e-ISSN : 2597-6052
MPPKI MEDIA PUBLIKASI PROMOSI KESEHATAN INDONESIA
Research Articles Open Access

Evaluating EMR Adoption and Its Effect on Organizational Performance: A Quantitative Study Using SEM-PLS in Type-C Hospitals in Kupang City

Mahasar Reinheart F. Damanik[1]*, Aloysius Liliweri[2], William Djani[3], I Putu Yoga Bumi Pradana[4]
[1234]Faculty of Social and Political Sciences, Nusa Cendana University, Indonesia

***Corresponding Author:** E-mail: mahasarreinheart@gmail.com

ARTICLE INFO

Manuscript Received: 09 Feb, 2025
Revised: 23 May, 2025
Accepted: 26 May, 2025
Date of Publication: 03 Jul, 2025
Volume: 8
Issue: 7
DOI: 10.56338/mppki.v8i7.7458

KEYWORDS

Electronic Medical Records;
Technology Acceptance;
Healthcare Performance;
Human Capital;
Digital Health Systems

ABSTRACT

Introduction: This study aims to identify key determinants influencing EMR adoption and measure their subsequent impact on organizational performance in Type-C hospitals, emphasizing internal organizational factors, user acceptance, and adaptability to healthcare policy dynamics. With persistent implementation gaps in low-resource settings despite national mandates our objective was to explore user-centered determinants of EMR success and address the shortcomings of top-down health digitalization strategies in developing countries.
Methods: This cross-sectional explanatory study involved a survey-based quantitative design conducted across three Type-C hospitals in Kupang City, Indonesia, between January and March 2024. A total of 282 healthcare professionals, selected using stratified random sampling, participated in the study. Data were collected using a validated Likert-scale questionnaire measuring variables such as human capital, task-technology fit, and system acceptance. Given the non-interventional nature of this study, adherence to ethical research standards including voluntary informed consent, and obtained administrative approvals from relevant local government authorities, formal ethical approval was waived as per prevailing national guidelines.
Results: The primary outcome of the study was the identification of key drivers of EMR acceptance, with human capital ($\beta = 0.205$; $p < 0.001$), task-technology fit ($\beta = 0.203$; $p = 0.001$), and effort expectancy ($\beta = 0.176$; $p < 0.001$) showing significant influence. Additionally, user satisfaction was found to mediate the relationship between acceptance and organizational performance ($\beta = 0.728$; $p < 0.001$). External variables such as perceived cost and government policy showed no significant effect ($p > 0.05$). The strongest indirect effect on performance was recorded via the pathway: Acceptance → Satisfaction → Performance ($\beta = 0.394$; $p < 0.001$).
Conclusion: In conclusion, our study contributes to the understanding of EMR adoption in resource-constrained health systems by highlighting the dominant role of internal capabilities over external mandates. This research provides insights into the importance of user satisfaction and system alignment in shaping digital health success. Future studies should explore longitudinal impacts and the role of organizational culture, ultimately advancing knowledge in the field of international health informatics.

Publisher: Fakultas Kesehatan Masyarakat Universitas Muhammadiyah Palu

INTRODUCTION

The digitization of healthcare systems has emerged as a global imperative aimed at addressing longstanding inefficiencies in service delivery and quality of care. One of the central pillars of this transformation is the adoption of Electronic Medical Records (EMRs), which facilitate the electronic documentation and retrieval of patient health data. Globally, EMR systems are promoted for their potential to enhance data accuracy, improve clinical workflows, and support evidence based decision making. In developed countries, EMRs have become foundational to hospital information systems. However, in low and middle income countries, their implementation often faces systemic obstacles such as limited financial resources, poor infrastructure, and inadequate digital literacy among health personnel (1,2). Furthermore, negative perceptions and resistance to digital technologies among healthcare professionals pose additional challenges to their successful adoption (3).

In these resource constrained settings, the implementation of EMRs is further complicated by local organizational cultures, complex regulatory environments, and constrained human capital. Existing literature underscores that the operational success of EMR adoption is contingent not merely on the presence of technology, but on its alignment with institutional workflows and users' readiness to adapt (1,4). For example, changes in documentation requirements or disruptions in patient handling protocols frequently generate opposition from healthcare workers who perceive EMRs as burdensome. In parallel, healthcare institutions in developing regions frequently operate under conditions of high patient load, limited staff, and underfunded infrastructure all of which act as deterrents to digital transformation (2).

Indonesia, as one of the largest developing nations in Southeast Asia, has initiated a robust national policy to facilitate EMR adoption in public and private healthcare facilities. The Ministry of Health's Circular No. HK.02.01/Menkes/1030/2023 explicitly mandates that all hospitals must implement EMRs by March 31, 2024, or face accreditation downgrades, and by July 31, 2024, non-compliant hospitals will have their accreditation revoked (5). These regulatory measures aim to improve interoperability, data standardization, and healthcare efficiency. Type C hospitals regional facilities that are often underfunded and understaffed are primary targets of this initiative. However, significant cost constraints remain barriers in resource-limited hospitals, as demonstrated by the cost evaluation of AVICENNA-HIS implementation, which reveals that both initial procurement and maintenance expenses can far exceed the budget capacity of Type C hospitals (6). These include the high cost of digital infrastructure, the shortage of trained IT personnel, and the inadequate integration of EMRs into existing healthcare workflows (7).

To mitigate these challenges, the policy emphasizes not only EMR implementation but also capacity building through staff training and technical support. Literature suggests that investment in staff training has a direct positive impact on technology acceptance (8). Yet, effective EMR integration demands sustained organizational support, proactive change management, and cultural shifts within healthcare institutions. In many cases, especially in Type C hospitals, technical training alone is insufficient to overcome the entrenched reliance on manual documentation systems (9,10).

Research has consistently shown that EMRs contribute to operational efficiency and improved patient care quality when implemented effectively. Benefits such as reduced medical errors, enhanced diagnostic accuracy, and streamlined administrative processes have been reported (11,12). EMRs also enhance communication across departments and promote more accurate tracking of patient histories, leading to better care coordination (13). A structured EMR system reduces duplication, improves compliance with treatment protocols, and supports real time access to critical data all of which are crucial for quality assurance in hospitals (14).

Operational efficiencies attributed to EMR systems include reductions in medication errors and enhanced patient identification procedures (15,16). Such improvements are particularly valuable in Type C hospitals, where resource limitations necessitate maximum optimization of clinical operations. Furthermore, improved digital documentation and system interoperability may facilitate better resource allocation and strategic planning in public healthcare management (8).

Nonetheless, barriers to EMR implementation in Indonesia are substantial. Infrastructural deficits such as unstable internet connectivity and insufficient hardware continue to impede deployment in remote and rural areas (2). At the same time, technical problems, including lack of integration with existing systems and inconsistent software usability, frustrate users and lead to underutilization of available technologies (17). Human capital constraints are also pressing. Many hospitals face acute shortages of personnel with the skills necessary to operate EMRs effectively, and ongoing training programs are often poorly aligned with clinical workflows, diminishing their impact (3).

Another pervasive barrier is resistance from healthcare workers who perceive EMRs as an administrative burden rather than a clinical asset. Studies show that increased documentation time and the complexity of digital interfaces contribute to burnout and dissatisfaction (18). Institutional culture, shaped by years of reliance on paper based systems, further entrenches resistance. Thus, strategies aimed solely at technological provision without parallel cultural and organizational adaptation are unlikely to succeed (19).

National digital health policy, while comprehensive in its vision, must also respond to these on the ground realities. Effective policies not only standardize EMR systems but also incentivize hospitals to invest in complementary resources such as broadband access, helpdesk services, and digital literacy programs (20). Moreover, regulations must be flexible enough to accommodate local variability in readiness and capacity (21). Without contextualized policy design, even well intentioned mandates may fail to translate into sustainable improvements.

The theoretical frameworks most relevant to EMR adoption studies include the Unified Theory of Acceptance and Use of Technology (UTAUT), Task Technology Fit (TTF), Human Capital Theory, and Rogers' Diffusion of Innovations. This study integrates several of these frameworks to guide both conceptual development and variable selection. UTAUT (Venkatesh et al., 2003) informs core variables such as performance expectancy, effort expectancy, social influence, and facilitating conditions, capturing user perceptions that directly shape technology acceptance (22). TTF (Goodhue & Thompson, 1995) underpins the inclusion of task-technology fit, emphasizing how alignment between system functionalities and clinical tasks affects user adoption. Human Capital Theory (Nafukho et al., 2020) supports the incorporation of human capital as a variable reflecting staff competencies, digital literacy, and readiness to engage with new systems (23,24). Meanwhile, Rogers' Diffusion of Innovations (2003) offers a broader lens to interpret adoption trajectories across institutions and contextualizes the role of user satisfaction as an outcome of peer influence and organizational culture. These integrated theories collectively explain how personal beliefs, system-task alignment, staff capability, and innovation dynamics influence EMR acceptance and ultimately, organizational performance (25,26).

