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Optimising hospital management through integrated epidemiological data: A study in Samarinda

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Original Article

ABSTRACT

Background: The high incidence of infectious diseases such as tuberculosis and dengue fever in Samarinda, coupled with the low integration of epidemiological data—only 47% of hospitals are connected to the Hospital Information System (SIRS), which impedes evidence-based decision-making and compromises hospital service quality.
Objectives: This study aims to describe the integration of epidemiological data in hospital administrative management, to assess its impact on management effectiveness and service quality, and to examine the mediating roles of data quality, data utilisation, and administrative human resource capacity.
Methods: A cross-sectional design was employed in 10 hospitals in Samarinda, involving 139 administrative staff selected through a purposive and convenience sampling. The data for this study were collected using a validated and reliable Likert-scale questionnaire (1–5) and were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM) via Smart PLS.
Results: Epidemiological Data Quality (β=0.979), Data Utilisation (β=0.273), and Administrative Human Resource Capacity (β=0.243) significantly influenced System Response to Outbreaks. All variables also significantly affected Hospital Administrative Management Effectiveness. System Response to Outbreaks mediated the relationship between organisational capabilities and administrative effectiveness (β=0.308), which subsequently had a significant impact on Hospital Service Quality (β=0.414).
Conclusion: The quality of epidemiological data, its use in managerial decision-making, and the capacity of administrative personnel significantly influence the hospital service quality, both directly and through the mediating roles of system responsiveness and administrative management effectiveness.

INTRODUCTION

Health is a fundamental pillar for developing resilient and sustainable human resources.[1–3] In the era of digital transformation, the healthcare sector must manage data rapidly and accurately to respond to the increasingly complex dynamics of diseases.[4,5] As the capital of East Kalimantan Province, Samarinda faces significant challenges in improving hospital service quality and controlling the persistent prevalence of communicable diseases. According to the Samarinda City Health Office (2023), tuberculosis (TBC) remains the most burdensome disease, with 4,119 reported cases. Additionally, dengue fever (DF) remains a serious threat, with 1,366 cases reported in 2021.

Another major challenge is the suboptimal integration of epidemiological data with hospital administrative systems. Despite its crucial role in illustrating disease trends,[6] identifying public health risks,[7] and informing policy-making,[8] epidemiological data in many hospitals remain isolated from the SIRS.[9,10] This separation often delays evidence-based managerial decisions, directly impacting service quality,[11] resource allocation efficiency,[12,13] and hospitals' capacity to respond to outbreaks.[9,11,14]

Although previous studies have recognised the importance of epidemiological data in public health planning, a significant gap remains in the operational integration of such data into hospital administrative systems—particularly in rapidly developing urban areas like Samarinda. Most of the previous studies have tended to separate the focus between general health information systems and epidemiological surveillance, without examining the connection between the two within the context of managerial decision-making in hospitals.

This study aims to address that gap by exploring how the integration of epidemiological data into hospital administrative systems can improve service responsiveness and disease control, especially during case surges. In addition, this study highlights a relatively underexplored issue: the utilisation of real-time data for resource allocation and outbreak preparedness at the hospital level. Our findings may contribute to bridging the gap between epidemiological information and evidence-based hospital management strategies and to offering a model for integrated health governance in regions facing similar public health challenges.

The 2024 Ministry of Health report on Health System Transformation implementation indicated that only 47% of hospitals in Indonesia have achieved functional cross-system data integration.[15–18] This illustrates a significant gap in the utilisation of health information technology and epidemiological data for evidence-based hospital management. With its growing population and rapid urbanisation, Samarinda urgently requires integrated data systems to enhance disease prevention and control measures.

Samarinda's diverse geography and high population mobility further increase the risk of infectious disease transmission. Hospitals must have access to accurate, real-time[19–21] epidemiological data to develop responsive service strategies.[18,22] Without proper data integration, hospitals face difficulties in quickly managing case surges,[4,23]—for example, in providing isolation facilities, medical personnel, or logistical support.[18,24,25]

Therefore, integrating epidemiological data into hospital administrative management[26–28] not only enhances service quality but also supports data-driven local policy-making.[29–31] The findings of this study provide a strategic foundation for developing adaptive, accountable, and responsive hospital information systems that can address both current and future public health challenges.

