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INTEROPERABILITY AND COMPATIBILITY OF ELECTRONIC MEDICAL RECORDS IN ENHANCING HEALTHCARE SERVICE QUALITY: A CASE STUDY AT DR. ABDUL AZIZ REGIONAL HOSPITAL, SINGKAWANG

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Abstract

The implementation of Electronic Medical Records (EMR) in hospitals is a strategic step toward improving the quality of healthcare services. However, compatibility and interoperability issues with external systems remain major challenges, particularly in regional hospitals. This study aims to analyze the compatibility and interoperability of the EMR system at RSUD dr. Abdul Aziz Singkawang, as well as its impact on service quality. It also addresses research gaps concerning the lack of in-depth studies on technical barriers and infrastructure limitations in EMR implementation. Using a descriptive case study approach, data were collected through interviews, observations, and document analysis. The findings indicate that while the EMR system is compatible with most internal hospital systems, it faces significant interoperability challenges with external platforms, mainly due to data format discrepancies and limited IT infrastructure. Nevertheless, EMR implementation has successfully improved administrative efficiency, reduced documentation errors, and enhanced the quality of patient services. This study contributes to the literature on health information system integration in regional hospitals and recommends improving system interoperability and upgrading IT infrastructure as strategic actions to support the digital transformation of healthcare services.

Keywords: *Electronic Medical Records, Interoperability, Health Information Systems, Service Quality Improvement.*

INTRODUCTION

The implementation of electronic medical records (RME) in Indonesia aims to create a more efficient and integrated health service system, in line with the government's commitment through the Ministry of Health to increase digitalization capacity in all health facilities in the country. The target of integrating the RME system in all health care facilities through the SATUSEHAT platform is expected to be achieved by 2025; However, the realization until mid-2023 still shows a figure that is far from expectations, only around 53% of hospitals and 32% of health centers are integrated with the system (Khasanah, 2023). The WHO report also highlights that only 58% of member countries have fully functional RME systems, reflecting the lack of equivalence between developed and developing countries in terms of digital infrastructure and technical readiness (Risdianty & Wijayanti, 2020; Panggulu et al., 2022).

Indonesia's main challenge in implementing RME is the issue of interoperability and system compatibility which leads to the low effectiveness of the use of information technology in health services. Data from the Ministry of Health in 2022 shows that only 41% of hospitals are able to operate interoperably across applications (Kassiuw et al., 2023). Mismatches between the characteristics of technology and healthcare workers' workflows lead to increased workload, duplication of records, and clinical miscommunication that has the potential to lower the overall quality of service (Khasanah, 2023). Therefore, the existence of a system that is able to support interoperability and compatibility between RME and the needs of health workers is a determining factor for the success of the transformation of the health service system in Indonesia (Yossiant & Hosizah, 2023).

Dr. Abdul Aziz Singkawang Hospital as one of the referral hospitals in West Kalimantan, faces challenges in optimizing the use of RME. Preliminary research shows that there are differences in perceptions among healthcare professionals regarding the ease of use and effectiveness of the system, as well as the availability of real-time clinical information (Meilia et al., 2019; Azzahra, 2023). This shows the importance of paying attention to the technical aspects, and the involvement of the end user in the system design and implementation process (Nurhayati et al., 2023). Previous research was only descriptive or focused on technical aspects without considering the causal relationship between the elements of the RME system and the output of the quality of service, so it required a more in-depth study (Rosalinda et al., 2021).

Therefore, this study seeks to explore this relationship using a quantitative approach with associative methods involving various health professions as a population. The purpose of modeling is to describe the dynamics of RME use in a more representative and multidisciplinary manner. The research framework uses the Technology-Organization-Environment/TOE Framework and Task-Technology Fit/TTF Theory. The TOE Framework provides a systemic understanding of how technological, organizational, and environmental aspects affect each other in the implementation of RME, while the TTF Theory highlights the importance of alignment between technology and the demands of user tasks. The integration of the two frameworks is expected to be able to explore the causal relationship between the technical attributes of the system and organizational factors that influence the acceptance and use of RME among health workers.

The theoretical contribution of the research is the development of an integrative analytical framework in the study of health information systems that emphasizes the importance of synergy between technology and the context of user organizations in improving the quality of services (Sartika & Gunawan, 2021). In addition, the research also methodologically strengthens the importance of using PLS-SEM in analyzing the digital health service system which is currently indispensable to support sustainable national health system reform (Suryanto & Subekti, 2020).

