Technical Readiness and Facilitating Conditions Drive Electronic Medical Record Use Beyond Performance Expectations and Social Influence

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ABSTRACT
The acceleration of digital transformation in Indonesia's health sector mandates the implementation of Electronic Medical Records (EMR) integrated with the SATUSEHAT platform. However, variations in healthcare workers' readiness and acceptance remain a major barrier, particularly in outpatient units. This study aimed to analyze factors influencing behavioral intention and actual use of EMR based on the Unified Theory of Acceptance and Use of Technology (UTAUT). A quantitative explanatory survey with a cross-sectional design was conducted among 207 healthcare workers selected through proportionate stratified random sampling from a population of 438 outpatient staff across five type-C hospitals in Lumajang Regency. Data were collected using a Likert-scale questionnaire and analyzed using Structural Equation Modeling–Partial Least Squares (SEM-PLS). The UTAUT constructs included performance expectancy, effort expectancy, social influence, and facilitating conditions, with age and experience as moderating variables. Effort expectancy and facilitating conditions significantly influenced both behavioral intention and EMR use, either directly or indirectly through intention. In contrast, performance expectancy and social influence showed no significant effects. Moderation analysis revealed that age weakened the effect of social influence on intention, while experience reduced the effect of facilitating conditions on usage behavior. The model explained 65.5% of the variance in intention and 37.8% in usage behavior. In conclusion, technical readiness and operational support play a more critical role in EMR adoption than perceived performance benefits or social influence. Strengthening infrastructure and user training is essential to support successful digital transformation in hospitals.
Keywords: electronic medical records; behavioral intention; usage behavior

INTRODUCTION
The rapid advancement of information technology as a consequence of the industrial revolution 4.0 has significantly transformed various sectors, including healthcare. This transformation is characterized by the increasing adoption of digital systems to support more effective, efficient, and integrated healthcare services. In response, the Indonesian government has accelerated digital health transformation through the implementation of Electronic Medical Records (EMR) across healthcare facilities. EMR refers to a digital system that records patients' medical data, including identity, clinical examinations, diagnoses, treatments, and follow-up care. The implementation of EMR is expected to improve work efficiency among healthcare providers, streamline service delivery processes, reduce documentation errors, and enhance the quality of clinical decision-making based on accurate and comprehensive data [1]. Furthermore, EMR facilitates better coordination among healthcare professionals and enables real-time data exchange across services.

As a regulatory foundation, the Ministry of Health of the Republic of Indonesia issued Regulation Number 24 of 2022 concerning Medical Records, mandating all healthcare facilities, both primary and secondary levels, to implement EMR integrated with the national SATUSEHAT platform. This policy aims to achieve national health data interoperability, ensuring that patient information can be accessed seamlessly across healthcare facilities while maintaining data security and confidentiality. This regulation is further reinforced by Circular Letter HK.02.01/MENKES/1030/2023, which stipulates a deadline for full EMR implementation by the end of 2024, accompanied by administrative sanctions for non-compliant facilities [1]. These policies reflect the government's strong commitment to digitalizing the healthcare system and improving service quality through standardized and data-driven approaches.

At the national level, EMR implementation has shown substantial progress. By early 2025, 3,142 out of 3,285 hospitals in Indonesia (96.53%) had been registered in the SATUSEHAT platform, with 3,039 hospitals actively submitting data. Regionally, East Java Province has also demonstrated high connectivity, with approximately 94.25% of hospitals integrated into the system [2]. Despite these achievements, high connectivity does not necessarily indicate optimal system utilization. In Lumajang Regency, although most hospitals have adopted EMR applications, several challenges persist. These include limited availability of computer devices in service units, incomplete implementation of electronic signatures, and server management practices that do not fully meet data security standards [3–5].

In addition to technical barriers, human resource factors also pose significant challenges. Not all healthcare workers possess adequate digital literacy or adaptability to new systems, particularly those with limited prior exposure to information technology. Insufficient training programs and limited managerial support further contribute to suboptimal EMR utilization. These conditions suggest that while infrastructure and connectivity have largely been achieved, the effective use of EMR remains suboptimal. Therefore, it is essential to identify key factors influencing successful EMR implementation, particularly from the perspective of end users who directly interact with the system.

