorporating comparative designs between urban and rural settings would enhance generalizability and offer deeper insight into contextual factors influencing technology adoption. Researchers may also integrate moderating variables such as age, gender, and digital literacy—factors that may mediate the strength of UTAUT relationships in different user groups [32]. Lastly, qualitative approaches, such as focus group discussions or ethnographic studies, could uncover deeper cultural and organizational dynamics affecting EMR adoption.

▪ CONCLUSION

This study demonstrates that the UTAUT model is applicable in elucidating the behavioral intention of healthcare professionals to implement Electronic Medical Records (EMRs) in rural Indonesian hospital settings. Every construct has the potential to have a major impact on intention to use, including performance expectancy, effort expectancy, social influence, and facilitating conditions. The best predictor was Effort Expectancy, which emphasizes the necessity of user-friendly systems and sufficient guidance. The findings offer empirical insights to inform health IT policies, particularly in low-resource contexts. Future research should explore longitudinal effects, multi-site comparisons, and cultural moderators to deepen understanding of EMR adoption across diverse healthcare environments.

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