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Unlocking the Potential: Electronic Health Records in Primary Care and Achieving the Quadruple Aim of Healthcare

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Abstract

Purpose: The purpose of this study is to analyze the factors influencing Quadruple Aim (QA) of healthcare services in primary care, with a focus on the role of electronic medical records (EMRs).

Design/methodology/approach: quantitative research was employed by a Cross-Sectional approach and utilizing stratified random sampling. Primary data was collected from 10 primary healthcare facilities in Samarinda City. Spearman's Rank test for bivariate analysis and Multiple Linear Regression was performed for the examined QA.

Finding: The bivariate analysis indicated that technology-clinical fit, technology as a control tool, and the duration of EMRs communication had a strong relationship with QA of healthcare services, while interoperability had a very strong relationship with QA of healthcare services. The multivariate analysis revealed that the duration of contact and communication contributed 0.242 times to QA, technology as a control tool contributed 0.129 times to QA, technology-clinical fit contributed 0.142 times to QA, and interoperability contributed 0.521 times to the QA of healthcare services. These findings provide recommendations for enhancing the implementation of EMRs and achieving the QA of healthcare services in primary healthcare.

Originality: This study uniquely contributes to decision sciences by empirically quantifying how specific EMRs factors, such as communication duration, technology control, clinical fit, and interoperability, impact the QA. It distinctively highlights interoperability as the key driver for achieving optimal healthcare outcomes in primary care settings.

Keywords: Quadruple Aim, EMRs, Healthcare Services, Primary Healthcare, Health Worker

JEL Classifications: I18, O33, J44, D81

1. Introduction

The Quadruple Aim (QA) is a system designed to optimize the performance of healthcare services. It encompasses improving patient experience, enhancing public health, reducing healthcare costs, and promoting healthcare worker well-being (Fitzpatrick et al., 2019). Factors such as increased disease burden, aging populations, and changes in patient expectations towards more efficient and patient-centered care further complicate efforts to improve healthcare services (Rahman, 2020). Several factors support the importance of implementing healthcare technology in improving healthcare services, including operational efficiency, quality of care, patient satisfaction, cost control, as well as disease prevention and management (Ohannessian et al., 2020).

Electronic Medical Records (EMRs) were widely used in various hospitals worldwide as replacements or supplements to paper-based health records (Huang et al., 2019). Although still relatively new in Indonesia, telemedicine services were widely adopted to digitize the patient data recording process. Ten out of twenty-four primary healthcare centers in Samarinda City had implemented telemedicine services for the community (Rahman et al., 2023). The implementation of EMRs systems in healthcare services involved several aspects that were inseparable from EMRs systems themselves, namely, the duration of communication contact, technology as a control tool, interoperability, and technology-clinical fit (Alami et al., 2020). According to Finset et al. (2020), reducing the duration of contact and communication can be interpreted as an action to limit or cut the time allocated for interaction and communication between medical staff and patients during the healthcare treatment process.

Technology as a control tool for EMRs is the implementation of an information system that enables the efficient collection, storage, management, and access of electronic medical record data (Woldemariam & Jimma, 2023). In this context, technology acts as a substitute for traditional physical medical record files (Srivani et al., 2023). EMRs system facilitates healthcare professionals in efficiently documenting medical information, encompassing patient histories, diagnoses, prescriptions, test results, and other pertinent data in an electronic format (Srivani et al., 2023; Woldemariam & Jimma, 2023).

Interoperability between EMRs systems is essential to ensure that healthcare providers have access to all relevant clinical information about their patients, enabling them to deliver high-quality care (Holmgren et al., 2017). Advancements in interoperability in hospitals in the United States have tended to be slow (Kennedy, 2023). The current healthcare IT infrastructure primarily focuses on transferring information between hospitals rather than ensuring that the information can be integrated for clinical utility (Almotairi, 2023).

Clinical-technological fit in EMRs entails the safe, effective, and efficient use of EMRs to meet patients' clinical needs. EMRs should be able to fulfill patients' clinical requirements, including the need for accurate, comprehensive, and up-to-date information (Adeniyi et al., 2024). The utilization of EMRs enhanced patient safety by reducing occurrences of medical errors through providing accurate and up-to-date information regarding the patient's health status (Laraichi, 2023; Sutha et al., 2025).