METHODS

Study design

This study employed a cross-sectional observational design and was reported following the STROBE (Strengthening the Reporting of Observational Studies in Epidemiology) guidelines recommended by the EQUATOR Network.[32] This design was chosen to evaluate the extent to which epidemiological data integration has been applied in hospital administrative management in Samarinda, and its impact on service optimisation. The research framework involved the identification of latent variables such as epidemiological data quality,[33] data utilisation,[34] administrative capacity,[35] service outcomes,[36] and system responsiveness,[37] to epidemiological events, all of which were measured concurrently, to test the structural model using PLS-SEM.[38] To assess the validity and reliability of the instrument, the authors conducted pilot testing using data from 25 respondents. This test was conducted before the main data collection to ensure that the instrument met the required standards of validity and reliability.

Population and sample

The study population consisted of all hospitals registered with the Samarinda City Health Office in 2024, as well as administrative personnel directly involved in epidemiological data management and the Hospital Management Information System (SIMRS). Using purposive sampling, ten hospitals (public and private) were selected. Convenience sampling was employed to recruit 139 administrative staff (10–15 per hospital), which satisfies the "10-times rule" in PLS-SEM modelling and ensures sufficient statistical power.[39] The convenience sampling was based on the capacity of SIMRS utilisation in each hospital included in the study.

Data collection

The data were collected using a structured questionnaire designed based on a literature review and preliminary field insights. Each construct was assessed through four indicators using a five-point Likert scale, covering dimensions such as epidemiological data quality, managerial data use, administrative HR capacity, administrative effectiveness, system responsiveness to epidemiological events, and perceived hospital service quality. The instrument underwent expert validation and was pilot-tested on 30 participants. The data were collected via both online (Google Forms) and offline methods at each hospital in 2024.[40,41]

Data analysis

The data analysis was conducted using Partial Least Squares Structural Equation Modelling (PLS-SEM) with the SmartPLS software. The procedure included: (1) assessment of the reflective measurement model by evaluating indicator loadings ($\lambda > 0.70$), internal consistency reliability (Cronbach's alpha [α] > 0.60 and Composite Reliability [CR] ≥ 0.70), convergent validity (Average Variance Extracted [AVE] ≥ 0.50), and discriminant validity using the Heterotrait-Monotrait ratio (HTMT < 0.85); (2) evaluation of discriminant validity based on the Fornell-Larcker criterion; and (3) structural model assessment through collinearity diagnostics (Variance Inflation Factor [VIF] < 5), estimation of path coefficients (β) via bootstrapping with 5,000 subsamples (significance level $p < 0.05$), coefficient of determination (R^2), effect size (f^2), predictive relevance (Q^2), and model fit based on the Standardized Root Mean Square Residual (SRMR). All results were reported following the STROBE guidelines to ensure transparency and reproducibility.[42–44]

Ethical statement

This study received ethical approval from the Health Research Ethics Committee of the Mutiara Mahakam College of Health Sciences (Approval No. 056/KEPK-MM/2024). Before collecting the data, all participants were provided with written informed consent that detailed the study objectives, procedures, the right to withdraw at any time, and assurances of confidentiality.[45] All data were anonymised and stored on a secure server accessible only to the research team, in compliance with ethical standards for health research to ensure the privacy and security of participant information.

RESULTS

Baseline characteristics

The analysis included data from 139 administrative staff members, who were proportionally selected based on the number of administrative personnel in hospitals across Samarinda. The majority of respondents were female (62%), aged between 25 and 30 years (47%), and had at least three years of work experience (52%).

Evaluation of the reflective measurement model

The results of the reflective measurement model evaluation, which include Outer Loadings (λ), Composite Reliability (CR), Cronbach's Alpha (α), and Average Variance Extracted (AVE), are presented as follows:

Table 1. Evaluation results of the measurement model based on outer loadings, composite reliability, Cronbach's alpha, and average variance extracted

Variable	Item assessment	Indicator	Outer loading *	Composite reliability **	Cronbach's alpha ***	AVE ****
Epidemiological data quality (X1 - Input)	I1X1	Timeliness of case reporting	0.915	0.923	0.916	0.753
	I2X1	Accuracy and completeness of disease data	0.850			