METHOD

The study uses a quantitative approach with associative methods to objectively and systematically analyze the cause-and-effect relationship between independent and dependent variables and to allow generalization of outcomes in a broader population (Wang et al., 2022). The study population was health workers at dr. Abdul Aziz Hospital, Singkawang, West Kalimantan who were directly involved in the use of electronic medical records (RME) as many as 165 people (Jiang et al., 2018). Sampling using the probability sampling technique used the Slovin formula with an error rate of 5% so that 119 respondents were obtained (Le, 2021). The sample was proportionally determined based on professional strata, including nurses, midwives, general practitioners, nutritionists, pharmacists, and medical recorders (Zucker et al., 2024).

The independent research variables are RME compatibility (X1) and RME interoperability (X2), as well as one dependent variable, namely: health service quality (Y) (Nishtala & Chyou, 2020). The research variables are operationalized through several dimensions and indicators on an ordinal scale (Luningham et al., 2020). Compatibility is measured based on the client's values and beliefs, experiences, and needs (Hasanpour et al., 2019). Interoperability includes the dimensions of the regulatory framework, information structure, technical infrastructure, supporting ICT systems, and access to information (Ceddia et al., 2019). The quality of health services is measured based on the dimensions of effectiveness, efficiency, accessibility, acceptability, fairness, and security (S. Lee, 2020). The research instrument is a closed questionnaire with an ordinal scale that has been tested for validity and reliability (Orlioglu et al., 2024). The questionnaire was developed based on previous theory and research and adjusted to the context of the hospital and the use of RME (S. Lee, 2019). Primary data was collected through the distribution of questionnaires to selected respondents (Chen et al., 2018). Direct dissemination by paying attention to research ethics, such as respondent consent and information confidentiality guarantees (Izuma et al., 2018). Secondary data from internal hospital documents as well as literature related to the use of RME (Shi et al., 2020).

The research was carried out through three stages. First, identify the characteristics of the respondents which include age, gender, profession, work unit, and length of service using percentage tabulation data. Second, identify the characteristics of compatibility, interoperability, and quality of hospital services descriptively using percentage tabulation data. Third, measure the compatibility and interoperability of electronic medical records (RME) to improve the quality of health services with a structural equation model using SEM-PLS through Smartpls software. The research was conducted through three main stages that are continuous and systematically designed to gain a comprehensive understanding of the relationship between the compatibility and interoperability of electronic medical record (RME) systems and hospital service quality (Le, 2021). The first stage aims to obtain an overview of the characteristics of respondents. Data was collected and analyzed descriptively through percentage tabulation of demographic variables, including: age, gender, profession, work unit, and length of service (Zucker et al., 2024). This approach provides a basic context regarding the profiles of respondents who contribute to the health care system, so as to strengthen the interpretation of the results of the subsequent analysis (Nishtala & Chyou, 2020). The second stage focuses on identifying system characteristics, namely compatibility, interoperability, and hospital service quality. Each variable was analyzed descriptively with a score of 1-5 using mean and categories with criteria that: not good: 1-1.8; poor: 1.81-2.6; good enough: 2.61-3.4; good: 3.41-4.2 ; and very good: 4.21-5 to uncover the perception and degree of application of these elements in the hospital environment (Luningham et al., 2020). This analysis provides an initial understanding of the extent to which the RME system has been integrated and functions optimally in supporting the quality of service (Hasanpour et al., 2019). The third phase aims to test the relationship between RME compatibility and interoperability to improving the quality of hospital services. The test was carried out through a quantitative approach using a Structural Equation Modeling (SEM) model based on Partial Least Squares (Ceddia et al., 2019). The analysis is carried out with SmartPLS software which allows the measurement of latent relationships between variables simultaneously and identifies the contribution of each construct to service quality empirically (Lee, 2020).

The analysis process is carried out systematically through several steps. First, the specification of the measurement and structural model by identifying exogenous constructs (compatibility and interoperability) and endogenous constructs (quality of service), including indicators that represent each construct (Manfrin et al., 2007). Furthermore, the survey results data are processed and input into SmartPLS for further analysis (Ricieri et al., 2009). Second, the assessment of the measurement model to test the validity and reliability of the indicator through the evaluation of convergent validity with the value of Average Variance Extracted (AVE≥0.50), the reliability of the construct through Composite Reliability (CR≥0.70) (Shibata et al., 2004). Third, the assessment of the structural model to evaluate the multicollinearity between constructs through the Variance Inflation Factor (VIF<5) value, the strength of the relationship through the determination coefficient (R^2), the relative contribution of the construct through the value of f^2, and the predictive relevance of the model through the Q^2 value obtained from the blindfolding technique (Panzarini et al., 2008). Fourth, test the significance of the relationship between constructs with the bootstrapping method to obtain t-statistical and p-value estimates (Lustosa-Pereira et al., 2006). Furthermore, the interpretation of path coefficients is generally carried out based on the following values: 0.00-0.10 (very weak/no effect), 0.10-0.30 (weak), 0.30-0.50 (moderate), 0.50-0.80 (strong), 0.80-1.00 (very strong). Fifth, the assessment of the goodness of fit of the model is carried out through the Standardized Root Mean Square Residual value (SRMR≤0.08) as an indicator of model suitability in general (Venkatramani et al., 2024). These stages are designed to form a strong analytical foundation in evaluating the effectiveness of the application of electronic medical record systems to improve healthcare in a structured, evidence-based, and quality-oriented manner.