Enhancing the QA of healthcare services relies on optimizing several key independent variables within EMRs. Effective communication and sufficient contact time between healthcare providers and patients

foster trust, satisfaction, and better outcomes, while integrating technology as a control tool streamlines processes, enhances accuracy, and improves efficiency. Interoperability between EMRs systems facilitates coordinated care and informed decision-making, reducing duplication and improving patient outcomes. Tailoring technology to clinical needs ensures accurate, comprehensive data, enhancing patient safety and overall service quality. By addressing these factors, healthcare providers can bolster the QA, promoting patient experience, population health, cost reduction, and workforce well-being.

Recent research indicates that electronic health records (EHRs) significantly impact on the working conditions of healthcare providers, often leading to deterioration. This is primarily due to the burdensome and time-intensive nature of data entry required for administrative and billing purposes, alongside challenges related to inadequate interfaces, ergonomics, and EHRs interoperability. These factors contribute to heightened frustration, dissatisfaction, stress, and exhaustion among healthcare providers. Such consequences contradict the QA, which emphasizes that the well-being of healthcare providers is crucial for enhancing the quality of care and patient experiences (Alami et al., 2020). Considering the explanation above regarding the factors influencing EMRs towards QA of healthcare services in Samarinda City. Accordingly, this study aims to analyze factors influencing the effectiveness of EMRs in achieving the QA of healthcare services from the perspective of primary care healthcare professionals.

This study contributes to existing research by explicitly identifying and quantifying key factors, such as communication duration, technology as a control tool, interoperability, and clinical-technology fit, influencing EMRs towards achieving the QA in primary healthcare settings. By empirically evaluating these variables from healthcare professionals' perspectives, the research offers practical insights and actionable recommendations for healthcare administrators seeking to optimize EMRs implementation to simultaneously enhance patient experience, improve population health, control costs, and promote healthcare workforce well-being.

The remainder of this paper is organized as follows. Section 2 presents the literature review and hypothesis development, outlining the theoretical foundations and prior empirical findings related to electronic medical records and the Quadruple Aim framework. Section 3 describes the research methodology, including the study design, sampling strategy, data collection procedures, and statistical analysis methods. Section 4 reports the empirical results of the univariate, bivariate, and multivariate analyses. Section 5 discusses the findings in relation to existing literature and highlights their implications for primary healthcare practice and policy. Finally, Section 6 concludes the paper by summarizing the main findings, discussing limitations, and suggesting directions for future research.

2. Literature Review and Hypothesis Development

The QA framework extends the Triple Aim by adding healthcare workforce well-being to the original goals of enhancing patient experience, improving population health, and reducing healthcare costs (Bodenheimer & Sinsky, 2014). Fitzpatrick et al. (2019) emphasize that healthcare systems adopting the QA consistently report increased staff satisfaction and improved patient outcomes, underlining the importance of considering provider well-being alongside patient care (Fitzpatrick et al., 2019).

The adoption of EMRs is fundamental to modernizing healthcare systems by improving clinical decision-making, patient safety, and operational efficiency (Huang et al., 2019). Srivani et al. (2023) highlight that successful EMRs implementation significantly enhances patient safety, documentation accuracy, and the quality of healthcare delivery, aligning with QA objectives (Srivani et al., 2023).

Interoperability, defined as seamless data sharing among different EMRs systems, has emerged as a critical component of effective healthcare technology implementation. Studies by Holmgren et al. (2017) and Kennedy (2023) have demonstrated that interoperability facilitates coordinated care, reduces redundant procedures, and ensures that healthcare professionals have timely access to comprehensive patient information, ultimately enhancing healthcare quality and efficiency (Holmgren et al., 2017; Kennedy, 2023).

Recent literature indicates that the usability of EMRs systems directly impacts healthcare professionals' well-being. Alami et al. (2020) highlight that poorly designed EMRs contribute to provider burnout, job dissatisfaction, and increased stress levels, undermining the QA goals (Alami et al., 2020). Conversely, user-friendly and clinically aligned EMRs improve job satisfaction, reduce provider stress, and enhance overall service quality (Wei et al., 2023).