The success of EMR implementation is not solely determined by technological availability but is also highly dependent on user acceptance and behavior. The Unified Theory of Acceptance and Use of Technology (UTAUT) is one of the most widely used models to explain technology adoption. This model proposes that behavioral intention and actual use are influenced by several key constructs, namely performance expectancy, effort expectancy, social influence, and facilitating conditions. Previous studies have demonstrated that these factors are significantly associated with the adoption of health information systems; however, findings vary depending on organizational context, user characteristics, and infrastructure readiness.

In the context of hospitals in Lumajang Regency, studies examining the acceptance and use of EMR remain limited. This is critical, as the success of EMR implementation largely depends on the readiness, perceptions, and attitudes of healthcare workers as primary users. Without adequate user acceptance, even well-developed systems may not be utilized effectively. Therefore, this study aims to analyze factors influencing behavioral intention and usage behavior of EMR in hospitals in Lumajang Regency using the UTAUT model, in order to provide a more comprehensive understanding to support successful digital transformation in the healthcare sector.

METHODS

This study employed a quantitative approach using an explanatory survey design with a cross-sectional design [6-9]. The research was conducted in five type-C hospitals located in Lumajang Regency, Indonesia, during the period of March to April 2025. The study population consisted of 438 healthcare workers assigned to outpatient units, including physicians, nurses, midwives, pharmacists, medical laboratory analysts, physiotherapists, medical record officers, and other supporting staff. A total of 207 respondents were selected as the study sample using the Isaac and Michael formula with a 5% margin of error. The sampling technique applied was proportionate stratified random sampling to ensure representation across different professional groups. Inclusion criteria comprised healthcare staff who were willing to participate, actively working in outpatient units of hospitals in Lumajang Regency, had independently used the electronic medical record (EMR) system, had access to input data, and had performed at least one EMR data entry. Exclusion criteria included staff who had never independently used the EMR system and respondents who submitted incomplete questionnaires.

The study variables were constructed based on the UTAUT framework [10-12]. Independent variables included performance expectancy, effort expectancy, social influence, and facilitating conditions. Behavioral intention was treated as an intervening variable, while use behavior served as the dependent variable. Additionally, gender, age, experience, and voluntariness of use were included as moderating variables. Data were collected using a structured questionnaire based on UTAUT indicators, measured on a Likert scale to capture respondents' perceptions and attitudes toward EMR usage. Each construct was operationalized through multiple items reflecting its theoretical dimensions.

Data analysis was conducted in two stages. First, descriptive analysis was performed to summarize respondent characteristics and variable distributions [13-15]. Second, inferential analysis was carried out using Structural Equation Modeling–Partial Least Squares (SEM-PLS) to examine the relationships between variables, including direct effects, indirect effects through the intervening variable, and moderating effects. The analysis also evaluated the measurement model (validity and reliability) and the structural model (path coefficients and explained variance).

RESULTS

This study involved 192 healthcare workers from outpatient units in hospitals in Lumajang Regency who had experience using EMR, representing a response rate of 92.75% from the initially targeted 207 respondents. A total of 15 questionnaires were excluded from analysis due to ineligibility, duplication, refusal to participate, or incomplete responses. This reduction did not substantially affect the robustness of the study, as the margin of error only increased slightly from ±4.95% to ±5.31%, which remains within the acceptable range (±5%–10%). The characteristics of respondents analyzed included gender, age, educational level, and work experience.

Table 1. Distribution of gender, age group, educational level, and work experience of healthcare workers from outpatient units in hospitals in Lumajang Regency

Demographic characteristics	Category	Frequency	Percentage
Gender	Male	71	36.98
	Female	121	63.02
Age	< 25 years	17	8.85
	25–35 years	91	47.40
	36–45 years	50	26.04
	> 45 years	34	17.71
Education	Senior high school	2	1.04
	Diploma	81	42.19
	Bachelor (S1)	60	31.25
	Master (S2)	32	16.67
	Residency (PPDS)	17	8.85
Work experience	< 1 year	16	8.33
	1–3 years	38	19.79
	4–6 years	33	17.19
	> 6 years	105	54.69

Table 2. The R^2 and Q^2 values

Variable	R^2	Adjusted R^2	SSO	SSE	Q^2 (1-SSE/SSO)
Behavioral intention	0.655	0.617	576	346.916	0.398
Use behavior	0.378	0.371	576	454.780	0.210

Table 3. Thes effect size (f^2)