RESULTS AND DISCUSSION

Respondent Characteristics

Analysis of respondent characteristics was conducted to obtain an overview of the profiles of health workers participating in the implementation and utilization of electronic medical records (RMEs*)*.

Table 1. Respondent Characteristics

Characteristic	Categories	Percentage %
Age	25–30	24,37

Characteristic	Categories	Percentage %
	31–40	57,98
	41–50	15,13
	>50	2,52
Gender	Male	20,17
	Female	79,83
Profession	Doctor	9,24
	Nurse Nurses	36,13
	Midwife	26,89
	Pharmacist	9,24
	Nutrisionis	9,24
	Medical recorder	9,24
Work Unit	IGD	8,40
	Maternity room	12,60
	Hospitalization	49,60
	Outpatient	1,70
	Nutrition installation	9,20
	Pharmaceutical Installations	9,20
	Medical records	9,20
Tenure (Years)	1–3	33,00
	3–5	15,50
	>5	51,50

Data source: Primary, 2025

Table 1 shows that the majority of respondents are in the productive age range, namely 31-40 years as many as 69 people (57.98%), followed by 25-30 years old at 24.37%. Only a small percentage of respondents were over 50 years old (2.52%) (Azzahra, 2023). This indicates that most health workers are in the phase of active working age and are adaptive to digital technology (Maryati, 2021). The distribution by gender showed the dominance of women as many as 95 people (79.83%), compared to men as many as 24 people (20.17%). This proportion reflects the general reality in the health service sector that women have greater involvement, particularly in the nursing and midwifery professions (Kusumah, 2022). Respondents from the profession showed varied backgrounds of health workers, the largest proportion was nurses as many as 43 people (36.13%), followed by midwives as many as 32 people (26.89%) (Yudianti & Arini, 2024). Other professions such as doctors, pharmacists, nutritionists, and medical recorders each contributed 9.24% (Larasugiharti, 2023). Diversity of professions is important to assess the compatibility and interoperability

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of RMEs because the system must accommodate the needs of cross-functional services (Yudianti & Arini, 2024). The respondents' work units also showed concentration on inpatient services at 49.60%, followed by maternity rooms (12.60%), emergency rooms (8.40%), and other supporting units such as nutrition installations, pharmaceuticals, and medical records at 9.20% each (Hufron & Hadi, 2024). This distribution shows that the majority of respondents work in units that have a high intensity in the use of RME as part of the clinical and administrative recording of patients (Adrian et al., 2023). Meanwhile, the length of service showed that more than half of the respondents (51.50%) had work experience of more than five years which reflected the level of professional maturity and the possibility of a better understanding of the hospital service system, including the use of information technology (Roziqin et al., 2022). Meanwhile, 33% of respondents have a working period of 1-3 years, which describes the presence of young health workers who are actively involved in the service process (Panggulu et al., 2022). Thus, the characteristics of the respondents show a relevant and representative composition in the context of the evaluation of an RME-based health information system. Variations in age, profession, and work unit allow the identification of differences in perceptions and experiences of interoperability and service quality, which are further analyzed at the structural model stage (Muhlizardy, 2020).

Characteristics of Compatibility, Interoperability, and Quality of Hospital Services

Analysis of the characteristics of compatibility, interoperability, and quality of hospital services showed that in general, respondents' perception of the implementation of electronic medical records (RME) was in the "Good" category with an average score that consistently exceeded the score of 3.5 (Table 2).