The Technology Acceptance Model (TAM) and Information Systems Success Model (ISSM) offer theoretical foundations for understanding EMRs acceptance and effectiveness (DeLone & McLean, 2003). These frameworks assert that system usability, perceived usefulness, information quality, and interoperability significantly influence user satisfaction and adoption outcomes in healthcare settings.

Based on the literature review, this study formally tests the following hypotheses:

- **H1:** Communication duration positively influences the achievement of the QA in primary healthcare.
- **H2:** Technology used as a control tool positively influences the achievement of the QA in primary healthcare.
- **H3:** Interoperability between EMRs systems positively influences the achievement of the QA in primary healthcare.
- **H4:** Clinical-technology fit positively influences the achievement of the QA in primary healthcare.

These hypotheses will be empirically examined to provide a deeper understanding of how EMRs-related factors can systematically enhance healthcare quality within the QA framework.

3. Methodology

3.1 Data and Sample

This research employed a quantitative approach with a cross-sectional methodology, where the researcher measured independent variables, namely the factors influencing electronic medical records, and dependent variables, namely the QA of healthcare services, simultaneously. This study employed a cross-sectional design, with all data collected once between December 8th and December 30th, 2023,

providing a single-time-point assessment of EMRs-related factors and Quadruple Aim achievement. The population consisted of healthcare workers involved in electronic medical records, totaling 391 individuals. Calculating the sample size using the Lemeshow formula for a known population yielded a result of 193 samples.

where n_0 is the initial sample size, Z is the standard normal deviate at a 95% confidence level (1.96), p is the estimated population proportion (0.5), and d is the margin of error (0.05). Because the total population was finite (N = 391), a finite population correction was applied using the following formula:

$$n = \frac{n_0}{1\frac{(n_0 - 1)}{N}}$$

The sampling technique used in this study was stratified random sampling to ensure adequate representation of various groups within the population. Initially, the population is segmented into homogeneous subgroups, or strata, based on the geographical distribution of the ten primary healthcare providers that utilize electronic medical records.

Each primary healthcare has a different number of nurses. For example, in the Palaran primary healthcare, there are 65 nurses. Representative sample from Palaran was 32 nurses, following the formula as follows:

$$s=TS\ (THA/TP),$$

where s is a representative sample; TS is the total sample based on the Lemeshow formula; THA is the total healthcare in one primary healthcare, and TP is the total population.

Although the final number of respondents was limited, this study was designed as an exploratory analysis in a setting where EMR implementation was still at an early stage. Only healthcare professionals who were actively involved in EMR-based workflows and met strict inclusion criteria were eligible, which constrained the attainable sample size. Therefore, the sample represents the entire accessible and relevant population within the selected primary healthcare facilities rather than a subset of a larger group.

Subsequently, random samples are selected from each stratum using an online and free online application. This approach is instrumental in ensuring that each subgroup is proportionately represented in the sample, thereby enhancing the validity and reliability of the study's findings. Data collection was conducted using a questionnaire comprising 48 questions related to factors influencing electronic medical records and 28 questions related to QA of healthcare services, with Cronbach's alpha coefficients of 0.778 and 0.940, respectively.

3.2 Statistical Analysis

This research employed three stages: univariate analysis, bivariate analysis using the Spearman Rank test, and multivariate analysis using Multivariate Linear Regression Analysis. This study employs Multiple Linear Regression (MLR) to analyse a four-point ordinal outcome measuring achievement of

the QA. Although ordinal logistic regression is theoretically preferred for purely ordinal outcomes, multiple linear regression (MLR) can be appropriately applied to questionnaire-based data when composite scores are constructed from multiple Likert-type items, thereby approximating continuous variables. When ordinal scales contain four or more categories and show reasonably smooth distributions, parametric methods are known to be robust and provide reliable estimates (Carifio & Perla, 2008; Norman, 2010). Moreover, MLR allows clear interpretation and comparison of effect sizes across predictors, which is widely valued in health services research for producing actionable implications for policy and practice (LaVela & Gallan, 2014; Manary et al., 2013).

To address the risk of spurious-like relationships highlighted in recent methodological studies (Cheng et al., 2022; Cheng et al., 2021; Wong & Yue, 2024; Wong & Pham, 2022a, 2022b), several precautions were taken. All independent variables were theoretically grounded in established EMR and Quadruple Aim frameworks, reducing the likelihood of purely data-driven associations. In addition, the consistency between the bivariate Spearman correlations and the multivariate regression results was examined; variables that were significant in the bivariate analysis remained significant in the regression model, supporting the structural stability of the relationships and lowering the risk of spurious findings.

