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PREDICTIVE MODEL OF HEALTH FACILITIES AND DATA FOR QUALITY IMPROVEMENT (QI) IN MATERNAL AND NEONATAL MORTALITY REDUCTION IN JEMBER REGENCY

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ABSTRACT

Background: Maternal and neonatal mortality remain serious global health problems, particularly in developing countries such as Indonesia. In 2020, the WHO recorded 287,000 maternal deaths and 2.4 million neonatal deaths. Jember Regency has the highest maternal mortality rate in East Java. This study analyzes the influence of health facilities and data on the implementation of Quality Improvement (QI) in reducing maternal and neonatal mortality. **Method:** This research employed a quantitative approach with a cross-sectional design, involving 105 pregnant women as respondents. Data analysis was conducted using Structural Equation Modeling (SEM) with LISREL. The research model involved three latent variables: health facilities, data, and QI implementation. **Result:** The Confirmatory Factor Analysis (CFA) results indicated that all indicators were valid and reliable. The SEM model demonstrated a good fit based on RMSEA, CFI, and TLI indices. Structural analysis revealed that health facilities had no significant effect on QI implementation (t-value = 0.37), whereas data had a significant and dominant effect (t-value = 4.99; coefficient = 0.88). **Conclusion:** These findings indicate that the mere existence of health facilities is insufficient without quality services and an effective referral system. In contrast, data play a crucial role in evidence-based decision-making, monitoring, and evaluation within the QI framework. Strengthening the data system is therefore essential to maximize maternal and neonatal health programs.

Keywords: Health Facilities, Maternal and Neonatal Mortality, Data, Quality Improvement

INTRODUCTION

According to the latest data from the World Health Organization (WHO), maternal mortality remains very high, with approximately 260,000 women dying during pregnancy and childbirth in 2023 (WHO, 2024). In 2020, an estimated 287,000 women died during pregnancy and after childbirth. Regarding neonatal deaths, 2.4 million newborns died within the first month of life in 2020, with an average of 6,700 neonatal deaths per day. The Sustainable Development Goal (SDG) target for maternal mortality by 2030 is to reduce the global maternal mortality ratio to less than 70 per 100,000 live births (Silva et al., 2024). The United Nations also set a goal to significantly reduce the neonatal mortality rate to 12 per 1,000 live births and under-five mortality to as low as 25 per 1,000 live births by 2030 (Vijay & Patel, 2020).

In Indonesia, maternal mortality ranks among the top three in ASEAN. Based on data from the Maternal Perinatal Death Notification (MPDN) system, developed by the Ministry of Health, maternal deaths reached 4,005 in 2022 and increased to 4,129 in 2023 (Silva et al., 2024). Infant deaths were also recorded at 20,882 in 2022 and 29,945 in 2023. The target for 2024 is to reduce the maternal mortality ratio (MMR) to 183 per 100,000 live births and the infant mortality rate (IMR) to 16 per 1,000 live births (Ministry of Health RI, 2024).

Jember Regency has the highest maternal mortality rate in East Java. In 2023, there were 50 cases, decreasing to 43 cases in 2024, and 13 cases were recorded from January to June 2025. The infant mortality rate in Jember Regency was 265 cases in 2024, with 137 cases reported from January to June 2025 (Jember District Health Office, 2025). Efforts to accelerate the reduction of maternal mortality focus on ensuring that all mothers can access quality health services, including maternal health care. In line with this, comprehensive, integrated, and sustainable promotive, preventive, curative, and rehabilitative efforts are also required for infant and child health (Ministry of Health RI, 2023).

Previous research conducted by Main, E.K. (2020) found that several countries worldwide have implemented Quality Improvement (QI) programs to increase access to health facilities, which contributed to reducing maternal morbidity (Main et al., 2020). Quality Improvement in healthcare is a series of actions undertaken by health service facilities to provide care that meets standards while prioritizing patient safety. Indonesia has also adopted Collaborative Quality Improvement (QI) programs to accelerate the reduction of maternal and neonatal morbidity and mortality. One example is strengthening the quality of basic emergency obstetric neonatal services provided at inpatient community health centers to manage obstetric and neonatal emergencies (Dwirani, 2024).