Latent variable relationship	f^2	Interpretation
Performance expectancy → behavioral intention	0.0050	Not significant
Effort expectancy → behavioral intention	0.1020	Small
Social influence → behavioral intention	0.0210	Small
Facilitating condition → behavioral intention	0.0910	Small
Facilitating condition → use behavior	0.0790	Small
Behavioral intention → use behavior	0.1300	Small
Gender → behavioral intention	0.0000	Not significant
Age → behavioral intention	0.0380	Small
Experience → behavioral intention	0.0630	Small
Voluntariness of use → behavioral intention	0.0000	Not significant
Gender x performance expectancy → behavioral intention	0.0200	Small
Age x performance expectancy → behavioral intention	0.0060	Not significant
Gender x effort expectancy → behavioral intention	0.0210	Small
Age x effort expectancy → behavioral intention	0.0090	Not significant
Experience x effort expectancy → behavioral intention	0.0050	Not significant
Gender x social influence → behavioral intention	0.0010	Not significant
Age x social influence → behavioral intention	0.0290	Small
Experience x social influence → behavioral intention	0.0160	Not significant
Voluntariness of use x social influence → behavioral intention	0.0010	Not significant
Age x facilitating condition → behavioral intention	0.0070	Not significant
Experience x facilitating condition → behavioral intention	0.0270	Small

Table 1 shows that the majority of respondents were under 40 years old (82.29%), indicating a predominantly productive-age workforce, with females accounting for 63.02%. In terms of educational background, most respondents held Diploma and Bachelor (S1) degrees (73.44%), reflecting an adequate level of formal education to support professional competencies. Additionally, more than half of the respondents had over six years of work experience (54.69%), suggesting substantial professional maturity. These findings indicate that respondents possess strong potential to support the implementation and optimization of EMR systems in hospital settings.

Prior to hypothesis testing, the structural model was evaluated using R^2, Q^2, and f^2 values to assess explanatory power, predictive relevance, and effect size of exogenous variables on endogenous constructs. Table 2 indicates that behavioral intention has an R^2 value of 0.655 (Adjusted R^2 = 0.617), meaning that 61.7% of its variance is explained by exogenous variables. Meanwhile, use behavior has an R^2 value of 0.378 (Adjusted R^2 = 0.371), indicating that 37.1% of its variance is explained through the model. Overall, the model demonstrates moderate explanatory power. The Q^2 values for behavioral intention (0.398) and use behavior (0.210) are both greater than zero, indicating that the model has adequate predictive relevance. Behavioral intention demonstrates strong predictive capability, whereas use behavior falls within the weak-to-moderate category. Effect size analysis indicates that effort expectancy (X2) and facilitating condition (X4), although categorized as having small effects, remain important determinants of behavioral intention (I). Behavioral intention itself shows a relatively stronger effect in influencing use behavior (Y), suggesting its central mediating role. In contrast, performance expectancy (X1), social influence (X3), and most moderating variables demonstrate negligible or non-significant contributions.

Table 4 presents the coefficients for each causal path between the variables, whereas Table 5 outlines the indirect effects among the variables.

Table 4. The path coefficients (the results of hypothesis testing)

Variable	O	M	StDev	t-statistics	p-value	Interpretation
Performance expectancy → behavioral intention	0.077	0.091	0.097	0.793	0.428	Not significant
Effort expectancy → behavioral intention	0.360	0.339	0.102	3.529	0.000	Significant
Social influence → behavioral intention	0.126	0.138	0.077	1.623	0.105	Not significant
Facilitating condition → behavioral intention	0.249	0.254	0.080	3.097	0.002	Significant
Facilitating condition → use behavior	0.296	0.300	0.088	3.373	0.001	Significant
Behavioral intention → use behavior	0.378	0.381	0.095	3.993	0.000	Significant
Gender → behavioral intention	-0.011	-0.019	0.052	0.209	0.835	Not significant
Gender x effort expectancy → behavioral intention	0.158	0.153	0.099	1.593	0.111	Not significant
Gender x performance expectancy → behavioral intention	-0.156	-0.149	0.096	1.625	0.104	Not significant
Gender x social influence → behavioral intention	-0.028	-0.025	0.064	0.440	0.660	Not significant
Age → behavioral intention	0.124	0.115	0.053	2.330	0.020	Significant
Age x social influence → behavioral intention	-0.144	-0.131	0.075	1.926	0.054	Significant
Age x facilitating condition → behavioral intention	-0.062	-0.056	0.069	0.897	0.370	Not significant
Age x performance expectancy → behavioral intention	0.099	0.104	0.103	0.961	0.337	Not significant
Age x effort expectancy → behavioral intention	0.106	0.087	0.105	1.009	0.313	Not significant
Experience → behavioral intention	0.175	0.179	0.061	2.861	0.004	Significant
Experience x social influence → behavioral intention	-0.105	-0.104	0.068	1.544	0.123	Not significant
Experience x effort expectancy → behavioral intention	0.070	0.047	0.095	0.743	0.458	Not significant
Experience x facilitating condition → behavioral intention	-0.113	-0.105	0.067	1.702	0.089	Significant
Voluntariness of use → behavioral intention	-0.004	0.005	0.054	0.075	0.940	Not significant
Voluntariness of use x social influence → behavioral intention	0.017	0.015	0.058	0.294	0.769	Not significant