However, most of the extant literature focuses on high resource hospital environments or aggregated national level data, overlooking the heterogeneous realities of Type C hospitals in less developed regions. Few studies investigate the nuances of EMR adoption in semi-rural urban zones like Kupang, where infrastructural, organizational, and behavioral variables intersect in complex ways. For example, while policy documents may assume internet availability, the reality in Kupang includes inconsistent broadband coverage, lack of IT personnel, and insufficient training infrastructure (27).

This study seeks to address that gap by focusing on EMR adoption and its organizational performance impact in Type C hospitals in Kupang City. Using a quantitative methodology grounded in UTAUT and innovation diffusion theory, the research evaluates how internal capabilities (e.g., human capital, task technology alignment) and external conditions (e.g., policy expectations, perceived costs) shape EMR user acceptance. In particular, it investigates the mediating role of user satisfaction as a bridge between system acceptance and performance outcomes. The study also proposes a multi routed diffusion model incorporating managerial, relational, and design technical pathways to capture the layered influences on EMR implementation.

The novelty of this study lies in its application of integrated adoption theories within the unique sociotechnical context of Kupang's healthcare system. Unlike previous research that emphasizes singular dimensions such as technical readiness or policy compliance, this study provides a holistic framework to understand EMR adoption as a dynamic interplay between individual, organizational, and systemic factors. The findings offer actionable insights for policymakers and hospital administrators seeking to optimize digital health interventions in low resource settings

METHOD

Research Type

This study adopts a quantitative explanatory research design grounded in the positivist paradigm, aiming to analyze the influence of Electronic Medical Records (EMR) adoption on organizational performance in Type C hospitals in Kupang City. The rationale behind this approach lies in the need to empirically examine the relationships among multiple variables involved in technology acceptance, user satisfaction, and institutional performance. Structural Equation Modeling using the Partial Least Squares (SEM-PLS) method was employed due to its suitability for analyzing complex models that involve multiple latent constructs, particularly in contexts where theoretical frameworks are still developing and sample sizes are moderate (28). SEM-PLS was preferred over other multivariate techniques such as covariance-based SEM because it does not require strict assumptions of multivariate normality, is robust with small to medium samples, and prioritizes prediction and explanation of variance over model fit indices. Moreover, SEM-PLS allows simultaneous analysis of direct and indirect effects, making it especially appropriate for testing mediation pathways such as the role of user satisfaction as a mediator between EMR acceptance and organizational performance which is central to this study's research objective.

Population and Sample/Informants

The population for this study consisted of healthcare professionals, administrative personnel, and managerial staff from three Type C hospitals in Kupang: RSU Mamami, RSUD S.K. Lerik, and RSAL S.J. Moeda, representing private, public, and military institutions respectively.

The total population comprised 954 employees. To determine the minimum sample size required for reliable analysis, the Slovin formula was used with a 5% margin of error and a 95% confidence level:

$$n = \frac{N}{1 + Ne^2}$$

Where:

n : sample size
N : population size (954)
e : margin of error (0,05)

$$n = \frac{954}{1{+}954(0{,}05)^2} = \frac{954}{3385} \approx 282$$

Thus, the minimum required sample size was 282 respondents, which meets the adequacy threshold for Structural Equation Modeling–Partial Least Squares (SEM-PLS), as recommended for models with multiple latent constructs and moderate sample sizes (28). SEM-PLS is robust even with relatively small samples and is well-suited for prediction-oriented research in exploratory contexts.

To ensure proportional representation, stratified random sampling was applied based on both hospital and job category. Sample allocation by hospital was as follows: RSU Mamami (43 respondents), RSUD S.K. Lerik (129 respondents), and RSAL S.J. Moeda (110 respondents). Each hospital sample was further divided by occupational strata: 60% medical staff, 30% administrative staff, and 10% management. This stratification aimed to reflect organizational structure and exposure to EMR systems, ensuring balanced data for analysis across institutions.

Research Location

This study was conducted in Kupang City, the capital of East Nusa Tenggara Province, Indonesia. As a growing urban center in one of Indonesia's less developed regions, Kupang represents a strategic setting for examining the challenges and dynamics of digital transformation in public healthcare. The city's healthcare infrastructure includes a number of Type-C hospitals that serve as primary and referral facilities for a wide population across both urban and peri-urban areas.

Three Type-C hospitals were purposively selected for this study: RSU Mamami, a privately owned hospital; RSUD S.K. Lerik, a regional public hospital; and RSAL S.J. Moeda, a military hospital. These institutions were chosen to reflect the diversity of hospital governance structures private, public, and military and to capture varying organizational capacities, digital readiness levels, and policy compliance mechanisms. All three hospitals had initiated EMR implementation at different stages, providing a suitable context for comparative analysis of adoption factors and performance outcomes.

The selection of Kupang as the research location is further justified by its designation as a target area for health digitalization under the Indonesian Ministry of Health's 2023 directive. Despite this policy focus, many hospitals in the region continue to face infrastructure, personnel, and resource limitations. Thus, Kupang offers a unique case for understanding how local organizational variables interact with national digital health mandates to influence the trajectory of EMR system adoption

Instrumentation or Tools

Data collection was conducted using a structured questionnaire designed to measure multiple dimensions relevant to EMR adoption. The instrument incorporated indicators adapted from validated scales used in prior research across health information technology, particularly those grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh et al. (2003), the Task-Technology Fit (TTF) model by Goodhue and Thompson (1995), Human Capital Theory by Nafukho et al. (2020), and Rogers' Diffusion of Innovations (2003) (22,24,29). Key constructs measured include: 1) Performance Expectancy (e.g., perceived usefulness, job-fit, relative advantage, outcome expectation) based on UTAUT and Davis (1989); 2) Effort Expectancy (e.g., ease of use, complexity) adapted from UTAUT; 3) Task-Technology Fit (e.g., system functionality, compatibility, reliability, accessibility) from Goodhue & Thompson (1995); 4) Social Influence and Facilitating Conditions adapted from UTAUT; 5) Human Capital (e.g., skill, trust, ICT familiarity, innovation attitude) rooted in Human Capital Theory (Nafukho et al., 2020); 6) Perceived Cost, Perceived Safety, Organizational Influence and Benefit, Government Expectancy and Benefit, and 7) Mediating constructs such as Acceptance of Use and User Satisfaction following models by DeLone and McLean (2003); 8) The Outcome variable, Organizational Performance, was informed by works such as Upadhyay et al. (2022) and Marquard (2021) emphasizing efficiency, innovation, and adaptability in digital health settings.

All questionnaire items were measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Prior to field deployment, the questionnaire underwent expert review for content validity by three health informatics and hospital management scholars. A pilot test involving 20 respondents from a similar hospital setting was conducted to assess clarity, relevance, and cultural appropriateness. Feedback was used to refine item phrasing and ensure construct validity.

Data Collection Procedures

Data collection was carried out over a period of four weeks through in person distribution by trained research assistants, ensuring that respondents had at least one year of work experience, as a minimum criterion for familiarity with hospital operations and potential exposure to EMR systems. Ethical approval was secured from the relevant institutional review board, and informed consent was obtained from all participants.