A preliminary study through interviews with the Collaborative Quality Improvement (QI) team revealed several challenges in program implementation. These include geographically hard-to-reach areas with limited access to adequate health facilities, suboptimal medical equipment (available but damaged), and technical issues with the data reporting system, such as server disruptions. Data plays a crucial role as an input for policy-making by the Health Office, healthcare workers, pregnant women, and families in making decisions regarding health services, interventions, and referrals. Therefore, this study aims to examine the influence of health facilities and data on the successful implementation of Quality Improvement (QI) programs in reducing maternal mortality rate(MMR) and infant mortality rate (IMR).

METHOD

The research approach used in this study is deductive with a quantitative method. The type of research applied is observational analytic with a cross-sectional design. This design is relevant to the research title as it allows the assessment of the extent to which health facilities and data influence the implementation of the Quality Improvement (QI) program. The research process began with data collection by distributing questionnaires on health facilities, data, and the implementation of QI. A four-point Likert scale was used in this study: 1. Strongly Disagree, 2. Disagree, 3. Agree, and 4. Strongly Agree.

The study population consisted of all pregnant women in the working areas of community health centers (Puskesmas) in Jember Regency, totaling 142 individuals from January to June 2025. The sample size was determined using Slovin's formula with a 5% margin of error, resulting in 105 respondents. This number meets Hair et al.'s (1995) recommendation for a representative sample in SEM analysis, which ranges from 100 to 200 respondents. The sampling technique employed was stratified random sampling, with strata divided into agricultural, plantation, and coastal areas (Efendi, 2023; Ahmed, 2024).

Data analysis was conducted using SEM with the aid of Lisrel 8.7 software. The initial stage in SEM was model specification, which involved defining the variables and their relationships. This study included three variables: one endogenous variable, namely the implementation of Quality Improvement (QI), and two exogenous variables, namely health facilities and data. In SEM analysis using Lisrel, the steps include: (1) Confirmatory Factor Analysis (CFA), (2) Structural Model analysis, which combines the measurement model with the structural model to explain the relationships among latent constructs, (3) Model Fit analysis to assess how well the SEM model aligns with the empirical data, and (4) Interpretation of results to understand the relationships between latent variables and draw conclusions from the SEM findings. This research obtained ethical approval from the Research Ethics Committee of the Faculty of Dentistry, University of Jember, with ethical clearance number 3357/UN25.8/KEPK/DL/2025.

RESULT

Confirmatory Factor Analysis (CFA) of Health Facilities, Data, and Implementation of Quality Improvement (QI)

Confirmatory Factor Analysis (CFA) is a statistical technique used to analyze the validity and reliability of a model that involves latent variables and their indicators. The validity analysis of the measurement model in the initial stage of CFA is carried out by testing whether the *t-value* of the standardized loading factor of the observed variables meets the validity requirements, where loading factors ≥ 0.50 and *t-values* ≥ 1.96. The reliability analysis of the measurement model is performed by calculating the standardized loading factors and error variance, where a construct is considered to have good reliability if it meets the criteria of Construct Reliability (CR) ≥ 0.70 and Average Variance Extracted (AVE) ≥ 0.50 (Umar & Nisa, 2020).

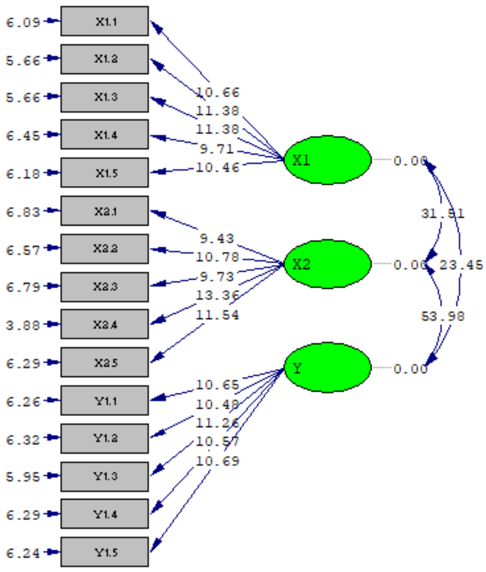

Figure 1. Structural Model of Confirmatory Factor Analysis (CFA)