Table 2. Characteristics of Compatibility, Interoperability, and Quality of Hospital Services

Aspects	Statement	Score					Mean	Categories
		5	4	3	2	1		
Compatibility	Client Requirements	5	84	27	3	0	3,765	Good
	Values and beliefs	4	94	20	1	0	3,849	Good
	Experience	4	93	22	0	0	3,849	Good
	Total	**13**	**195**	**69**	**4**	**0**	**3,821**	**Good**
Interoperability	Accses to Information	1	72	44	2	0	3,605	Good
	Information Structure	10	74	35	0	0	3,790	Good
	Regulatory Framework	1	73	43	2	0	3,613	Good
	Supportive & Interoperable ICT Sytem	1	78	39	1	0	3,664	Good

	Technical Infrastructure	3	53	60	3	0	3,471	Good
	Total	**16**	**350**	**221**	**6**	**0**	**3,629**	**Good**
Quality of Service	Fair	37	51	30	1	0	4,042	Good
	Safe	37	51	30	1	0	3,891	Good
	Accessible	38	62	19	0	0	4,160	Good
	Acceptable	28	64	27	0	0	4,008	Good
	Effective	5	81	33	0	0	3,765	Baik
	Efficient	8	72	37	2	0	3,723	Good
	Total	**153**	**381**	**176**	**4**	**0**	**3,9315**	**Good**

Data source: Primary, 2025

Table 2 shows that in terms of compatibility, the three main indicators are client needs, values and beliefs, and experience, all of which obtain an average score above 3.7 (Maji & Laha, 2022). The highest scores were achieved by values and beliefs and experience, each with a mean of 3.849 (Imhanrenialena et al., 2024). This indicates that the RME system is quite capable of adapting to the context of the organization's culture, user expectations, and the accumulation of knowledge and experience of health workers (Safitri, 2021). This is an important indicator that information system integration considers alignment with work needs and internal values of the institution (C.-W. Lee & Huruta, 2022). The interoperability aspect was assessed through five indicators with an overall average score of 3.629 which indicated the consistency of perception with the "Good" category (Nurliza et al., 2020). The highest score was in the information structure (3,790), while the lowest score was recorded in the technical infrastructure (3,471) (Aminah & Syafri, 2023). However, there are no indicators that fall under the "adequate" category, meaning that although there is room for improvement, especially in technical readiness and ICT system support, generally the performance of information systems has met the expectations of users across service units (Twumasi et al., 2022). This confirms the existence of adequate connectivity in the exchange and integration of data between units and between professions (Rahayu et al., 2022).

The service quality aspect shows that all six indicators obtained high scores with an overall average score of 3,932 (Twumasi et al., 2022). The highest indicator is service accessibility with a mean value of 4,160, meaning that the RME system has facilitated easy access to patient information quickly and accurately (Kaluwa et al., 2022). Other indicators such as fairness, security, and service acceptance also show scores above 3.8, meaning that the RME system improves technical efficiency, and strengthens non-technical dimensions of service quality such as user trust and satisfaction (Baba et al., 2023). So, the RME system implemented has shown good performance in compatibility and interoperability, thus contributing significantly to improving the quality of hospital services (Sudirahayu & Harjoko, 2016). The success of the RME integration depends not only on the technical aspects, but also on the suitability of the system to the needs of the user as well as the system's ability to bridge the exchange of data between units efficiently and reliably (Ariani, 2023).

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Electronic Medical Record (RME) Compatibility and Interoperability for Healthcare Quality Improvement

The analysis of the compatibility and interoperability of electronic medical records (RME) for improving the quality of health care begins with the specification of the measurement and structural model, by identifying exogenous constructs (compatibility and interoperability) and endogenous constructs (quality of service), including indicators representing each construct (Figure 1).

Table 3. *Outer loadings (loading factor)*

	Interoperabilitas	Kompatibilitas	Mutu Layanan Kesehatan
Accses to Information	**0.761**		
Fair			**0.719**
Safe			**0.747**
Accessible			**0.751**
Acceptable			**0.857**
Effective			**0.804**
Efficient			**0.841**
Information Structure	**0.782**		
Client Needs		**0.759**	
Values and Beliefs		**0.815**	
Experience		**0.821**	
Regulatory Framework	**0.777**		
Supportive & Interoperable ICT Sytem	**0.736**		
Technical Infrastructure	**0.740**		

Table 3 above shows the results of the analysis of outer loadings, all indicators have values above 0.70, or strong convergent validity and significant contribution to the measured construct. The interoperability construct shows that indicators such as Access to Information (0.761), Information Structure (0.784), Regulatory Framework (0.777), Supportive & Interoperable ICT System (0.736), and Technical Infrastructure (0.740) show the important role of technical infrastructure and policies in supporting system connectivity. The compatibility construct shows that the indicators of Client Needs (0.759), Values and Beliefs (0.815), and Experience (0.821) reflect the importance of the system's suitability with the social context and user needs. Meanwhile, the health service quality construct shows that the indicators are Fair (0.719), Safe (0.747), Accessible (0.751), Acceptable (0.858), Effective (0.804), and Efficient (0.841), with emphasis on the dimensions of acceptance, effectiveness, and efficiency of services. This strengthens the reliability of measurement models in explaining the interconnectedness between constructs in the context of digital healthcare quality.