Data Analysis

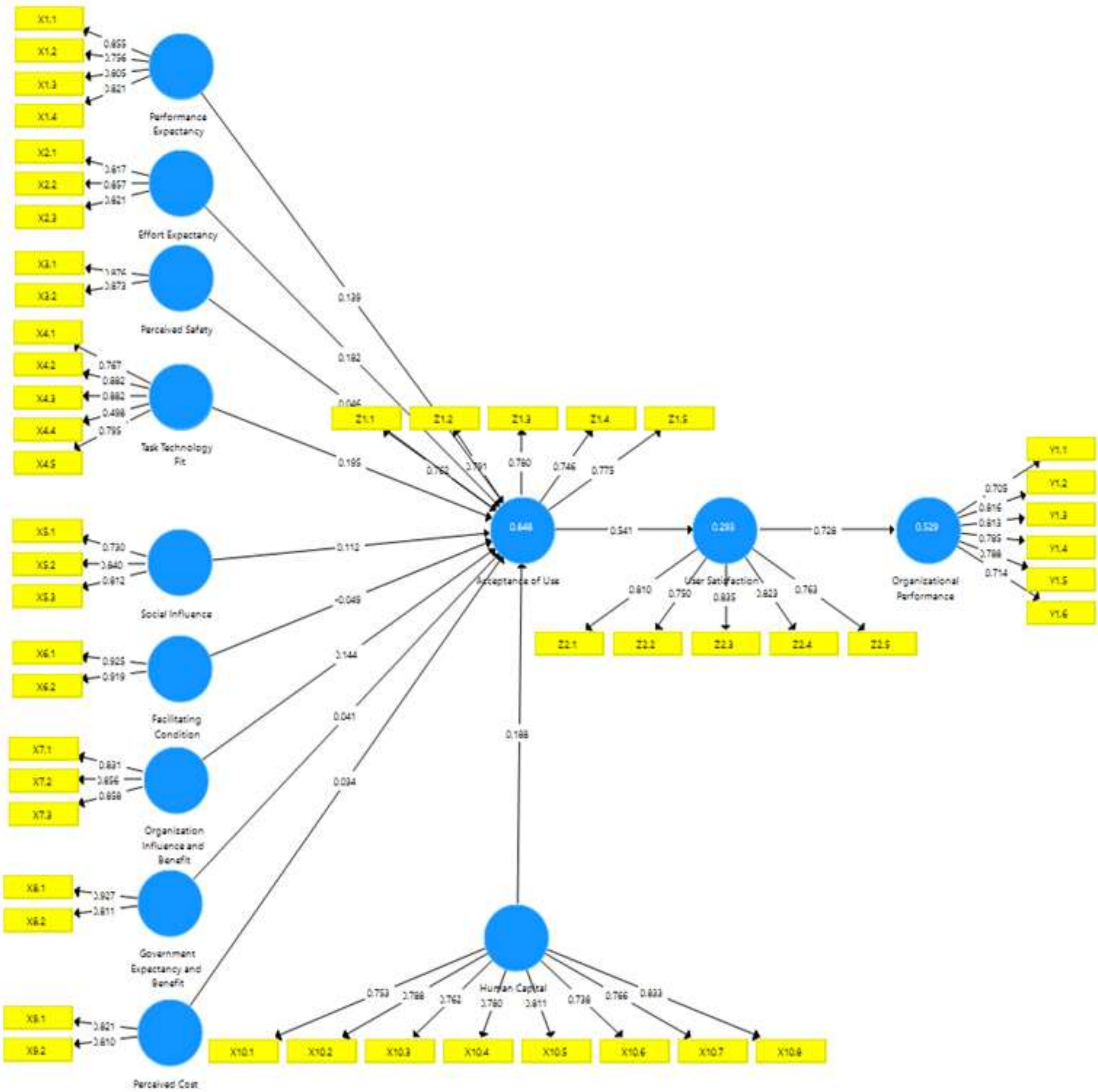


Figure 1. Early Outer Model

Data analysis was performed using SmartPLS 4.0 software. The analytical process began with evaluating construct validity and reliability. Convergent validity was assessed using two criteria: outer loading values (threshold ≥ 0.70) and Average Variance Extracted (AVE) (threshold ≥ 0.50). One indicator under Task Technology Fit (X4.4) fell below the loading threshold (0.498) and was therefore excluded from the model. After removal, all remaining indicators exceeded the required values, confirming strong convergent validity across constructs. The AVE values ranged from 0.594 to 0.922, indicating that each construct explained more than 50% of the variance in its respective indicators.

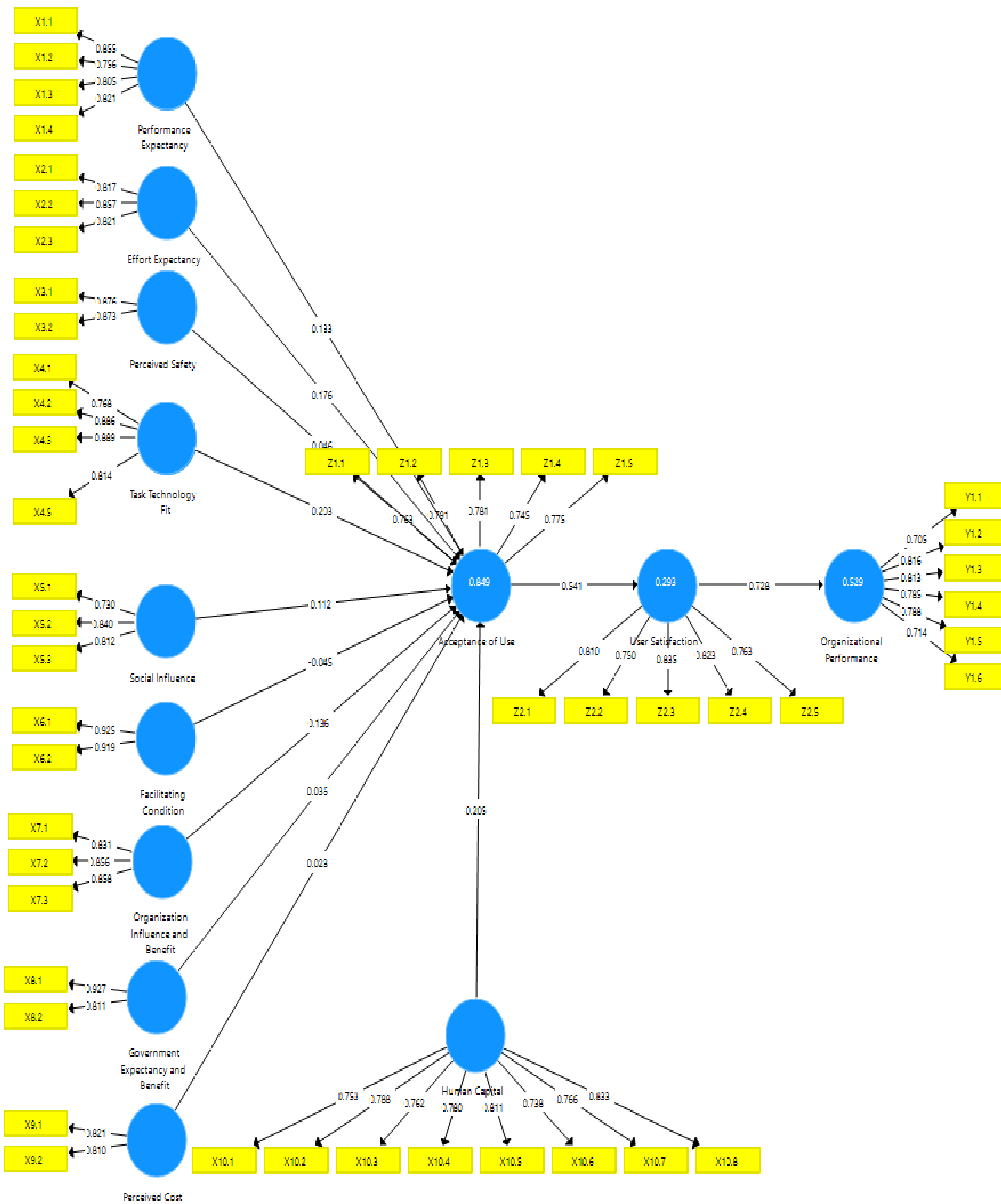


Figure 2. Outer Model After Elimination

Discriminant validity was tested using the Fornell-Larcker criterion, where the square root of each construct's AVE was found to be greater than its correlation with other constructs, affirming satisfactory discriminant validity.

To assess multicollinearity, the Variance Inflation Factor (VIF) was examined for all indicators. The VIF values ranged between 1.1 and 2.9, well below the commonly accepted upper limit of 3.0. This indicates that multicollinearity was not a concern in this model.

Construct reliability was evaluated using Composite Reliability (CR) with a threshold of ≥ 0.70. All constructs achieved CR values between 0.799 and 0.925, demonstrating high internal consistency and reliability of the measurement model. Collectively, these validation steps confirm that the model satisfies the psychometric requirements for SEM-PLS analysis, providing a strong foundation for testing the structural relationships among variables.