Table 1. Validity Test Results of Health Facilities (X1)

Indicator	Factor Loadings	T-values	Remarks
X1.1 Attitude	0,89	10,66	Valid
X1.2 Action	0,93	11,38	Valid
X1.3 Awareness	0,93	11,38	Valid
X1.4 Responsiveness	0,84	9,71	Valid
X1.5 Assurance	0,88	10,46	Valid

Source: Processed SEM Data using Lisrel 8.7, 2025

The results of the Confirmatory Factor Analysis (CFA), indicator X1.1 has a factor loading of 0.89 with a T-value of 10.66; indicators X1.2 and X1.3 both have the same factor loading of 0.93 with a T-value of 11.38; indicator X1.4 has a loading value of 0.84 with a T-value of 9.71; and indicator X1.5 has a loading value of 0.88 with a T-value of 10.46. All of these values exceed the recommended minimum thresholds, namely factor loading ≥ 0.50 and T-value ≥ 1.96 (Hair et al., 2021), indicating that all indicators are valid. Therefore, it can be concluded that the five tested indicators are valid in measuring construct X1 and can be used in subsequent analyses.

Table 2. Reliability Test Results of Health Facilities (X1)

Indicator	Factor Loadings	error	Construct Reliability	Average Variance Extracted	Remarks
X1.1 Attitude	0,89	0,31	0,930	0,800	Reliabel
X1.2 Action	0,93	0,24			
X1.3 Awareness	0,93	0,24			
X1.4 Responsiveness	0,84	0,40			
X1.5 Assurance	0,88	0,32			

Source: Processed SEM Data using Lisrel 8.7, 2025

The results of Confirmatory Factor Analysis (CFA) for construct X1, the factor loadings for each indicator range from 0.84 to 0.93, indicating that all indicators have a strong contribution to the construct being measured. The error values range from 0.24 to 0.40, which are still within acceptable limits for the measurement model. The Construct Reliability (CR) value is 0.930, demonstrating excellent construct reliability as it exceeds the minimum threshold of 0.70. In addition, the Average Variance Extracted (AVE) value of 0.800 also shows a very good result, as it is well above the minimum threshold of 0.50. This indicates that the construct is able to explain more than 80% of the variance of its indicators, meaning that convergent validity has been achieved. Therefore, based on the CR and AVE values, it can be concluded that construct X1 is reliable and valid, and thus suitable for further analysis.

Table 3. Results of Data Validity Test (X2)

Indicator	Factor Loadings	T-values	Remarks
X2.1 On Time	0,82	9,43	Valid
X2.2 Vision	0,89	10,78	Valid
X3.3 Procedure	0,83	9,73	Valid
X4.4 Quality	1,01	13,36	Valid
X5.5 Solution	0,93	11,54	Valid

Source: Processed SEM Data using Lisrel 8.7, 2025

The results of the construct validity analysis, all indicators used in this study were declared valid. This is evidenced by the Factor Loadings values, all of which exceed the minimum threshold of 0.50, as well as T-values greater than 1.96 at the 5% significance level. Indicator X2.1 has a factor loading of 0.82 and a T-value of 9.43, indicating a strong contribution to the measured construct. Indicator X2.2 shows a loading value of 0.89 with a T-value of 10.78, which demonstrates a very strong relationship with the latent variable. Furthermore, indicator X3.3 obtained a loading value of 0.83 and a T-value of 9.73, also categorized as valid. Indicator X4.4 recorded the highest factor loading of 1.01 with a T-value of 13.36, showing that it is highly representative of its construct. The last indicator, X5.5, also shows strong results with a factor loading of 0.93 and a T-value of 11.54. Therefore, all indicators tested in this study meet the construct validity criteria and are appropriate to be used in the subsequent structural model measurement.