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Second, the results of the outer model test show that the three main constructs, namely interoperability, compatibility, and quality of health services, have met the criteria of convergent validity and reliability (Table 4).

Table 4. Validity and Reliability of Indicators

The Variables/Structural Model	*CR*	*AVE*
Interoperability	0,872	0,577
Compatibility	0,841	0,638
Quality of Health Services	0,907	0,621
Means	0,873	0,612

Data source: Primary, 2025

Table 3 above shows that the results of the validity and reliability testing of the constructs of all variables in the structural model meet the suggested criteria. The Composite Reliability (CR) value for all constructs is above the threshold of 0.70, which indicates that the constituent indicators of each construct have high internal consistency. The Interoperability construct has a CR value of 0.872 and AVE of 0.577, meaning that more than 50% of the variance of the indicator can be explained by the construct latently. The same applies to the Compatibility construct (CR: 0.841; AVE: 0.638) and Quality of Health Services (CR: 0.907; AVE: 0.621) which both meet the requirements of convergent validity and composite reliability. The average CR value of 0.873 and AVE of 0.612 indicate that the model has good reliability and validity in general. This indicates that the constructs in the model are able to represent the observed phenomenon consistently and validly, and support the feasibility of the model to be further analyzed using PLS-SEM.

Third, the assessment of a structural model to evaluate multicollinearity between constructs through the value of the Variance Inflation Factor (VIF<5) (Table 4).

Table 5. Collinearity statistic (VIF/Variance Inflation Factor)

	VIF
Access to information	1,597
Fair	1,769
Safe	1,807
Accessible	1,867
Acceptable	2,789
Effective	2,142
Efficient	2,322
Information structure	1,755
Client Requirements	1,400
Values and beliefs	1,397
Experience	1,428
Regulatory framework	1,662

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	VIF
Supportive & interoperable ICT system	1,603
Technical infrastructure	1,595

Data source: Primary, 2025

The results of the Variance Inflation Factor (VIF) analysis showed that all indicators in the model were below the general threshold of 3.3, meaning that there was no serious multicollinearity problem between the indicators in the structural model. The VIF values obtained ranged from 1,397 to 2,789. The indicators "Values and beliefs" (1,397), "Client needs" (1,400), and "Experience" (1,428) show the lowest VIF values, reflecting the low linear correlation between other constructs thus ensuring the stability of the regression coefficient estimation. It also shows that these constructs contribute unique information in the model. In contrast, the "Acceptable" indicator shows the highest VIF value of 2.789, but it remains below the threshold. This suggests a moderate correlation with other constructs but is still at a statistically acceptable level. Thus, the model is free from the threat of multicollinearity that can interfere with parameter estimation in Partial Least Squares Structural Equation Modeling (PLS-SEM) so that the interpretation of the relationships between constructs can be carried out with a high level of confidence, and the contribution of each variable to the model validly.

Fourth, the assessment of the strength of the relationship through the coefficient of determination (R^2) (Table 5), the relative contribution of the construct through the value of f^2 (Table 6), and the predictive relevance of the model through the value of Q^2 (Table 7) obtained from the blindfolding technique.

Table 62. R^2 and adj. R^2 Values

Endogenous Dependent Variable	R^2	Adj. R^{2*}
Quality of Health Services	0.614	0.608

Data source: Primary, 2024

Table 6 above explains the results of the determination test in the structural model showing that the R^2 value for the endogenous variable of Health Service Quality is 0.614, meaning that 61.4% of the variation in Health Service Quality can be explained by the predictor variables in the model, namely Interoperability and Compatibility. The Adjusted R^2 value of 0.608 provides a more conservative estimate by taking into account the number of predictive constructs of the model, but remains in the strong category. Furthermore, the f^2 value of the effect size analysis of f^2 emphasizes that in the context of improving the quality of information system-based health services, interoperability is the main factor that needs to be prioritized in the development and implementation of the system. Meanwhile, compatibility remains relevant but serves as a complement in supporting effective system integration.