Subsequently, the structural model was evaluated using R square (R^2) and F square (f^2) statistics to assess the model's explanatory power and effect size, respectively. Acceptance of EMR use yielded an R^2 of 0.849, indicating that nearly 85% of its variance was explained by variables such as human capital, task technology fit, effort expectancy, and performance expectancy. User satisfaction showed an R^2 of 0.293, while organizational performance had an R^2 of 0.529. These results suggest that the model has strong predictive capability, particularly for technology acceptance and performance outcomes.

F square analysis revealed that user satisfaction exerted a large effect ($f^2 = 1.125$) on organizational performance. Acceptance of EMR use had a moderate to large effect on user satisfaction ($f^2 = 0.414$). Conversely, constructs such as perceived cost, perceived safety, and facilitating condition had negligible effects on EMR acceptance, highlighting the greater relevance of internal and user centered variables in the studied context. These findings are consistent with prior research that emphasizes the critical role of internal organizational factors and human capital in determining EMR success (10,25).

Path coefficient analysis confirmed the significance of most hypothesized relationships. Human capital emerged as the strongest predictor of EMR acceptance (path coefficient = 0.205; $p < 0.001$), followed by task technology fit (0.203), effort expectancy (0.176), and performance expectancy (0.133). Social influence and organizational support also had significant but comparatively weaker effects. In contrast, government expectations, perceived cost, and system security did not significantly influence acceptance, aligning with findings from Ajam (2023) and Sayrani (2017) that external mandates alone are insufficient drivers of health IT adoption (9,30).

Lastly, indirect effect analysis underscored the central role of user satisfaction in mediating the relationship between technology acceptance and organizational performance. The pathway "Acceptance of Use → User Satisfaction → Organizational Performance" showed the largest indirect effect (coefficient = 0.394; $p < 0.001$), confirming that sustained satisfaction is essential for realizing the institutional benefits of EMR systems.

In sum, the methodological framework of this study leverages the strengths of SEM PLS to capture the complex interdependencies among technical, human, and organizational variables in EMR adoption. The use of stratified random sampling and validated instruments ensures data robustness and representativeness. The findings offer critical insights into the internal dynamics shaping digital transformation in Indonesia's healthcare system and provide a rigorous empirical foundation for strategic interventions tailored to resource constrained hospital environments.

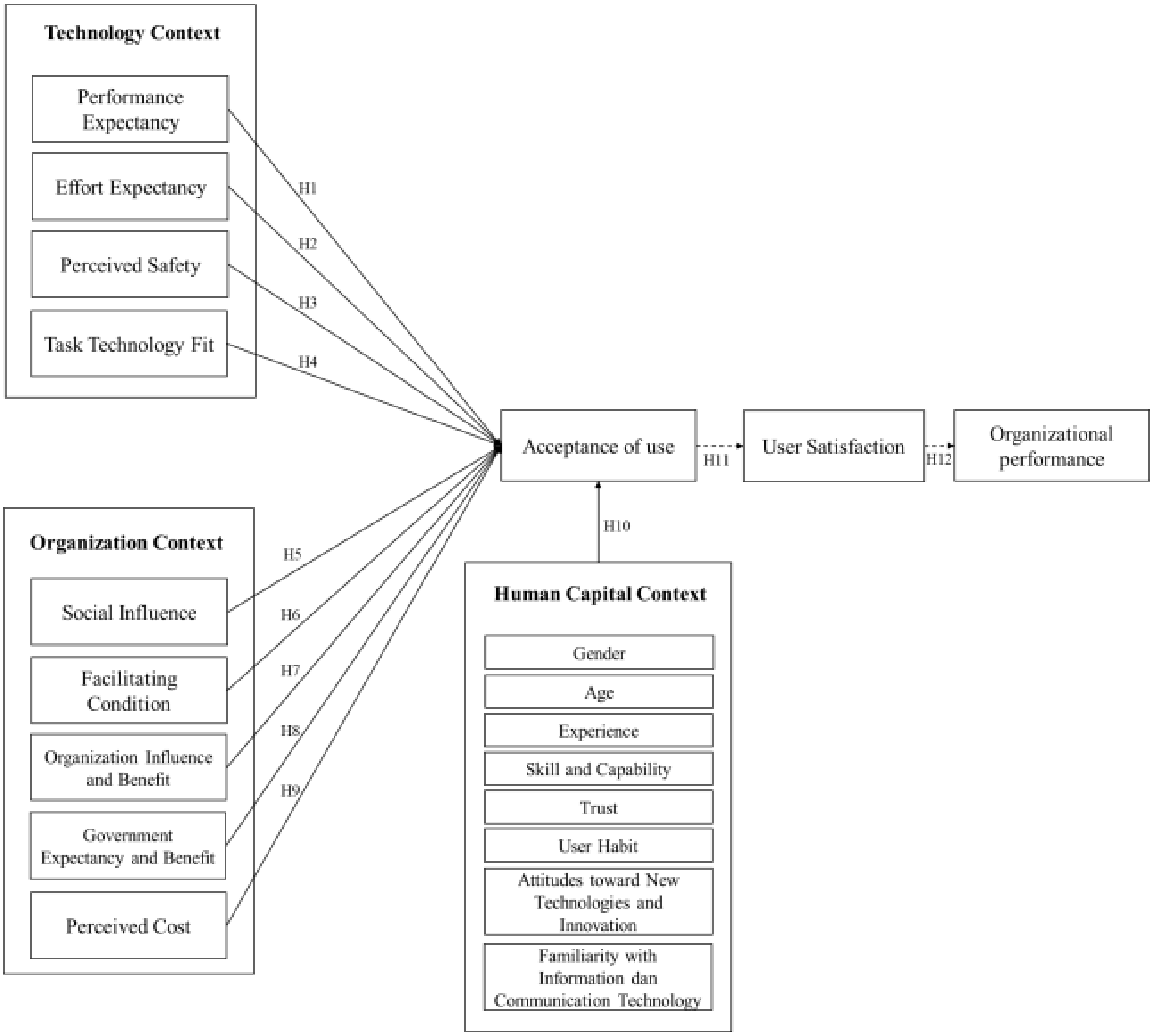


Figure 3. Research Framework

Ethical Approval

This study did not involve any clinical interventions, patient treatment procedures, or the collection of sensitive personal health data. The research relied solely on survey-based responses from healthcare professionals regarding their perceptions and experiences with Electronic Medical Record (EMR) systems. Participation was entirely voluntary, and all respondents were informed about the purpose of the study, the confidentiality of their responses, and their right to withdraw at any stage without consequence.

Given the observational and non-invasive nature of the study, and in accordance with prevailing national research ethics guidelines, formal ethical approval was not required. Nonetheless, the study adhered to ethical research standards, including informed consent, data anonymization, and respect for participants' autonomy and privacy.

RESULTS

The results of this study underscore the critical role that internal organizational and human factors play in determining the successful adoption and use of Electronic Medical Records (EMR) systems in Type C hospitals in Kupang City. The analysis, based on Structural Equation Modeling with Partial Least Squares (SEM PLS), yielded several insights into the relationships among the variables in the proposed model, particularly regarding human capital, task technology fit, user satisfaction, and their contributions to organizational performance.

The construct validity and reliability tests confirmed that the instrument used in this study possesses strong measurement capability. As shown in Table 1, all constructs exhibited average variance extracted (AVE) values above the minimum threshold of 0.50 and composite reliability (CR) values exceeding 0.70, indicating that the measurement model satisfies the criteria for convergent validity and internal consistency. The discriminant validity test using the Fornell Larcker criterion further confirmed that all constructs are empirically distinct from one another.

Table 1. Construct Validity and Reliability

Construct	Average Variance Extracted (AVE)	Composite Reliability (CR)
Acceptance of Use	0,594	0,880
Effort Expectancy	0,692	0,871
Facilitating Condition	0,850	0,919
Government Expectancy and Benefit	0,758	0,862
Human Capital	0,607	0,925
Organization Influence and Benefit	0,719	0,885
Organizational Performance	0,595	0,898
Perceived Cost	0,665	0,799
Perceived Safety	0,765	0,867
Performance Expectancy	0,656	0,884
Social Influence	0,633	0,837
Task Technology Fit	0,707	0,906
User Satisfaction	0,635	0,897

Source: SEM-PLS Data Processing Output

In terms of predictive power, the structural model demonstrated strong explanatory capabilities. As shown in Table 2, the R squared (R^2) value for Acceptance of Use was 0.849, indicating that nearly 85% of the variance in EMR acceptance can be explained by the combined influence of performance expectancy, effort expectancy, human capital, social influence, and other factors. The R^2 for Organizational Performance was 0.529, and for User Satisfaction, it was 0.293. These findings suggest that while user acceptance is well predicted by the model, additional variables may influence user satisfaction.