Finally, standard diagnostic tests were conducted to validate the regression model. The independence of residuals was confirmed using the Durbin–Watson test (DW = 1.85), indicating no autocorrelation. Multicollinearity was not detected, as all VIF values were well below accepted thresholds, and tests of residual normality and homoscedasticity were satisfied. Together, these results support the appropriateness of using MLR for questionnaire-based data in this study and suggest that the estimated associations are statistically stable and unlikely to reflect spurious relationships, while remaining interpretative as associative rather than causal.

The independent variables in the multivariate analysis were the duration of contact and communication, technology as a control tool, interoperability, and technology-clinical fit. This study utilized a multiple linear regression model as follows:

$$QA = \beta_0 + \beta_1 CTC + \beta_2 TCT + \beta_3 INT + \beta_4 TCF + \varepsilon, \quad (1)$$

where QA represents the Quadruple Aim, CTC represents the duration of Contact and Communication, TCT represents Technology as a Control Tool, INT represents Interoperability, TCF represents Technology-Clinical Fit, and ε represents the error term.

Table 1. Descriptive Statistics of Respondents' Age

	N	Minimum	Maximum	Mean
Age	193	23	57	37.27

According to Table 1, the average age of the 193 respondents is 37 years. The highest respondent age is 57 years old, while the lowest is 23 years old.

Table 2. Characteristics of the respondent based on QA

		Quadruple Aim								Total
		Fair		Adequate		Good		Excellent		
		N	%	N	%	N	%	N	%	
Gender	Male	1	2.4%	2	4.9%	16	39%	22	53.7%	100

	Female	4	2.6%	2	1.3%	81	53.3%	65	42.8%	100
Year of services	0-5 years	1	2.1%	1	2.1%	27	57.4%	18	38.3%	100
	6-10 years	1	2%	2	4%	26	52%	21	42%	100
	11-15 years	0	0%	0	0%	29	54.7%	24	45.3%	100
	16-20 years	0	0%	1	5%	9	45%	10	50%	100
	≥ 21 years	3	13%	0	0%	6	26.1%	14	60.9%	100
Agency	Palaran	2	6.3%	0	0%	10	31.3%	20	62.5%	100
	Segiri	0	0%	0	0%	10	71.4%	4	28.6%	100
	Sidomulyo	0	0%	0	0%	10	71.4%	4	28.6%	100
	Lempake	0	0%	1	3.8%	11	42.3%	14	53.8%	100
	Temindung	0	0%	0	0%	9	56.3%	7	43.8%	100
	Sambutan	1	7.7%	3	23.1%	5	38.5%	4	30.8%	100
	Baqa	2	10.5%	0	0%	11	57.9%	6	31.6%	100
	Wonorejo	0	0%	0	0%	8	50%	8	50%	100
	Trauma Centre	0	0%	0	0%	11	40.7%	16	59.3%	100
	Samarinda Kota	0	0%	0	0%	12	75%	4	25%	100

Note: Agency, representative primary healthcare in Samarinda city, East Kalimantan, Indonesia.

Result in Table indicate 2, QA is a healthcare framework that focuses on four areas: population health, patient experience, cost, and staff experience. The table shows the percentage of people who have a certain characteristic based on QA. The majority of respondents are female, totaling 152 respondents. Respondents with 11-15 years of work experience and excellent QA results amount to 24 respondents (45.3%). Most respondents with excellent QA results are from Palaran Primary Healthcare Center, totaling 20 respondents (62.5%).