Table 7. Result of f^2

	f^2
Interoperability→ Quality of Service	0,535
Compatibility → Quality of Service	0,041

Data source: Primary, 2025

Table 7 above shows that the Interoperability → Health Service Quality pathway has an f^2 value of 0.535 which is in the large category, meaning that interoperability makes a substantial contribution to improving the quality of health services. The higher the level of interoperability of the information system, the greater the impact on improving service quality. Meanwhile, the Compatibility → Health Service Quality track has an f^2 value of 0.041 which is in the small category, meaning that system compatibility has a relatively weak influence on service quality compared to interoperability, although it still contributes.

The predictive relevance (Q^2) results obtained through the blindfolding procedure showed that the model has substantial and reliable predictive quality for decision-making and policy planning for improving health services based on information systems.

Table 8.3 Value of Q^2

	SSO	SSE	Q^2 (1-SSE/SSO)
Interoperability	595.000	595.000	
Compatibility	357.000	357.000	
Quality of Health Services	714.000	446.920	0,374

Data source: Primary, 2024

Table 8 shows that the Health Service Quality Variable has a Q^2 value of 0.374. Meanwhile, the Interoperability and Compatibility variables have SSO = SSE values so Q^2 values are not calculated (since they are both exogenous variables). The Q^2 value of 0.374 for Health Service Quality indicates the strong predictive relevance of the model to the variable. A value above 0.35 indicates a high category, meaning that the developed structural model has a good ability to predict the quality of health services based on interoperability and system compatibility.

Fifth, the significance test of the relationship between constructs was carried out by the bootstrapping method to obtain t-statistical estimates (CR ratio) (Figure 1) and p-value (Table 9).

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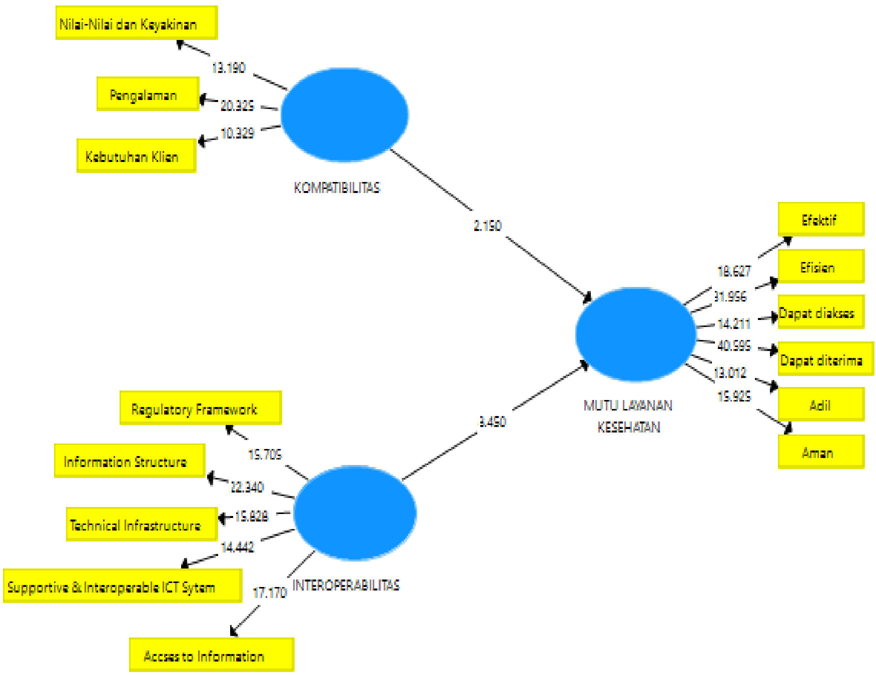

Figure 1. Critical Ratio (CR)

Figure 1 above shows that the two exogenous latent variables, namely Compatibility and Interoperability, have an influence on the endogenous variables of Health Service Quality. The path of influence from Interoperability to Health Service Quality shows a coefficient of 3,450, while the path from Compatibility to Health Service Quality is 2,150. This indicates that Interoperability has a stronger influence in improving service quality than Compatibility. Compatibility shows that the most dominant indicator is Experience (20,325), followed by Values and Beliefs (13,190), and Client Needs (10,329). Meanwhile, Interoperability shows that the indicators of Information Structure (22,340) and Supportive & Interoperable ICT System (17,170) have the greatest contribution weight, emphasizing the importance of information structures and supporting technology systems in service integration. Health Service Quality shows that the indicators of Acceptable (40,595) and Efficient (31,956) are the highest contributors to the formation of quality constructs, showing that the perception of service acceptance and efficiency is a key factor in assessing the quality of digital health services. Other indicators such as Effective (18,627), Accessible (14,211), Safe (15,925), and Fair (13,012) also strengthened the validity of the construct. Overall, this model confirms that increasing interoperability, especially through strengthening technical infrastructure and supporting information systems, has a significant influence on promoting the quality of health services that are effective, efficient, and acceptable to users.