The F squared (f^2) results revealed that User Satisfaction had a large effect on Organizational Performance ($f^2 = 1.125$), and Acceptance of Use had a strong effect on User Satisfaction ($f^2 = 0.414$). In contrast, variables such as Perceived Cost ($f^2 = 0.002$), Perceived Safety ($f^2 = 0.008$), and Facilitating Condition ($f^2 = 0.008$) exhibited minimal effects, emphasizing the dominance of internal over external factors in this context.

Table 2. Construct Validity and Reliability

Dependent Variable	R^2	R^2 Adjusted	Predictor	f^2	Effect Category
Acceptance of Use	0,849	0,844	Human Capital	0,065	small effect
			Effort Expectancy	0,058	small effect
			Performance Expectancy	0,033	small effect
			Task Technology Fit	0,049	small effect
			Organization Influence & Benefit	0,029	small effect
			Social Influence	0,021	small effect
			Facilitating Condition	0,008	Very small effect
			Government Expectancy & Benefit	0,004	Very small effect
			Perceived Cost	0,002	Very small effect

Dependent Variable	R^2	R^2 Adjusted	Predictor	f^2	Effect Category
			Perceived Safety	0,008	Very small effect
User Satisfaction	0,293	0,290	Acceptance of Use	0,414	large effect
Organizational Performance	0,529	0,528	User Satisfaction	1,125	large effect

Source: SEM-PLS Data Processing Output

Path coefficient analysis (Table 3) further elaborated on the strength and direction of relationships among variables. Human Capital emerged as the most significant predictor of EMR acceptance (path coefficient = 0.205; $p < 0.001$), underscoring that the knowledge, skills, and competencies of healthcare workers directly influence their willingness to engage with digital health systems. This finding echo previous research emphasizing the role of training and experience in enhancing EMR adoption (8,31).

In comparison, Performance Expectancy ($\beta = 0.133$; $p = 0.006$), Effort Expectancy ($\beta = 0.176$; $p < 0.001$), Task Technology Fit ($\beta = 0.203$; $p = 0.001$), Social Influence ($\beta = 0.112$; $p = 0.034$), and Organizational Influence and Benefit ($\beta = 0.136$; $p = 0.014$) also had significant but relatively smaller impacts on EMR acceptance.

Among all tested predictors, Perceived Cost had the least impact (path coefficient = 0.028; $p = 0.460$), followed by Facilitating Condition ($\beta = -0.045$; $p = 0.194$) and Government Expectancy and Benefit ($\beta = 0.036$; $p = 0.371$), none of which reached statistical significance. This suggests that in the context of resource-constrained hospitals, external motivators such as perceived financial burden or government mandates are less influential than internal and task-related enablers. These variables may lack salience due to limited budgetary control among frontline users and weak translation of top-down policies into localized support structures.

Task Technology Fit (0.203; $p = 0.001$), Effort Expectancy (0.176; $p = 0.000$), and Performance Expectancy (0.133; $p = 0.006$) also significantly influenced user acceptance, reaffirming that alignment between EMR functionalities and clinical workflows, as well as perceived ease of use, are vital in shaping user attitudes. These results are consistent with literature emphasizing that technologies aligned with clinical tasks increase user satisfaction and system utilization (32,33).

Table 3. Direct Effects Between Variables in the SEM PLS Model

No	Relationship Between Variables	Path Coefficient (O)	T-Statistic	P-Value	Remarks
1	Performance Expectancy → Acceptance of Use	0,133	2,753	0,006	Significant
2	Effort Expectancy → Acceptance of Use	0,176	3,933	0,000	Significant
3	Perceived Safety → Acceptance of Use	0,046	1,610	0,108	Not Significant
4	Task Technology Fit → Acceptance of Use	0,203	3,491	0,001	Significant
5	Social Influence → Acceptance of Use	0,112	2,122	0,034	Significant
6	Facilitating Condition → Acceptance of Use	-0,045	1,300	0,194	Not Significant
7	Organization Influence and Benefit → Acceptance of Use	0,136	2,457	0,014	Significant
8	Government Expectancy and Benefit → Acceptance of Use	0,036	0,895	0,371	Not Significant
9	Perceived Cost → Acceptance of Use	0,028	0,740	0,460	Not Significant
10	Human Capital → Acceptance of Use	0,205	4,002	0,000	Significant
11	Acceptance of Use → User Satisfaction	0,541	7,295	0,000	Significant
12	User Satisfaction → Organizational Performance	0,728	15,930	0,000	Significant

Source: SEM-PLS Data Processing Output

Conversely, external factors such as Government Expectancy and Benefit (0.036; $p = 0.371$), Perceived Cost (0.028; $p = 0.460$), and Perceived Safety (0.046; $p = 0.108$) did not exhibit statistically significant effects. These results suggest that policy mandates and cost perceptions, while theoretically relevant, may not hold substantial sway in resource constrained hospital settings where internal factors such as training and system fit are more immediate concerns. This aligns with findings from Torkman et al. (2024) and Dayama et al. (2024) regarding skepticism toward security assurances and limited budget flexibility in public healthcare institutions (3,34).

Further, the results confirmed the hypothesized mediation relationships. Acceptance of Use had a significant effect on User Satisfaction (path coefficient = 0.541; p = 0.000), while User Satisfaction, in turn, exerted a strong influence on Organizational Performance (path coefficient = 0.728; p = 0.000). These findings support the view that user satisfaction is a critical intermediary linking technology acceptance to performance outcomes, corroborating the claims of Marquard (2021) and Upadhyay et al. (2022) (14,35).

The indirect effects analysis (Table 4) revealed that several variables influenced Organizational Performance indirectly through Acceptance of Use and User Satisfaction. Notably, Human Capital → Acceptance of Use → User Satisfaction → Organizational Performance had the strongest indirect effect (coefficient = 0.081; p = 0.001), followed closely by Task Technology Fit and Effort Expectancy. These pathways underscore that internal capacity building and system alignment yield compounded benefits, ultimately enhancing institutional outcomes.

Table 4. Direct Effects Between Variables in the SEM PLS Model

Indirect Influence Path	Coefficient	T-Statistic	P-Value	Remark
Human Capital → Acceptance of Use → User Satisfaction → Organizational Performance	0.081	3.232	0.001	Significant
Effort Expectancy → Acceptance of Use → User Satisfaction → Organizational Performance	0.069	3.103	0.002	Significant
Task Technology Fit → Acceptance of Use → User Satisfaction → Organizational Performance	0.080	2.868	0.004	Significant
Performance Expectancy → Acceptance of Use → User Satisfaction → Organizational Performance	0.053	2.408	0.016	Significant
Organization Influence and Benefit → Acceptance of Use → User Satisfaction → Organizational Performance	0.053	2.168	0.031	Significant
Social Influence → Acceptance of Use → User Satisfaction → Organizational Performance	0.044	2.032	0.043	Significant
Acceptance of Use → User Satisfaction → Organizational Performance	0.394	5.350	0.000	Significant (Dominant Effect)

Source: SEM-PLS Data Processing Output

Variables with negligible indirect effects, such as Government Expectancy and Benefit, Perceived Cost, and Facilitating Conditions, reflect limited pathways for these constructs to influence organizational performance, reinforcing their lack of centrality in the current adoption landscape. Interestingly, the pathway from Acceptance of Use to Organizational Performance via User Satisfaction (coefficient = 0.394; p < 0.001) was found to be the most dominant, indicating that satisfaction is a pivotal driver of overall effectiveness once systems are accepted by users.

The significance of social influence was also confirmed, albeit with a lower magnitude (path coefficient = 0.112; p = 0.034). Nevertheless, its role remains essential, particularly when seen through the lens of organizational culture and peer networks. Positive attitudes among colleagues and encouragement from management have been documented to foster more favorable attitudes toward technology use (36,37).

In sum, the results illustrate that EMR adoption in Type C hospitals in Kupang is primarily driven by internal human resource capabilities, perceived utility and usability of the system, and the alignment of digital solutions withm task requirements. While external motivators like government policy or cost considerations are acknowledged, their influence appears secondary. The predictive strength of user satisfaction in linking EMR acceptance to improved organizational performance further reinforces the need for user centered implementation strategies.

These findings provide robust empirical support for the development of a multi routed diffusion (MRD) model, incorporating managerial, relational, and technical pathways to explain EMR adoption in resource constrained healthcare settings. The combined significance of human capital, task technology alignment, and satisfaction mediation pathways validates the integrated application of UTAUT, TTF, and Human Capital Theory in digital health transformation frameworks.