Table 3. Distribution of QA Levels Based on Variables

Variable	Category	Quadruple Aim								Total
		Fair		Adequate		Good		Excellent		
		N	%	N	%	N	%	N	%	
Contact Time and Communication	Fair	2	50%	0	0%	2	50%	0	0%	100
	Adequate	0	0%	3	75%	1	25%	0	0%	100
	Good	2	1.9%	1	0.9%	77	71.3%	28	25.9%	100
	Excellent	1	1.3%	0	0%	17	22.1%	59	76.6%	100
Technology as a Control Tool	Fair	1	25%	0	0%	0	0%	3	75%	100
	Adequate	0	0%	3	75%	1	25%	0	0%	100
	Good	3	3.9%	1	1.3%	66	86.8%	6	7.9%	100
	Excellent	1	0.9%	0	0%	30	27.5%	78	71.6%	100
Interoperability	Fair	2	50%	0	0%	1	25%	1	25%	100
	Adequate	0	0%	3	75%	1	25%	0	0%	100
	Good	2	2%	1	1%	89	89.9%	7	7.1%	100
	Excellent	1	1.2%	0	0%	6	7%	79	91.9%	100
Technology and Clinical fit	Fair	0	0%	0	0%	3	75%	1	25%	100
	Adequate	0	0%	3	42.9%	4	57.1%	0	0%	100
	Good	4	3.8%	1	1%	80	76.2%	20	19%	100
	Excellent	1	1.3%	0	0%	10	13.0%	66	85.7%	100

Note: This table illustrates the distribution of QA (Quadruple Aim) levels across four key variables: Contact Time and Communication, Technology as a Control Tool, Interoperability, and Technology and Clinical fit, categorized by levels of the Quadruple Aim: Fair, Adequate, Good, and Excellent.

Result in Table 3 indicate, QA is a healthcare framework that focuses on four areas: population health, patient experience, cost, and staff experience. In the variable of duration of contact and communication, there were 77 respondents who achieved a good QA level. In the technology as a control tool variable,

there were 78 respondents who achieved an excellent QA level. In the interoperability variable, there were 89 respondents who achieved a good QA level. Lastly, in the technology-clinical fit variable, there were 80 respondents who achieved a good QA level.

4. Result

4.1 Rank Spearman Test

Table 4 Rank Spearman correlation based on QA

Variable	P-Value	r	Relationship's power
Contact Time and Communication	< 0.001	0.545***	Strong
Technology as a Control Tool	< 0.001	0.596***	Strong
Interoperability	< 0.001	0.820***	Very Strong
Technology and Clinical fit	< 0.001	0.648***	Strong

Note: This table presents the results of the Rank Spearman correlation. Significance levels are denoted by ***, **, and * for 1%, 5%, and 10%, respectively.

The results of the Spearman Rank correlation coefficients in Table 4 indicated that contact time and communication had a strong relationship with QA of healthcare services (r = 0.545). For the variable of technology as a control tool, the correlation coefficient showed a strong relationship with QA of healthcare services (r = 0.596). Interoperability had a very strong relationship with QA of healthcare services (r = 0.820). Additionally, the variable of technology and clinical fit had a strong relationship with QA of healthcare services (r = 0.648). This study reveals the analysis, it can be inferred that contact time and communication, technology as a control tool, interoperability, and technology and clinical fit can enhance QA of healthcare services.

The positive direction of the relationship with positive values indicates a positive correlation. Increased contact time and communication, technology as a control tool, interoperability, and technology and clinical fit in electronic medical records can also enhance QA of healthcare services.

Table 4 indicates a correlation coefficient (R) of 0.788. The coefficient of determination (R Square) was 0.622, suggesting that 62.2% of the dependent variable could be explained by the independent variables, while the remaining variables outside of this model explained 37.8%.

4.2 Multiple Linear Regression Test

Table 5. Multiple Linear Regression Results Grouped by QA

Coefficients	Coefficients					Collinearity Statistics	
	β	Std.Error	Beta	t	Sig	R^2	VIF
Constant	-.115	.212		-.542	.589		
Contact Time and Communication (CTC)	.242	.056	.229	4.314	.000 ***	.713	1.403
Technology as a Control Tool (TCT)	.129	.054	.126	2.385	.018 **	.717	1.394
Interoperability (INT)	.521	.057	.503	9.091	.000 ***	.657	1.522
Technology and Clinical Fit (TCF)	.142	.054	.139	2.642	.009 ***	.727	1.376
Shapiro-wilk					.845		
Jarque-Bera					.946		