Meanwhile, path coefficients describe the strength and direction of the relationship between independent and dependent variables in the SEM model (Table 8).

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Table 8. Result of P-Values

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Interoperability -> Quality of Health Services	0.647	0.649	0.077	8.389	**0.000**
Compatibility -> Quality of Health Services	0.178	0.180	0.083	2.145	**0.032**

Data source: Primary, 2025

Table 8 above shows that the two pathways of influence—Interoperability → Health Service Quality and Compatibility → Health Service Quality—had a p< value of 0.05, meaning that both were statistically significant. The Interoperability → Quality of Health Services pathway has a coefficient of 0.647 with a t-statistical value of 8.389 and a p-value of 0.000, indicating a very strong and significant influence. This shows that the higher the level of interoperability, the higher the quality of health services felt. Meanwhile, the Health Service Quality → Compatibility pathway showed an influence coefficient of 0.178 with a t-statistical value of 2.145 and a p-value of 0.032, which is also significant even though the contribution is lower compared to interoperability. These findings confirm that both independent variables play an important role in influencing the perception of health service quality, with interoperability as the dominant factor that needs to be prioritized in the development of digital healthcare systems.

Figure 2 shows a structural model with path coefficients that illustrates the relationship between latent variables in the study.

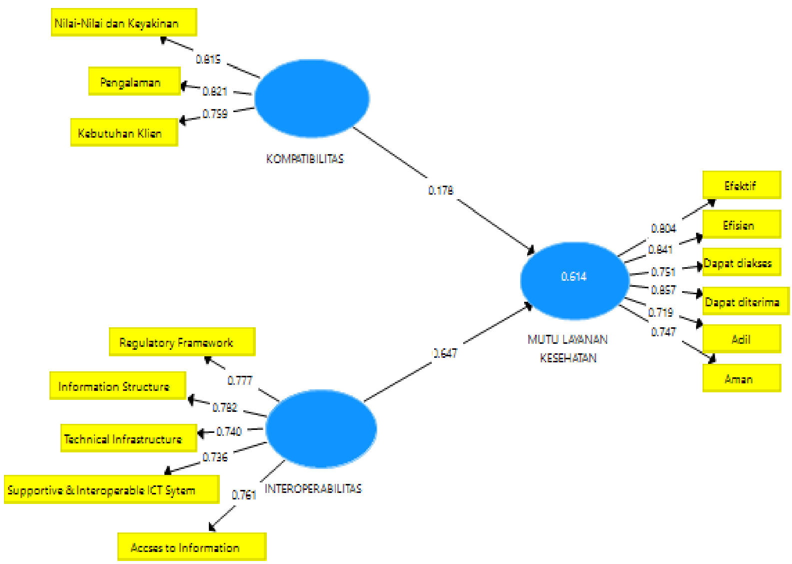

Figure 2*. Path Coefficients*

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Figure 2 shows that there are two main paths, namely: Compatibility → Health Service Quality with a coefficient of 0.215, and Interoperability → Health Service Quality with a coefficient of 0.345 (Manfrin et al., 2007). The value of the coefficient indicates the direction and strength of the influence between variables. The path from interoperability to health service quality has a stronger influence than the path from compatibility, which means that increasing interoperability in digital healthcare systems directly contributes more to improving the perception of service quality (Ricieri et al., 2009). Compatibility also showed a positive relationship with service quality, although the effect was lower (Shibata et al., 2004). This shows that the suitability of the system to the needs, values, and user experience remains relevant, but the integration and interconnectedness of the system across platforms (interoperability) is a key aspect that is more decisive in shaping the quality of effective and coordinated health services (Panzarini et al., 2008).

Sixth, the assessment of the goodness of fit of the model is also presented through the Standardized Root Mean Square Residual value (SRMR ≤ 0.08) as an indicator of model fit in general. SEM-PLS does not directly use goodness-of-fit (GoF) as in covariance-based SEM (CB-SEM) but the GoF measure to assess the overall fit of the model shows that the constructed SEM-PLS model successfully matches the observed data as follows:

$$\mathrm{GoF} = \sqrt{\mathrm{AVE}_{\mathrm{avg}} \times R^2_{\mathrm{avg}}}$$

$$\mathrm{GoF} = \sqrt{0{,}612 \mathrm{x} 0{,}614} = \sqrt{0{,}376} = 0{,}613$$

The GoF value obtained was 0.613. This value indicates that the model used in this study has a good match to the data. This value is greater than the minimum recommended limit, which is 0.36, which means the model can account for most of the data variability. Overall, these results show that the model constructed has an adequate level of suitability, both for the measurement model and the analyzed structure, and can provide a solid basis for further interpretation of the research results.