Table 4. Reliability Test Results (X2)

Indicator	Factor Loadings	error	Construct Reliability	Variance Extracted	Remarks
X2.1 On Time	0,89	0,43	0,933	0,800	Reliabel
X2.2 Vision	0,93	0,30			
X3.3 Procedure	0,93	0,40			
X4.4 Quality	0,84	0,08			
X5.5 Solution	0,88	0,23			

Source: Processed SEM Data using Lisrel 8.7, 2025

The results of the Confirmatory Factor Analysis (CFA) presented in the table above, it can be seen that all indicators show high factor loadings, ranging from 0.84 to 0.93. These values exceed the recommended minimum threshold of 0.50, indicating that each indicator has a strong contribution to the measured construct. The Construct Reliability (CR) value is 0.933, which is well above the minimum threshold of 0.70, demonstrating that the construct has very good internal consistency. This means that the indicators consistently measure the same construct. Furthermore, the Variance Extracted (VE) or Average Variance Extracted (AVE) value is 0.800, which also exceeds the recommended minimum threshold of 0.50. Based on these results, it can be concluded that all indicators within this construct have good convergent validity, and the construct is reliable for use in further analysis.

Table 5. Validity Test Results of Quality Improvement (QI) Implementation (Y)

Indicator	Factor Loadings	T-values	Remarks
Y1.1 Laboratory	0,89	10,65	Valid
Y1.2 Healthcare Worker (Midwife)	0,88	10,48	Valid
Y1.3 Communication	0,92	11,26	Valid
Y1.4 Bureaucratic Structure	0,80	10,57	Valid
Y1.5 Resources	0,89	10,69	Valid

Source: Processed SEM Data using Lisrel 8.7, 2025

The results of the construct validity analysis for variable Y1, which represents the implementation of quality improvement (QI), it was found that all indicators had factor loadings above 0.70 and t-values greater than 1.96. This indicates that all indicators are statistically significant and valid in measuring the intended construct. Indicator Y1.1 has a factor loading of 0.89 with a t-value of 10.65. Indicator Y1.2 shows a factor loading of 0.88 with a t-value of 10.48. Meanwhile, indicator Y1.3 has the highest factor loading of 0.92 with a t-value of 11.26, indicating the strongest contribution to forming construct Y1. Indicators Y1.4 and Y1.5 also demonstrate good validity, with factor loadings of 0.80 and 0.89 and t-values of 10.57 and 10.69, respectively. Therefore, all five indicators are considered valid and suitable for further analysis

Table 6. Reliability Test Results of Quality Improvement (QI) Implementation (Y)

Indicator	Factor Loadings	error	Construct Reliability	Variance Extracted	Remarks
Y1.1 Laboratory	0,89	0,89	0,818	0,800	Reliabel
Y1.2 Healthcare Worker (Midwife)	0,93	0,88			
Y1.3 Communication	0,93	0,92			
Y1.4 Bureaucratic Structure	0,84	0,88			
Y1.5 Resources	0,88	0,89			

Source: Processed SEM Data using Lisrel 8.7, 2025

The results of the construct variable analysis presented in the table, it can be seen that all indicators of variable Y have high factor loadings, ranging from 0.84 to 0.93, indicating that each indicator contributes significantly to the measured construct. The Construct Reliability (CR) value of 0.818 shows that the construct reliability meets the recommended criterion, which is above 0.70. In addition, the Average Variance Extracted (AVE) value of 0.800 also exceeds the minimum threshold of 0.50, indicating that this variable has good convergent validity, where more than 50% of the variance of the indicators can be explained by the measured construct. Thus, based on the CR and AVE values, it can be concluded that this construct is reliable and valid for further analysis.