R	.788	Adjusted R Square	.613
R Square	.622	Std. Error of the Estimate	.410

Note: This table presents the results of a multiple linear regression analysis assessing the effects of four predictors—Contact Time and Communication (CTC), Technology as a Control Tool (TCT), Interoperability (INT), and Technology and Clinical Fit (TCF) on a dependent variable. All variables are statistically significant at conventional levels, with Interoperability and Contact Time and Communication showing the strongest effects, followed by Technology and Clinical Fit and Technology as a Control Tool. Variance Inflation Factors (VIFs) range from 1.376 to 1.522, indicating no multicollinearity issues. Significance levels are denoted by ***, **, and * for 1%, 5%, and 10%, respectively. Both the Shapiro-Wilk and Jarque-Bera statistic was used to test yield p-values > 0.05, failing to reject the null hypothesis of normality that the data have a normal distribution

As presented in **Table 5**, the regression results indicate that the constant value of −0.115 represents the expected Quadruple Aim (QA) score when all independent variables are held at zero. A one-unit increase in Contact Time and Communication is associated with a 0.242-unit increase in the QA score, holding all other variables constant. Similarly, a one-unit increase in Technology as a Control Tool corresponds to a 0.129-unit increase in the QA score, while Interoperability shows the strongest effect, with a one-unit increase associated with a 0.521-unit rise in QA. Finally, a one-unit increase in Technology–Clinical Fit is associated with a 0.142-unit increase in the QA score, controlling for the other variables in the model. To ensure the validity of these estimates, diagnostic tests were conducted to verify the assumptions of the multiple linear regression model for cross-sectional data. Heteroscedasticity was assessed using the Breusch Pagan test and showed no statistically significant results ($p > 0.05$), indicating homoscedastic residuals. Multicollinearity was examined using variance inflation factors (VIF), which ranged from 1.376 to 1.522, well below commonly accepted thresholds, suggesting no multicollinearity concerns (Hui et al., 2017). The normality of residuals was evaluated using the Shapiro Wilk and Jarque Bera tests, both yielding non-significant p-values ($p > 0.05$). Overall, these results confirm that the assumptions underlying the multiple linear regression model were satisfactorily met and that improvements across all EMRs-related dimensions, particularly interoperability are essential for enhancing the QA of healthcare services.

5. Discussion

The findings of this study, indicate that the influence of contact time and communication, technology as a control tool, interoperability, and technology and clinical fit in electronic medical records on QA of healthcare services. QA is a comprehensive framework that can be utilized to enhance the overall healthcare system (Bodenheimer & Sinsky, 2014). This framework acknowledges that public health is not solely determined by the quality of care received but also by other factors such as patient experience and healthcare costs. This is consistent with research by Jacobs et al. (2018), stating that healthcare institutions implementing QA and prioritizing healthcare professionals can positively enhance the well-being and performance of healthcare personnel in delivering healthcare services.

Study revealed, it is noted that Contact Time and Communication, Technology as a Control Tool, Interoperability, and Technology and Clinical fit all achieved a good level in contributing to the QA of healthcare services in primary care settings. These factors play a significant role in enhancing the quality of healthcare services and aligning with the QA framework, which focuses on improving patient experience, population health, cost reduction, and healthcare workforce well-being. The substantial and statistically significant coefficient for interoperability ($\beta = 0.521$, $p < 0.001$) indicates that facilitating seamless data exchange between systems serves as the most influential determinant in

advancing the QA within this context. Its effect size notably exceeds that of the other predictors, highlighting its critical role in optimizing healthcare outcomes.

By emphasizing the importance of integrating strategies to strengthen these elements within EMRs systems, the study underscores the potential for healthcare facilities to elevate performance and effectively achieve QA objectives. Implementation of targeted interventions aimed at fortifying Contact Time and Communication, Technology as a Control Tool, Interoperability, and Technology and Clinical fit within EMRs systems holds promise for driving tangible improvements in healthcare outcomes and advancing QA goals on a broader scale.

Contact time and communication between healthcare professionals and patients can be defined as the extent to which a healthcare professional engages in contact and communication with the patient while utilizing electronic medical records (Finset et al., 2020). Good contact time and communication serve as one of the factors in improving QA of healthcare services in Samarinda City. Effective contact time and communication through electronic medical records can also assist healthcare professionals in providing safer care to patients. The research has elucidated that electronic medical records can serve as a means to share health information among healthcare professionals, such as patients' social and medical data. This allows healthcare professionals to comprehensively understand the patient's condition, potentially saving time and effort while enhancing healthcare service efficiency.