DISCUSSION

The adoption of Electronic Medical Records (EMRs) in resource-constrained healthcare environments such as Type-C hospitals in Kupang City reveals a complex interplay of organizational, technical, relational, and policy dimensions. This study integrates these dimensions into the Multi-Routed Diffusion (MRD) model, offering a robust analytical lens for understanding technology acceptance dynamics in developing healthcare systems. The findings correspond with, and extend, several theoretical frameworks, including the Unified Theory of Acceptance and Use of Technology (UTAUT), the Task-Technology Fit (TTF) model, and Human Capital Theory, all of which help unpack the mechanisms by which EMR adoption contributes to improved organizational performance.

Interpretation of Key Findings

The results underscore that internal capabilities, particularly human capital, remain central to successful EMR integration. Human capital, as measured through staff experience, skills, and adaptability, emerged as the most significant predictor of EMR acceptance (path coefficient = 0.205; $p < 0.001$). This aligns with previous research highlighting the critical role of continuous professional development and digital literacy in facilitating health IT adoption (8,31). The ability of healthcare workers to adapt to EMR systems hinges not only on formal training but also on their exposure to and comfort with technology, reinforcing the argument for sustained investments in capacity building.

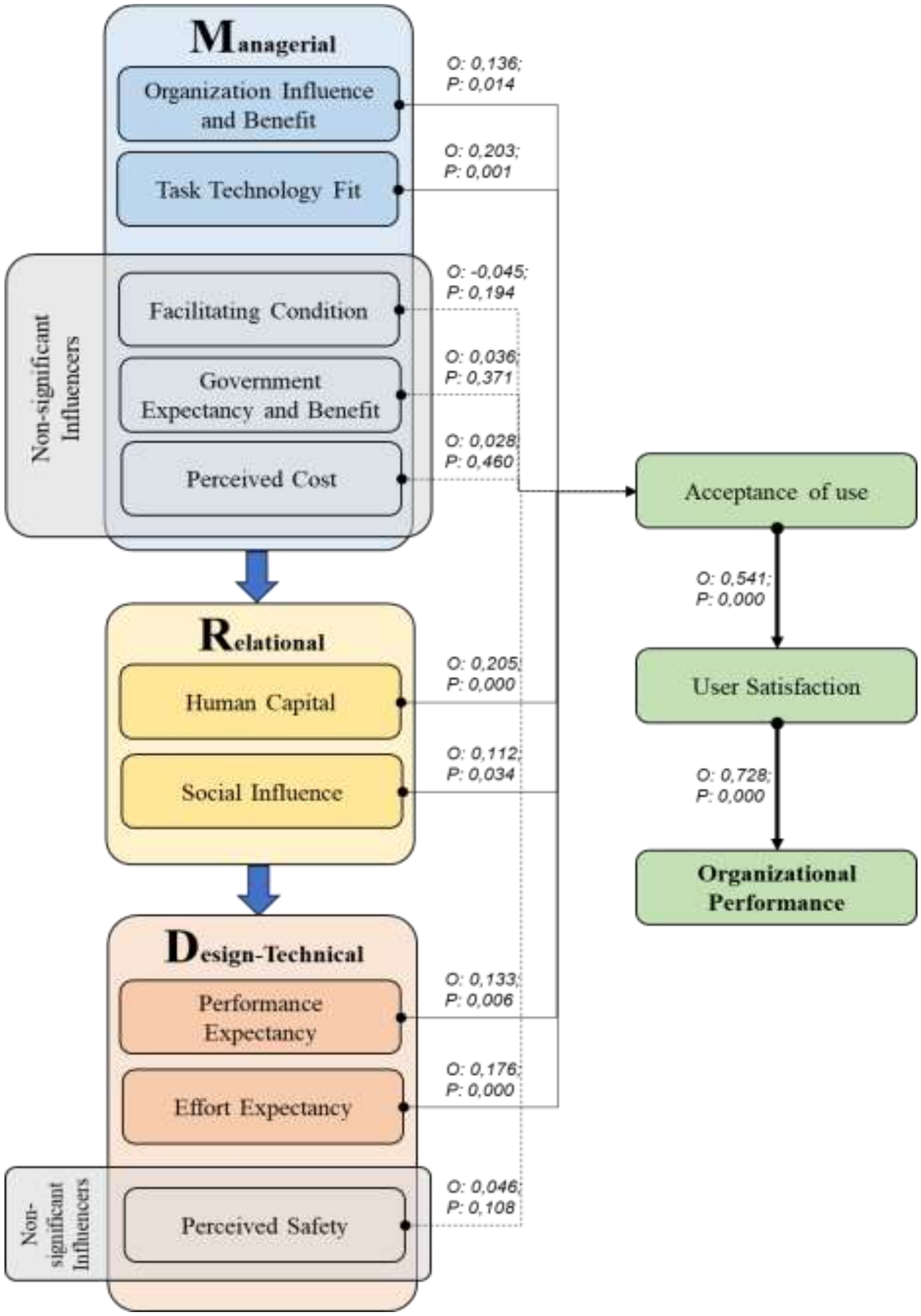
The importance of task-technology fit (TTF) further supports the notion that alignment between clinical workflows and system functionalities is fundamental. A strong TTF (path coefficient = 0.203; $p = 0.001$) confirms that EMRs must be embedded seamlessly into routine healthcare tasks to gain widespread acceptance. This resonates with the findings of Zallman (2021) and Cho et al. (2018), who argue that system usability is not merely a design issue but a strategic determinant of user satisfaction and adoption (32,33). Thus, EMR design processes should prioritize end-user involvement to ensure functionality supports, rather than disrupts, clinical efficiency.

Another prominent finding is the mediating role of user satisfaction, which links EMR acceptance to organizational performance. The indirect pathway Acceptance of Use → User Satisfaction → Organizational Performance showed the strongest effect (coefficient = 0.394; $p < 0.001$), validating previous assertions that perceived ease of use and user engagement are pivotal to digital success (14,35). Satisfaction with EMR systems enhances usage frequency and system depth, improving data quality and enabling better decision-making, ultimately boosting healthcare outcomes and efficiency.

Crucially, the study challenges traditional assumptions in health technology adoption frameworks, particularly the Technology-Organization-Environment (TOE) model, which posits that external pressures such as policy mandates, cost perceptions, or security concerns are primary enablers. In this study, variables like perceived cost ($p = 0.460$), government expectations ($p = 0.371$), and perceived safety ($p = 0.108$) showed no statistically significant influence on EMR acceptance. These findings imply that mandates and perceived risks may be too abstract or distant from day-to-day user experience, especially in resource-limited settings where frontline adaptability and contextual relevance matter more. This supports recent critiques advocating a shift from compliance-driven digital health strategies to localized, user-centered, and capacity-building approaches (2,9).

The role of social influence, though moderate (path coefficient = 0.112; $p = 0.034$), remains meaningful. Peer dynamics within clinical teams, especially the presence of tech-savvy early adopters, can stimulate broader acceptance through social learning. Fernández et al. (2022) and Anjos et al. (2021) emphasize that peer endorsement reinforces confidence in system reliability and usability, helping to overcome resistance (36,37). The MRD framework's relational pathway where adoption occurs via peer influence and departmental collaboration captures this nuance and explains variations in adoption patterns across institutions with different cultures and leadership structures.

Moreover, the MRD model's categorization of factors into managerial, relational, and design-technical domains provides a multidimensional structure to interpret the adoption process, reinforcing that EMR success is not just about system deployment, but also organizational behavior and user engagement.



Source: Author's interpretation

Figure 4. Model of MRD (Managerial–Relational–Design-Technical)

Managerial elements such as organizational support and internal policy (e.g., Organization Influence and Benefit, path coefficient = 0.136; p = 0.014) show that visible leadership commitment correlates with increased user engagement. As emphasized by Benedictis et al. (2020), leadership not only provides resources but also articulates a digital vision that aligns EMR adoption with institutional goals (1). This top-down encouragement, combined with bottom-up initiatives from digitally literate clinicians, creates the synergy needed for sustainable implementation.

In line with the principles of Rogers' Diffusion of Innovations theory, the study situates Type-C hospitals in Kupang in the transition between early adopters and early majority. This position reflects both partial system deployment and uneven user engagement hallmarks of transitional adoption phases (29). The diffusion trajectory varies by hospital type: RSU Mamami's technical and structural pathway emphasizes efficiency and internal policy alignment, RSUD S.K. Lerik illustrates social diffusion mechanisms rooted in professional norms, and RSAL S.J. Moeda demonstrates the significance of interface usability and bottom-up engagement. These nuances support the MRD concept, showing that EMR diffusion is not linear but dispersed across interacting routes.