The Health Facilities variable (X1), Data variable (X2), and Quality Improvement (QI) Implementation variable (Y) are latent variables, each measured using observed indicators that have been proven to possess good validity in reflecting the latent variables. This is supported by the analysis results showing that all indicators have factor loadings above 0.70 and t-values greater than 1.96. The findings also indicate that all observed variables meet the reliability requirements. This is reinforced by the fact that the Construct Reliability (CR) values meet the recommended criterion of being above 0.70. Furthermore, the Average Variance Extracted (AVE) values also exceed the minimum threshold of 0.50, leading to the conclusion that the constructs are reliable. Therefore, it can be concluded that all observed variables are both valid and reliable, and can consistently represent the latent variables.

Structural Predictive Model Analysis of Health Facilities and Data on the Implementation of Quality Improvement (QI) in Reducing Maternal and Neonatal Mortality.

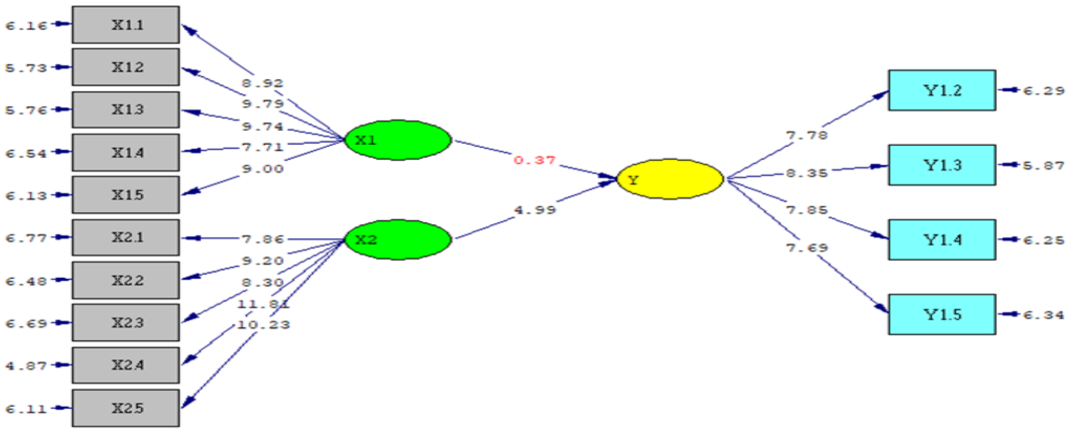

Figure 2. Complete Structural Model of Structural Equation Modeling (SEM) using LISREL

Table 7. Results of the Overall Model Fit Test

Fit Indicators	Model Value	Normal Value Range	Remarks
Chi-Square (p-value)	126.90 (p = 0.0034)	p > 0.05	*Not fit*
RMSEA	0.062	< 0.08 (good), < 0.05 (ideal fit)	*Fit*
RMSEA CI 90%	0.033 – 0.087	Lower CI < 0.05, Upper < 0.08	*Fit*
P-close (RMSEA < 0.05)	0.22	> 0.05	*Fit*
ECVI	1,81. ECVI for Saturated Model = 2.31. ECVI for Indepen6dence Model = 31.87	Close to Saturated Model	*Fit*
CFI (Comparative Fit Index)	0.99	≥ 0.95	*Fit*

NFI (Normed Fit Index)	0.96	≥ 0.90	*Fit*
NNFI (Non-Normed Fit Index / TLI)	0.98	≥ 0.95	*Fit*
IFI (Incremental Fit Index)	0.99	≥ 0.95	*Fit*
RFI (Relative Fit Index)	0.95	≥ 0.90	*Fit*
PNFI (Parsimony NFI)	0.80	≥ 0.50	*Fit*
RMR (Root Mean Square Residual)	0.010	< 0.08	*Fit*
Standardized RMR	0.045	< 0.08	*Fit*
GFI (Goodness of Fit Index)	0.86	≥ 0.90	*Not Fit*
AGFI (Adjusted GFI)	0.81	≥ 0.90	*Not Fit*
PGFI (Parsimony GFI)	0.63	≥ 0.50	*Fit*
Critical N (CN)	99.84	≥ 200	*Not Fit*
NCP	34,77	Interval (9,62 ; 67,96)	Fit
RMSEA	0,22	> 0,05	Fit
AIC	Model AIC = 187,77 Independence AIC = 3314.26 Saturated AIC = 240.00	The value close to the saturated AIC	Fit
CAIC	Model CAIC = 308.35. Independence CAIC = 3369.07. Saturated CAIC = 678.48	Values close to the saturated CAIC	Not Fit