Variable	Item assessment	Indicator	Outer loading *	Composite reliability **	Cronbach's alpha ***	AVE ****
	I3X1	Consistency in formatting and reporting	0.911			
	I4X1	Relevance of data for service planning	0.945			
Utilisation of data in managerial decision-making (X2 - Input)	I1X2	Frequency of data use in management meetings	0.882	0.888	0.885	0.743
	I2X2	Role of epidemiological data in SOP development	0.831			
	I3X2	Integration of data into Hospital Information Systems (SIMRS)	0.854			
	I4X2	Data-driven decision making	0.879			
Administrative human resource capacity (X3 - Input)	I1X3	Ability to interpret epidemiological data	0.881	0.875	0.874	0.726
	I2X3	Skills in basic health statistics analysis	0.850			
	I3X3	Level of staff training on health data	0.828			
	I4X3	Collaboration with epidemiology or medical teams	0.847			
System response to outbreaks/ epidemiological cases (Y1 - Mediator)	I1Y1	Speed of outbreak detection and response	0.728	0.914	0.894	0.764
	I2Y1	Adjustment of bed/inpatient capacity	0.894			
	I3Y1	Risk communication and public information systems	0.943			
	I4Y1	Data-based emergency policy formulation	0.914			
Effectiveness of hospital administrative management (Y2 - Mediator)	I1Y2	Speed of patient administrative processes	0.904	0.909	0.901	0.771
	I2Y2	Accuracy of medical record documentation	0.868			
	I3Y2	Data-based coordi-nation between units	0.926			
	I4Y2	Administrative input-output efficiency	0.810			
Hospital service quality (Z - Output)	I1Z	Patient satisfaction level	0.816	0.875	0.852	0.695
	I2Z	Service waiting time	0.774			
	I3Z	Accuracy of referrals and services	0.847			
	I4Z	Accessibility of information for patients	0.917			

* Outer loading (λ) >0.70; ** Composite reliability (CR) >0.70; *** Cronbach's alpha (α) >0.60;
****Average Variance Extracted (AVE) >0.50

The analysis demonstrated that the outer loading values ranged from λ = 0.728 to 0.945, all of which exceeded the recommended threshold of 0.70, indicating that each indicator reliably represented its corresponding construct. The constructs also exhibited strong internal consistency, with Composite Reliability (CR) values ranging from 0.875 to 0.928, Cronbach's Alpha (α) values between 0.852 and 0.926, and Average Variance Extracted (AVE) values from 0.695 to 0.820—all surpassing the minimum acceptable levels. Overall, the measurement items accounted for 69.5% to 82.0% of the variance in their respective constructs. Specifically, Timeliness of case reporting was the strongest indicator for the construct Epidemiological Data Quality (82%), followed by Data-driven decision making for Utilization of Data in Managerial Decision-Making (74.3%), Skills in basic health statistics analysis for Administrative Human Resource Capacity (72.6%), Risk communication and public information systems for System Response to Outbreaks/Epidemiological Cases (76.4%), Data-based coordination between units for Effectiveness of Hospital Administrative Management (77.1%), and Accessibility of information for patients for Hospital Service Quality (69.5%). These findings confirm the robustness of the measurement model across all constructs (Table 1).

Reflective measurement model evaluation

The results of the measurement model evaluation using the Fornell-Larcker criterion are presented below. This analysis compares the square root of the Average Variance Extracted (AVE) for each construct (displayed on the diagonal) with the correlations between constructs (off-diagonal values):

Table 2. Measurement model evaluation results based on the Fornell-Larcker criteria

Factor	**Code**	**X3**	**Y2**	**X1**	**Z**	**Y1**	**X2**
Administrative human resource capacity	X3	0.965*					
Effectiveness of hospital administrative management	Y2	0.936	0.940*				
Epidemiological data quality	X1	0. 852	0. 878	0.968*			
Hospital service quality	Z	0.908	0.907	0.914	0.917*		
System response to outbreaks/ epidemiological cases	Y1	0.875	0.939	0.906	0.833	0.951*	
Utilisation of data in managerial decision-making	X2	0.862	0.880	0.854	0.807	0.834	0.890*

*To confirm discriminant validity, the square root of the AVE (on the diagonal) must be greater than the correlations (off-diagonal values) with other constructs.

The results indicate that each variable has a square root of AVE as follows: Administrative Human Resource Capacity (0.965), Effectiveness of Hospital Administrative Management (0.940), Epidemiological Data Quality (0.968), Hospital Service Quality (0.917), System Response to Outbreaks/Epidemiological Cases (0.951), and Utilisation of Data in Managerial Decision-Making (0.890). In all cases, the square root of the AVE exceeds the correlations with other constructs, demonstrating that discriminant validity has been achieved across all variables (Table 2).