Table 6. The indirect effects

Variable	O	M	StDev	t-statistics	p-value	Interpretation
Performance expectancy → behavioral intention → use behavior	0.029	0.035	0.040	0.737	0.461	Not significant
Effort expectancy → behavioral intention → use behavior	0.136	0.128	0.049	2.790	0.005	Significant
Social influence → behavioral intention → use behavior	0.048	0.054	0.035	1.369	0.171	Not significant
Facilitating condition → behavioral intention → use behavior	0.094	0.094	0.034	2.807	0.005	Significant
Gender → behavioral intention → use behavior	-0.004	-0.007	0.021	0.200	0.841	Not significant
Gender x effort expectancy → behavioral intention → use behavior	0.060	0.057	0.040	1.484	0.138	Not significant
Gender x performance expectancy → behavioral intention → use behavior	-0.059	-0.056	0.039	1.496	0.135	Not significant
Gender x social influence → behavioral intention → use behavior	-0.011	-0.010	0.025	0.419	0.675	Not significant
Age → behavioral intention → use behavior	0.047	0.044	0.024	1.961	0.050	Significant
Age x social influence → behavioral intention → use behavior	-0.055	-0.050	0.032	1.696	0.090	Significant
Age x facilitating condition → behavioral intention → use behavior	-0.023	-0.021	0.027	0.868	0.386	Not significant
Age x performance expectancy → behavioral intention → use behavior	0.037	0.039	0.040	0.932	0.351	Not significant
Age x effort expectancy → behavioral intention → use behavior	0.040	0.032	0.041	0.972	0.331	Not significant
Experience → behavioral intention → use behavior	0.066	0.070	0.033	1.993	0.046	Significant
Experience x social influence → behavioral intention → use behavior	-0.040	-0.040	0.030	1.310	0.190	Not significant
Experience x effort expectancy → behavioral intention → use behavior	0.027	0.019	0.038	0.694	0.488	Not significant
Experience x facilitating condition → behavioral intention → use behavior	-0.043	-0.041	0.030	1.429	0.153	Not significant
Voluntariness of use → behavioral intention → use behavior	-0.002	0.001	0.021	0.072	0.942	Not significant
Voluntariness of use x social influence → behavioral intention → use behavior	0.006	0.007	0.023	0.278	0.781	Not significant

DISCUSSION

The findings of this study emphasize that effort expectancy and facilitating condition are the most influential factors in shaping healthcare workers' Behavioral Intention to use EMR. This indicates that the perceived ease of system use and the availability of adequate supporting facilities are critical determinants in fostering user intention. In the context of type-C hospitals, which generally operate with limited resources, healthcare workers tend to prioritize practical and operational aspects of the system over social influence or long-term performance benefits. This suggests that usability and technical support are more immediate concerns for users than abstract or future-oriented advantages.

These results are consistent with the UTAUT proposed by Venkatesh et al. [16], which identifies effort expectancy and facilitating conditions as key determinants of technology acceptance. In healthcare settings, similar findings have been reported in various international studies. For instance, Derecho et al. [17] in Canada and Alzghaibi & Hutchings [18] in Saudi Arabia found that perceived ease of use and organizational support significantly influence healthcare professionals' acceptance of EMR systems. A cross-national study by Woldemariam et al. [19] further confirmed that infrastructure readiness and operational simplicity are crucial factors in enhancing the effectiveness of EMR systems across different countries. Likewise, studies conducted in developing countries, such as those by Karahoca et al. [20] in Turkey and Yakubu & Dasuki [21] in Nigeria, demonstrated that facilitating condition and effort expectancy significantly contribute to the intention to adopt health information systems. These consistent findings highlight that technical readiness and system usability remain universal determinants, particularly in resource-constrained settings.