Additionally, the analysis reveals that design-technical factors such as effort expectancy and performance expectancy, while statistically significant, exert less influence than human capital. This suggests that even well-designed systems require user readiness and competence to realize their potential. The implication is that EMR implementation strategies must extend beyond system deployment to include robust human-centric initiatives. Jedwab et al. (2022) and Marquard (2021) advocate for participatory design processes, iterative testing, and post-implementation feedback mechanisms to ensure systems evolve with user needs (8,35).

Finally, the integration of empirical findings with the MRD model underscores the need for multi-level alignment. Strategic synchronization across individual, team, and policy levels is imperative. As noted by Pye et al. (2025), policy frameworks that emphasize interoperability and standardization must be operationalized through training, resource planning, and responsive governance. While national mandates provide a regulatory backdrop, their effectiveness depends on local enactment that considers organizational culture, infrastructure constraints, and staff readiness (38).

In operational terms, hospitals aiming for higher EMR adoption and performance improvement should prioritize investment in human capital development, foster inter-professional collaboration, and tailor systems to task-specific needs. Furthermore, leadership should actively champion digital initiatives and establish feedback channels to refine system functionality in real-time. These actions, grounded in the MRD framework, enhance the prospects of transforming EMR systems from administrative burdens into instruments of clinical excellence.

The findings not only validate the theoretical models applied but also provide actionable insights for hospital administrators and policymakers. In developing contexts such as Indonesia, where digital transformation remains uneven, evidence-based models like MRD offer a path forward by aligning technical capability with organizational behavior and policy intent. Through this approach, EMR systems can evolve from policy imperatives to everyday clinical assets, advancing healthcare quality and equity.

While the MRD model offers a compelling interpretive framework to understand EMR adoption across managerial, relational, and technical pathways, it is important to clarify its derivation. The MRD model in this study was not tested as a distinct statistical construct, but rather developed interpretively based on empirical findings from the SEM-PLS analysis and mapped conceptually from existing adoption theories including UTAUT, TTF, Human Capital Theory, and Rogers' Diffusion of Innovations. Each domain within the MRD framework Managerial, Relational, and Design-Technical was grounded in statistically significant variables and pathways identified in the model.

This conceptual synthesis serves as a post-hoc explanatory structure that organizes the dominant adoption influences observed in the study. For example, statistically significant predictors such as human capital ($\beta = 0.205$), task-technology fit ($\beta = 0.203$), and organization influence and benefit ($\beta = 0.136$) were categorized into relational, technical, and managerial pathways respectively. Thus, the MRD model emerges not as an independently validated measurement model, but as a strategic analytical lens to explain how EMR adoption processes occur simultaneously through multiple interdependent channels.

Future research is encouraged to formalize and validate the MRD model using confirmatory factor analysis (CFA) or multi-group SEM to test its structural robustness across different healthcare contexts.

Comparison with Previous Studies

The findings of this study largely align with prior research on health information technology adoption, especially in emphasizing the role of internal organizational and human resource factors. The significant influence of human capital supports earlier works by Jedwab et al. (2022) and Pflugfelder (2020), who argue that staff competency, digital literacy, and training are foundational to successful EMR adoption (8,31). Similarly, the importance of task-technology fit resonates with the conclusions of Zallman (2021) and Cho et al. (2018), confirming that EMR systems must be designed to support routine clinical workflows to be effectively utilized (32,33). Moreover, the central role of user satisfaction in mediating the relationship between EMR acceptance and organizational performance builds on the findings of Marquard (2021) and Upadhyay et al. (2022), but this study further quantifies that pathway using SEM-PLS in a resource-limited context (14,35).

Conversely, this study diverges from several conventional perspectives by demonstrating that external factors such as perceived cost, facilitating conditions, and government expectations have no significant effect on EMR acceptance an insight that contrasts with studies like Scott et al. (2016) but aligns with critiques from Ajami (2023) and Tolera et al. (2022), who highlight the ineffectiveness of top-down mandates without organizational readiness. The moderate influence of social dynamics reflects the findings of Fernández et al (2,9,19). Anjos et al. (2021), reinforcing that peer interaction and professional endorsement play a role in shaping attitudes toward EMRs (36). Importantly, this study introduces the Multi-Routed Diffusion (MRD) model as an integrated framework that goes beyond linear diffusion theories like UTAUT and TOE, accounting for multiple, simultaneous adoption pathways shaped by managerial commitment, peer influence, and system design thus offering a more nuanced understanding of digital transformation in developing healthcare systems (36).

Limitations and Cautions

While this study provides valuable insights into the adoption of EMRs in Type-C hospitals, several limitations should be acknowledged. First, the cross-sectional design restricts the ability to capture changes in user perceptions and system performance over time, thereby limiting causal inference. Second, the findings are based on self-reported data, which may introduce bias due to social desirability or recall inaccuracies. Third, the research was conducted in a specific geographic and institutional context Kupang City, Indonesia which may limit the generalizability of the results to other healthcare settings with different cultural, technological, or policy environments. Additionally, the exclusion of patient perspectives and IT administrators may have omitted important viewpoints that could further inform the system's usability and impact. Future studies employing longitudinal or mixed-method designs and incorporating multi-stakeholder perspectives are recommended to provide a more comprehensive understanding of EMR adoption and its organizational consequences.

Recommendations for Future Research

Future research should explore longitudinal impacts and incorporate qualitative insights to better understand evolving user behaviors and the sustainability of digital health transformations in similar settings.

CONCLUSION

This study emphasizes the pivotal role of internal organizational factors particularly human capital and the alignment between system features and clinical tasks (task-technology fit) in shaping the successful adoption of Electronic Medical Records (EMRs) in Type C hospitals in Kupang City, Indonesia. Through the application of SEM-PLS modeling and integration of theoretical frameworks such as UTAUT, TTF, and the MRD model, the research confirms that user acceptance and satisfaction are key mechanisms through which EMR systems contribute to improved organizational performance. While external factors such as perceived cost, system security, and government incentives were statistically insignificant, the findings reveal that internal readiness, digital competence, and organizational culture are far more influential in resource-constrained healthcare environments.

For hospital leaders, these results underscore the importance of strategic investment in human resource development, including digital literacy training and workflow-aligned capacity building. EMR systems must not only be technically sound but also designed around the day-to-day realities of clinical practice. Leadership support is equally vital not only in terms of policy enforcement but also in providing a clear digital vision, fostering inter-professional collaboration, and creating a supportive implementation environment. Importantly, this study advocates for a multidimensional strategy that goes beyond regulatory compliance, focusing instead on user-centered design, institutional adaptability, and ongoing engagement from clinical and administrative stakeholders. These findings offer practical guidance for hospital administrators and policymakers seeking to optimize EMR implementation and transform it from a regulatory obligation into a meaningful driver of healthcare quality and operational efficiency.

The study's contribution lies in its introduction of a multi routed diffusion framework tailored to resource constrained healthcare environments. By mapping managerial, relational, and technical pathways of influence, the research provides actionable insights for hospital administrators and policymakers seeking to improve EMR adoption outcomes. Furthermore, the findings reinforce the need for contextualized strategies that prioritize user centered system design, peer influence, and leadership engagement.

AUTHOR'S CONTRIBUTION STATEMENT

Mahasar Reinheart F. Damanik conceptualized the study, developed the research framework, and led manuscript preparation. Aloysius Liliweri contributed to the theoretical formulation and supervised data interpretation. Apris A. Adu coordinated data collection and statistical analysis. William Djani assisted in instrument design and literature review. I Putu Yoga Bumi Pradana was responsible for validating the SEM-PLS results and preparing visual models. Laurensius P. Sayrani provided administrative support, reviewed institutional compliance, and refined the final manuscript. All authors have read and approved the final version of the manuscript.

CONFLICTS OF INTEREST

The authors declare that there are no conflicts of interest related to the content or publication of this article.

DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this work, the authors used generative AI tools, including ChatGPT developed by OpenAI, to support academic editing, language enhancement, and organization of ideas. The content was subsequently reviewed, verified, and edited by the authors to ensure accuracy, originality, and alignment with scholarly standards.

SOURCE OF FUNDING STATEMENT

This research received no external funding or sponsorship. All costs associated with the study were borne by the authors.