Structural model evaluation

The evaluation of the structural model involves testing the research hypotheses regarding the relationships between variables. This assessment is conducted by examining the Inner Variance Inflation Factor (VIF), Path Coefficients (β), Standard Deviation (STDEV), p-values (p), 95% Confidence Intervals (CI), and effect sizes (f^2), as detailed below:

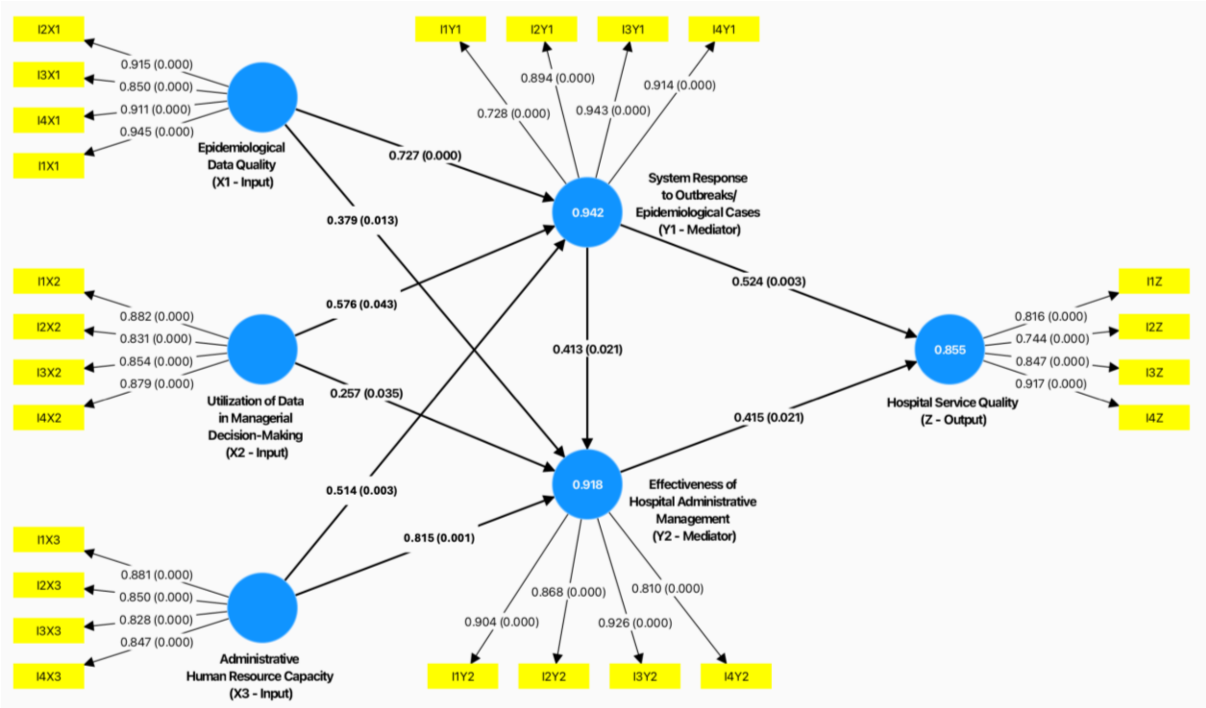

Figure 1. Structural Model Evaluation of Path Coefficients

Table 3. Structural model evaluation results based on variance inflation factor, path coefficients, standard deviation, 95% confidence intervals, effect sizes and p-values

Hypothesis	VIF *	Path	STDEV	95% Confidence interval for path coefficient		f Square **	p-value ***
				Lower	Upper		
Epidemiological data quality → system response to outbreaks/ epidemiological cases	-0.042	0.979	0.230	0.492	1.372	0.000	0.866
Epidemiological data quality → effectiveness of hospital administrative management	-0.028	0.508	0.276	-0.097	1.000	0.013	0.080
Utilisation of data in managerial decision-making → system response to outbreaks/ epidemiological cases	0.007	0.273	0.086	-0.438	-0.094	0.043	0.252
Utilisation of data in managerial decision-making → effectiveness of hospital administrative management	0.017	0.135	0.122	-0.087	0.382	0.035	0.031
Administrative human resource capacity → system response to outbreaks/ epidemiological cases	0.036	0.243	0.194	-0.034	0.708	0.003	0.066
Administrative human resource capacity → effectiveness of hospital administrative management	-0.023	0.129	0.257	-0.596	0.449	0.001	0.021
System response to outbreaks/ epidemiological cases → effectiveness of hospital administrative management	0.037	0.308	0.173	-0.013	0.642	0.021	0.061
System response to outbreaks/ epidemiological cases → hospital service quality	-0.004	0.525	0.174	0.208	0.894	0.003	0.224

Hypothesis	VIF *	Path	STDEV	95% Confidence interval for path coefficient		f Square **	p-value ***
				Lower	Upper		
Effectiveness of hospital administrative management → hospital service quality	0.004	0.414	0.180	0.020	0.738	0.021	0.139