Furthermore, Behavioral Intention was found to have a strong and significant influence on Use Behavior ($f^2 = 0.130$; $p < 0.001$). This supports the Theory of Planned Behavior [22], which posits that intention is the most direct predictor of actual behavior. In practical terms, this implies that strengthening healthcare workers' intention to use EMR—through continuous training, effective socialization, and organizational incentives—can directly enhance actual system utilization. Supporting evidence from Tavares & Oliveira [23] also indicates that improving behavioral intention through user engagement and educational strategies has a substantial impact on the sustained use of electronic health record systems in healthcare facilities.

Interestingly, this study found that Performance Expectancy and Social Influence did not have a significant effect on behavioral intention. This contrasts with findings from studies conducted in more developed healthcare systems, such as those by Derecho et al. [17] and Woldemariam et al. [19], where perceived performance benefits and social influence were key determinants of technology adoption. This discrepancy can be explained by differences in system maturity and digital readiness. In developed countries, healthcare information systems are more established, and users generally have higher confidence in their long-term benefits. In contrast, in type-C hospitals in Indonesia, challenges such as limited network infrastructure, insufficient training, and increased administrative workload lead healthcare workers to focus more on immediate usability and available support rather than perceived long-term gains [18,19]. Similar findings were reported by Nguyen et al. [24], who concluded that perceived usefulness alone is insufficient to drive actual system use when infrastructure and organizational readiness are still limited.

In addition, demographic factors such as age and work experience were found to play a significant role. More experienced healthcare workers tended to demonstrate better adaptability to system changes and digital workflows. This finding aligns with the study by Ngusie et al. [25] in Ethiopia, which highlighted that work experience, age, and self-efficacy positively influence healthcare workers' readiness and satisfaction in using Electronic Health Record systems. Similarly, Alasmary et al. [26] in Saudi Arabia reported that digital literacy and professional experience are closely associated with user comfort and effectiveness in utilizing EMR systems. These findings suggest that user characteristics remain an important consideration in technology implementation strategies.

From a theoretical perspective, this study reinforces the applicability of the UTAUT model while also highlighting the need for contextual adaptation in developing countries. The findings suggest that the relative importance of UTAUT constructs may vary depending on organizational conditions, resource availability, and digital maturity. As noted by Dwivedi et al. [27], socio-economic context and digital readiness can moderate the relationships between UTAUT variables. A systematic review by Rahimi et al. [28] also supports the continued relevance of UTAUT in healthcare settings, while emphasizing the importance of adapting the model to local organizational and cultural contexts.

From a practical standpoint, these findings underscore that EMR implementation strategies should prioritize strengthening technical aspects and organizational support. This includes providing continuous and structured training programs, simplifying system interfaces, and improving infrastructure such as internet connectivity and data backup systems. By enhancing perceived ease of use and facilitating conditions, healthcare organizations can effectively increase both the intention and actual use of EMR systems.

However, this study has several limitations. First, the research was limited to type-C hospitals in a single region, which may restrict the generalizability of the findings to other hospital types or regions. Second, the cross-sectional design does not allow for the observation of changes in user behavior over time. Third, important contextual factors such as organizational culture and leadership were not included in the model, despite evidence suggesting their significant role in digital transformation in healthcare [9,28]. Therefore, future research is recommended to adopt longitudinal designs and incorporate additional contextual variables to provide a more comprehensive understanding of EMR implementation success.

CONCLUSION

The successful implementation of EMR in type-C hospitals is mainly driven by effort expectancy and facilitating condition, which shape healthcare workers' behavioral intention and ultimately influence use behavior. Age and work experience also support acceptance, while Performance Expectancy, Social Influence, and most moderating variables are not significant. These findings indicate that technical readiness and individual factors are more critical than social or performance-related aspects. Therefore, implementation should focus on improving system usability, infrastructure, and continuous training. Future studies should involve higher-level hospitals for broader insights.

Ethical consideration, competing interest and source of funding

-This study obtained ethical approval from the Health Research Ethics Committee of Universitas Jember with reference number No. 2949/UN25.8/KEPK/DL/2025. All ethical procedures, including informed consent, confidentiality, and voluntary participation, were strictly maintained throughout the research process.

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