The result of evaluation the model feasibility (Goodness of Fit) based on Table 7 is conducted to assess the extent to which the constructed model can represent the empirical data. Based on the analysis results, the Chi-Square value of 126.90 with a p-value = 0.0034 indicates a statistically significant result ($p < 0.05$), suggesting that the model is not fit according to this criterion. However, because Chi-Square is highly sensitive to sample size, several additional fit indices were considered.

The RMSEA value of 0.062, with a 90% confidence interval of 0.033–0.087 and a p-close = 0.22, shows that the model's approximation error is within an acceptable range, indicating a reasonable fit. Other fit indices also support the model's adequacy, including CFI = 0.99, NFI = 0.96, NNFI = 0.98, IFI = 0.99, and RFI = 0.95, all of which meet the recommended thresholds (≥ 0.90 or ≥ 0.95). The RMR = 0.010 and Standardized RMR = 0.045 indicate that the residual errors in the model are small. Parsimony indices, such as PNFI = 0.80 and PGFI = 0.63, also demonstrate satisfactory model fit. Furthermore, the ECVI value of the model (1.81) and the AIC value (187.77), which are close to those of the saturated model, indicate good predictive accuracy.

Nonetheless, some indices, such as GFI = 0.86, AGFI = 0.81, and Critical N = 99.84, do not reach the ideal thresholds, suggesting the need for a larger sample size or further model modification. Overall, although not all indices meet the criteria, the majority of fit indices indicate that the structural model is acceptable (fit) and suitable for testing the relationships between variables in this study (Wijayanto, 2021)

Table 8. Evaluation of Structural Model Coefficients and The Relationship with Research Hypotheses

Path	Estimasi	T-Value	Conclusion
Healthcare Facility (X1) → Implementation of Quality Improvement (QI)	0,06	0,37	Not Significant H_{01} Accepted H_{a1} Rejected
Data (X2) → Implementation of Quality Improvement (QI) (Y)	0,88	4,99	Significant Ho2 Rejected Ha2 Accepted

The result of analysis show that the healthcare facility variable (X1) has no significant effect on the implementation of Quality Improvement (QI), with an estimate of 0.06 and a T-Value of 0.37 (H_{01} accepted, H_{a1} rejected). On the other hand, the data variable (X2) has a significant effect on the implementation of Quality Improvement (QI) with an estimate of 0.88 and a T-Value of 4.99 (H_{02} rejected, H_{a2} accepted). These findings emphasize that the quality and utilization of data play a more crucial role in the successful implementation of QI compared to the availability of healthcare facilities.

DISCUSSION

In the structural model analysis between the latent variable of health facilities and the latent variable of quality improvement (QI) implementation, it can be seen that the first hypothesis regarding the relationship between health facilities and QI implementation (Ha) is rejected, and the null hypothesis (H0) is accepted because the obtained t-value was 0.37 with an estimated coefficient of 0.06. This value is considered not significant since t-value < 1.96, indicating that there is no relationship between the latent variable of health facilities and the latent variable of QI implementation.

Reducing maternal and neonatal mortality has been associated with increased coverage of antenatal care services at health facilities. Quality improvement (QI) strategies are widely supported by human resource capacity development processes. Reviews indicate that these quality improvement programs focus on multiple factors, one of which is health facility management (Goyet et al., 2019). Research by Khatri et al. (2021) shows that even though health facilities are available in many regions, the quality of maternal and neonatal services is uneven. The lack of training for health workers in managing obstetric and neonatal complications leads to interventions that are insufficiently effective in saving mothers and infants (Adhikari et al., 2025). A study by Pambudi et al. (2023) reports that many facilities do not have responsive and effective referral systems. Without coordination between primary and secondary levels, the mere presence of facilities does not have a significant impact on reducing mortality rates (Sastrawan et al., 2025).