The description of this discussion provides several important points as follows. First, the main focus in the development of digital healthcare systems is directed at improving interoperability by strengthening integration between platforms and facilitating efficient data exchange between various health systems. Second, while compatibility remains important, the development of systems that can function well across multiple platforms and existing systems will be more effective in improving the overall quality of healthcare.

Implikasi hasil penelitian menunjukkan bahwa keberhasilan implementasi sistem layanan kesehatan digital tidak hanya bergantung pada kesesuaian sistem dengan kebutuhan pengguna (kompatibilitas), tetapi lebih pada kemampuan sistem untuk berinteraksi dan terintegrasi dengan berbagai sistem lainnya (interoperabilitas). Oleh sebab itu, kebijakan dan perencanaan pengembangan sistem digital di sektor kesehatan harus memprioritaskan interoperabilitas untuk memastikan kelancaran alur informasi dan meningkatkan koordinasi antar pemangku kepentingan. Selain itu, perhatian terhadap kompatibilitas juga tetap diperlukan untuk memastikan bahwa sistem tersebut tetap relevan dan dapat digunakan secara optimal oleh pengguna akhir.

The results of the study show that the implementation of Electronic Medical Records (RME) at dr. Abdul Aziz Singkawang Hospital has made a positive contribution to the quality of health services. This finding is reflected in the assessment of respondents who placed the variables of compatibility, interoperability, and quality of health services in the good category, with an average score above 3.5. This condition indicates that the RME system has been accepted and used quite well by health workers as part of clinical services and daily administration.

RME Compatibility to User Needs

The compatibility aspect obtained an average score of 3,821, with indicators of organizational values and user experience as the two highest components. This shows that the RME system is relatively in accordance with the value of professional work and is able to be operated by users according to the technological experience they have had. Good technology adaptation usually occurs when the system does not increase the workload and is in line with the clinical flow of the healthcare worker, as the results show that the experience indicator obtains the highest loading factor in the compatibility construct. Although the contribution of compatibility to quality of service was significant (p-value 0.032), the value of $f^2 = 0.041$ indicated a relatively small effect. This means that compatibility has an effect, but it is not the main factor driving service quality improvement. The important implication is that improved user-experience, advanced training, and more adaptive interface design can amplify the effect of compatibility on healthcare performance.

Interoperability as a Determinant of Service Quality

Interoperability is the aspect that contributes the most to service quality, as can be seen from the value of $f^2 = 0.535$ (large category) and the path coefficient of 0.647 with very strong significance ($p = 0.000$). These findings show that the better the data integration between applications and between service units, the higher the quality of service felt by patients and health workers. However, the technical infrastructure indicator has the lowest average score in its group, indicating that implementation barriers are still largely related to network readiness, hardware capacity, and data compatibility between systems. This is in line with the national phenomenon where the integration of RME with the SATUSEHAT platform is still uneven. Therefore, future policy strategies should focus on improving server networks, standardizing data formats, and integrating service platforms.

The Impact of RME Implementation on Service Quality

All service quality indicators were in the good category with an average of 3,931, and the highest score in terms of information accessibility (4,160). This condition shows that RME helps healthcare workers obtain patient data quickly, accurately, and in real-time, thereby speeding up clinical processes, minimizing duplication of records, and reducing the potential for medical errors. The acceptability and efficiency indicators also have a high loading factor, indicating good user acceptance and increased service process efficiency. An R^2 of 0.614 indicates that the combination of compatibility and interoperability explains 61.4% of the variation in service quality, so the model has strong predictive capabilities. The value of $Q^2 = 0.374$ also confirms that the research model has good predictive relevance in the context of information system-based service quality planning.

CONCLUSION

The implementation of Electronic Medical Records (RME) at dr. Abdul Aziz Singkawang Hospital has made a positive contribution to improving the quality of health services, especially in terms of administrative efficiency and reduction of medical recording errors. However, there are still challenges related to compatibility and interoperability between RME systems and other systems outside of hospitals. Technical constraints, such as data format differences and infrastructure limitations, hinder comprehensive data integration. The maximum benefits of implementing RME require further efforts to improve system interoperability and upgrade information technology infrastructure. In addition, policy support, ongoing training for medical and administrative personnel, and collaboration with relevant parties are essential to accelerate the transition to a more integrated health information system and support the improvement of the quality of services in hospitals.

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