The implementation of technology as a control tool in EMRs has a positive impact on QA, involving the improvement of population health, enhancement of patient experience, reduction of healthcare costs, and increased provider satisfaction (Wei et al., 2023). Technology as a control tool can be utilized to detect medical conditions more quickly and accurately, develop more individualized treatment plans, and monitor treatment outcomes more diligently. In line with the study by Smith et al. (2020), the study affirmed the convenience for healthcare professionals in using electronic medical records to access patient data and history efficiently, saving time, being more effective, and ensuring well-preserved patient data that was less prone to loss.

Azarm et al. (2020) stated that the implementation of electronic medical records interoperability systems had a positive impact on QA in healthcare services, particularly in Samarinda City. In the research, the authors stated that good interoperability supports achieving the principles of QA in enhancing the experience of providing care to patients and healthcare providers. Electronic medical records interoperability can help improve population health by facilitating the sharing of health information among healthcare providers. As stated in a study by Wei et al. (2023), the electronic medical records in population health can be utilized to identify potential local diseases that may arise, intervene, and track community health (Wei et al., 2023). The alignment of technology and clinical aspects in electronic medical records can contribute to achieving QA. The suitability of electronic medical record technology can provide benefits to patients, healthcare professionals, and the healthcare system as a whole. In line with the study by Haris et al. (2021), it is stated that electronic medical record services can enhance the accessibility of healthcare services, thus improving the public health status (Haris et al., 2021). The alignment of technology and clinical aspects in electronic medical records can enhance the quality, effectiveness, and efficiency of healthcare services, thereby increasing provider satisfaction.

The study's findings suggest a significant relationship between each variable contact time and communication, technology as a control tool, interoperability, and technology and clinical fit in electronic medical records and QA of healthcare in primary care services. Moreover, the research results indicate that, overall, the independent variables, encompassing contact time and communication, technology as a control tool, interoperability, and technology and clinical fit in electronic medical records, exert an influence on enhancing QA of healthcare services.

6. Conclusion

This study examined the influence of four key elements of EMRs—contact time and communication, technology as a control tool, interoperability, and technology-clinical fit on achieving the QA in primary healthcare. The results indicate that all four factors significantly contribute to QA, with interoperability emerging as the most influential predictor. The strong effect of interoperability underscores its role in facilitating seamless data exchange and coordinated care, which directly supports improvements in patient experience, population health, cost efficiency, and provider well-being.

The findings carry important practical and managerial implications for healthcare administrators, policymakers, and decision-makers. Prioritizing EMRs interoperability and ensuring alignment with clinical workflows can enhance care coordination, reduce duplication of services, and improve efficiency. Investments in optimizing contact time and communication, leveraging technology as a control tool, and ensuring clinical fit of EMRs systems can further strengthen the quality of healthcare delivery. These strategies can collectively advance QA objectives, ultimately leading to a more resilient and patient-centered primary healthcare system.

From an academic perspective, this study provides novel empirical evidence by disaggregating EMRs features and quantifying their specific impacts on QA in a low-resource setting. By focusing on individual EMRs components rather than treating EMRs as a homogeneous construct, the research offers a more nuanced understanding of their role in healthcare performance. Furthermore, the study presents a replicable framework for evaluating digital health implementation that can be adapted to other contexts, thereby contributing to the global discourse on health information systems and performance optimization.

Although diagnostic and robustness checks were conducted, the possibility of spurious-like relationships cannot be completely ruled out, particularly due to the cross-sectional nature of the study and the reliance on self-reported questionnaire data. As emphasized in recent methodological discussions on spurious regression in behavioral and applied research (Cheng et al., 2021; Wong & Yue, 2024), future studies should adopt more rigorous designs, such as longitudinal analyses, instrumental variable techniques, or causal modeling frameworks, to further verify the stability and causal direction of the observed relationships.

This study also has several limitations, including its cross-sectional design, its geographic focus on primary healthcare facilities in Indonesia, and the exclusion of patient perspectives, which may restrict the generalizability of the findings. Future research should involve larger and more diverse samples, incorporate viewpoints from multiple stakeholders including patients, and consider contextual

determinants such as infrastructure readiness, regulatory support, and policy environments. These approaches would provide a more comprehensive understanding of how EMRs systems can be optimized to effectively advance the Quadruple Aim across different healthcare settings.

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