From the above explanation, it can be concluded that the existence of health facilities does not always directly correlate with reductions in maternal and neonatal mortality, especially if not accompanied by service quality, accessibility, efficient referral systems, and socio-cultural approaches that match community characteristics. Therefore, strengthening systems and empowering communities based on local needs is crucial in efforts to reduce maternal and neonatal mortality.

In the structural model analysis between the latent variable of data and the latent variable of QI implementation, it can be seen that the second hypothesis regarding the relationship between data and QI implementation (Ha) is accepted, and the null hypothesis (H0) is rejected, because the obtained t-value was 4.99 with an estimated coefficient of 0.88. This value is considered significant since t-value > 1.96, indicating that there is a relationship between the latent variable of data and the latent variable of QI implementation.

Data is a key component of health information systems, interconnected with other components such as information, indicators, procedures, devices, technology, and human resources, managed in an integrated manner to provide support for decision-making, program planning, monitoring, and evaluation at every level of health administration (Sahat Manase, 2023).

Studies conducted by Ameh et al. (2021) in the *BMC Health Services Research* journal show that the systematic use of maternal and perinatal death audit data improves the quality of obstetric and neonatal services (Russell et al., 2022). Research by Ezeh et al. (2022) highlights that data-based performance monitoring in QI programs in rural communities has been proven to improve adherence to protocols for managing pregnancy complications, including preeclampsia and postpartum hemorrhage. They emphasize that a strong system for data collection and analysis forms the foundation for continuous learning and responsive decision-making (Avan et al., 2024).

In a study by Has et al. (2025), national population data was used to model predictors of survival for low birth weight infants. These findings provide a basis for data-driven QI to strengthen the management of high-risk neonates from birth, as interventions supported by data have been shown to improve neonatal outcomes (Has et al., 2025). In the digital era, the use of data is not limited to administrative recording and reporting but has evolved into a tool for predictive analytics, enabling early detection of high-risk mothers and newborns. Thus, data is not just a reporting tool but a core component in the Quality Improvement (QI) cycle: identifying problems, designing solutions, implementing interventions, and evaluating outcomes. Without valid and continuous data, the QI process will lose its direction in program planning and effectiveness in reducing maternal and neonatal mortality.

CONCLUSION

This study aims to analyze the influence of health facilities and data on the implementation of Quality Improvement (QI) programs in efforts to reduce maternal and neonatal mortality in Jember Regency. Based on the results of the structural model analysis using SEM Lisrel, several conclusions were drawn:

Health facilities do not have a significant effect on the implementation of Quality Improvement (QI). The hypothesis test showed a t-value of 0.37 and an estimated coefficient of 0.06, indicating that there is no significant relationship between the availability of health facilities and the successful implementation of QI. This finding reinforces previous studies emphasizing that merely having facilities is insufficient to reduce maternal and neonatal mortality without accompanying service quality, human resource competence, an effective referral system, and contextually appropriate social approaches.

Data has a highly significant effect on the implementation of Quality Improvement (QI). The hypothesis test showed a t-value of 4.99 and an estimated coefficient of 0.88. This indicates that data plays a dominant and strategic role in supporting QI implementation. Data serves as the foundation for decision-making, planning, execution, and continuous program evaluation. The use of accurate and real-time data enables early risk detection, strengthens maternal and neonatal emergency care protocols, and enhances the health system's responsiveness to high-risk populations.

The SEM model used is statistically adequate for further interpretation. Although some indices indicate a less-than-optimal fit, most key fit indicators—such as RMSEA, CFI, and TLI—show that the model is sufficiently representative to explain the relationships among variables. Based on the coefficient of determination, the data variable accounts for 99.54% of the variation in QI implementation, far exceeding the contribution of health facilities, which only explains 0.46%. This emphasizes that the strength of information systems and data quality is the main pillar for the success of programs aimed at reducing maternal and neonatal mortality, particularly in regions with geographic challenges such as Jember Regency.

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