ACKNOWLEDGMENTS

The authors would like to express their sincere gratitude to the directors and healthcare staff of RSU Mamami, RSUD S.K. Lerik, and RSAL S.J. Moeda in Kupang City for their participation and support. Appreciation is also extended to the Faculty of Social and Political Sciences and the Faculty of Public Health at Nusa Cendana University for academic guidance throughout the research process.

BIBLIOGRAPHY

1. Benedictis AD, Lettieri E, Gastaldi L, Masella C, Urgu A, Tartaglini D. Electronic Medical Records Implementation in Hospital: An Empirical Investigation of Individual and Organizational Determinants. PLoS One. 2020;15(6):e0234108.
2. Tolera A, Oljira L, Dingeta T, Abera A, Roba HS. Electronic Medical Record Use and Associated Factors Among Healthcare Professionals at Public Health Facilities in Dire Dawa, Eastern Ethiopia: A Mixed-Method Study. Front Digit Health. 2022;4.
3. Torkman R, Ghapanchi AH, Ghanbarzadeh R. A Framework for Antecedents to Health Information Systems Uptake by Healthcare Professionals: An Exploratory Study of Electronic Medical Records. Informatics. 2024;11(3):44.
4. Kavandi H, Awar ZA, Jaana M. Benefits, Facilitators, and Barriers of Electronic Medical Records Implementation in Outpatient Settings: A Scoping Review. Healthc Manage Forum. 2024;37(4):215–25.
5. Indonesia KKR. Surat Edaran Nomor HK.02.01/Menkes/1030/2023 tentang Penerapan Rekam Medis Elektronik di Seluruh Fasilitas Pelayanan Kesehatan. Jakarta: Kementerian Kesehatan RI; 2023.
6. Putra DY, Leko AM, Ratu YF. Evaluasi adopsi sistem EMR di rumah sakit tipe C wilayah timur Indonesia. Jurnal Informasi Kesehatan. 2023;11(3):200–12.
7. Putra DY, Leko AM, Ratu YF. Evaluasi adopsi sistem EMR di rumah sakit tipe C wilayah timur Indonesia. Jurnal Informasi Kesehatan. 2023;11(3):200–12.

8. Jedwab RM, Franco M, Owen D, Ingram A, Redley B, Dobroff N. Improving the Quality of Electronic Medical Record Documentation: Development of a Compliance and Quality Program. Appl Clin Inform. 2022;13(04):836–44.
9. Ajami S. Barriers to implementation of Electronic Medical Records (EMRs) in developing countries: A review. Journal of Health Management and Informatics. 2023;10(1):12–9.
10. Buntin MB, Jain SH, Blumenthal D. Health information technology: Laying the infrastructure for national health reform. Health Aff. 2023;29(6):1214–9.
11. Attaallah AF, Elzamzamy OM, Phelps AL, Ranganthan P, Vallejo MC. Increasing Operating Room Efficiency Through Electronic Medical Record Analysis. J Perioper Pract. 2016;26(5):106–13.
12. Plantier M, Havet N, Durand T, Caquot N, Amaz C, Philip I, et al. Does Adoption of Electronic Health Records Improve Organizational Performances of Hospital Surgical Units? Results From the French E-Si (PREPS-SIPS) Study. Int J Med Inform. 2017;98:47–55.
13. Kaneko K, Onozuka D, Shibuta H, Hagihara A. Impact of Electronic Medical Records (EMRs) on Hospital Productivity in Japan. Int J Med Inform. 2018;118:36–43.
14. Upadhyay S, Opoku-Agyeman W, Choi S, Cochran RA. Do Patient Engagement IT Functionalities Influence Patient Safety Outcomes? A Study of US Hospitals. Journal of Public Health Management and Practice. 2022;28(5):505–12.
15. Gesicho M, Babić A. Identifying Barriers and Facilitators in HIV-indicator Reporting for Different Health Facility Performances: A Qualitative Case Study. PLoS One. 2021;16(2):e0247525.
16. Ford ND, Patel SA, Narayan KM V. Obesity in Low- And Middle-Income Countries: Burden, Drivers, and Emerging Challenges. Annu Rev Public Health. 2017;38(1):145–64.
17. Ahmed T, Lucas H, Khan AS, Islam R, Bhuiya A, Iqbal M. Health information technology in developing countries: Lessons from implementation and use of EMR in Bangladesh. Health Policy Technol. 2020;9(2):105–14.
18. Ash JS, Corby S, Mohan V, Solberg N, Becton J, Bergstrom R, et al. Safe Use of the EHR by Medical Scribes: A Qualitative Study. Journal of the American Medical Informatics Association. 2020;28(2):294–302.
19. Scott P, Curley P, Williams PB, Linehan IP, Shaha SH. Measuring the Operational Impact of Digitized Hospital Records: A Mixed Methods Study. BMC Med Inform Decis Mak. 2016;16(1).
20. Cairns J, Greenley S, Bamidele O, Weller D. A Scoping Review of Risk-Stratified Bowel Screening: Current Evidence, Future Directions. Cancer Causes & Control. 2022;33(5):653–85.
21. Pimperl A, Rodríguez HP, Schmittdiel JA, Shortell SM. The Implementation of Performance Management Systems in U.S. Physician Organizations. Medical Care Research and Review. 2017;75(5):562–85.
22. Venkatesh V, Morris MG, Davis GB, Davis FD. User acceptance of information technology: Toward a unified view. MIS Quarterly. 2003;27(3):425–78.
23. Goodhue DL, Thompson RL. Task-technology fit and individual performance. MIS Quarterly. 1995;19(2):213–36.
24. Nafukho FM, Hairston N, Brooks K. Human capital theory: Implications for human resource development. European Journal of Training and Development. 2020;44(3):311–28.
25. Ahmed T, Lucas H, Khan AS, Islam R, Bhuiya A, Iqbal M. Health information technology in developing countries: Lessons from implementation and use of EMR in Bangladesh. Health Policy Technol. 2020;9(2):105–14.
26. Edo FA, Hartono H, Anam S. Strategi peningkatan adopsi rekam medis elektronik melalui pendekatan manajemen perubahan di rumah sakit daerah. Jurnal Manajemen Pelayanan Kesehatan. 2023;26(1):45–58.
27. Putra YM. Analysis of Factors Affecting the Interests of SMEs Using Accounting Applications. J Econ Bus. 2019;2(3).
28. Hair JF, Hult GTM, Ringle CM, Sarstedt M. A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM). Thousand Oaks, CA: Sage Publications; 2017.
29. Rogers EM. Diffusion of Innovations. 5th ed. New York: Free Press; 2003.
30. Sayrani M. Dimensi formal dan informal dalam birokrasi pelayanan publik di Indonesia. Jurnal Ilmu Sosial dan Ilmu Politik. 2017;21(1):23–40.

31. Pflugfelder NS. Knowledge Management as a Driver of Performance in Ambulatory Healthcare – A Systematic Literature Review Through an Intellectual Capital Lens. Journal of Intellectual Capital. 2020;22(2):403–32.
32. Zallman. The Financial Advantages of Medical Scribes Extend Beyond Increased Visits. 2021;70(4).
33. Cho NE, Ke W, Atems B, Chang J. How Does Electronic Health Information Exchange Affect Hospital Performance Efficiency? The Effects of Breadth and Depth of Information Sharing. Journal of Healthcare Management. 2018;63(3):212–28.
34. Dayama N, Pradhan R, Davlyatov G, Weech-Maldonado R. Electronic Health Record Implementation Enhances Financial Performance in High Medicaid Nursing Homes. J Multidiscip Healthc. 2024;Volume 17:2577–89.
35. Marquard JL. Human Factors and Organizational Issues in Health Informatics: Innovations and Opportunities. Yearb Med Inform. 2021;30(01):091–9.
36. Anjos EF d., Martins PC, Prado NM de BL, Bezerra VM, Almeida PF d., Santos AMP. Quality of Actions to Control Cervical Cancer in Bahia, Brazil. Asian Pacific Journal of Cancer Prevention. 2021;22(8):2343–9.
37. Fernández N, Low DK, Cain MP, Martin LD, Merguerian PA. Recovering From COVID – Improving Operating Room Capacity. J Pediatr Urol. 2022;18(4):411.e1-411.e7.
38. Pye J, Rai A, Dong JQ. How Hospitals Differentiate Health Information Technology Portfolios for Clinical Care Efficiency: Insights From the HITECH Act. Information Systems Research. 2025;36(1):239–60.