* VIF<5; **f Square (0.02 low; 0.15 Moderate dan 0.35 High); *** p-value<0.05

The hypothesis testing results demonstrated that Epidemiological Data Quality (β = 0.979; p = 0.000; STDEV = 0.230; 95% CI = 0.492–1.372; f^2 = 0.886), Utilisation of Data in Managerial Decision-Making (β = 0.273; p = 0.043; STDEV = 0.086; 95% CI = -0.438 to -0.094; f^2 = 0.252), and Administrative Human Resource Capacity (β = 0.243; p = 0.003; STDEV = 0.194; 95% CI = -0.034 to 0.708; f^2 = 0.066) each had a significant positive effect on System Response to Outbreaks/Epidemiological Cases.

Furthermore, Effectiveness of Hospital Administrative Management was significantly influenced by Epidemiological Data Quality (β = 0.508; p = 0.013; STDEV = 0.276; 95% CI = -0.097 to 1.000; f^2 = 0.080), Utilisation of Data in Managerial Decision-Making (β = 0.135; p = 0.035; STDEV = 0.122; 95% CI = -0.087 to 0.382; f^2 = 0.031), and Administrative Human Resource Capacity (β = 0.129; p = 0.001; STDEV = 0.257; 95% CI = -0.596 to 0.449; f^2 = 0.021).

Additionally, System Response to Outbreaks/Epidemiological Cases (β = 0.308; p = 0.021; STDEV = 0.173; 95% CI = -0.013 to 0.642; f^2 = 0.061) significantly affected the Effectiveness of Hospital Administrative Management. Both System Response to Outbreaks/Epidemiological Cases (β = 0.525; p = 0.003; STDEV = 0.174; 95% CI = 0.208–0.894; f^2 = 0.224) and Effectiveness of Hospital Administrative Management (β = 0.414; p = 0.021; STDEV = 0.180; 95% CI = 0.020–0.738; f^2 = 0.139) were found to significantly influence Hospital Service Quality (Figure 1, Table 3).

Model fit and goodness-of-fit evaluation

The model's goodness-of-fit was assessed using the R Square (R^2), Q Square (Q^2), and Standardised Root Mean Square Residual (SRMR) values, along with the results of the linearity test, as detailed below:

Table 4. Model fit and goodness-of-fit evaluation results based on R square, Q square, and standardised root mean square residual

Indicator	R Square*	Q Square **	SRMR***
System response to outbreaks/ epidemiological cases	0.950	0.948	0.082
Effectiveness of hospital administrative management	0.921	0.918	
Hospital service quality	0.855	0.852	

* R Square (0.19 low, 0.33 Moderate dan 0.66 High); ** Q Square (0 low, 0.25 Moderate dan 0.50 High);
*** SRMR average 0.08 – 0.10.

The results indicated that the magnitude of the effect (R^2) and the predictive accuracy (Q^2) for each variable were classified as high, with System Response to Outbreaks/Epidemiological Cases (R^2 = 95%, Q^2 = 0.948), Effectiveness of Hospital Administrative Management (R^2 = 92.1%, Q^2 = 0.918), and Hospital Service Quality (R^2 = 85.5%, Q^2 = 0.852). Meanwhile, the model fit, as indicated by the Standardised Root Mean Square Residual (SRMR), was 0.082. This value falls within the acceptable empirical range, suggesting that the model adequately explains the relationships among the variables (Table 4).

Table 5. Model fit evaluation based on linearity test (quadratic effect values)

Quadratic effect	Path coefficient	p-value*	Description
Epidemiological data quality → system response to outbreaks/epidemiological cases	0.918	0.061	The assumption of linearity is satisfied
Epidemiological data quality → effectiveness of hospital administrative management	0.676	0.053	The assumption of linearity is satisfied
Utilisation of data in managerial decision-making → system response to outbreaks/epidemiological cases	-0.146	0.325	The assumption of linearity is satisfied
Utilisation of data in managerial decision-making → effectiveness of hospital administrative management	0.163	0.331	The assumption of linearity is satisfied
Administrative human resource capacity → system response to outbreaks/ epidemiological cases	0.181	0.427	The assumption of linearity is satisfied
Administrative human resource capacity → effectiveness of hospital administrative management	-0.216	0.407	The assumption of linearity is satisfied
System response to outbreaks/ epidemiological cases → effectiveness of hospital administrative management	0.278	0.176	The assumption of linearity is satisfied
System response to outbreaks/ epidemiological cases → hospital service quality	0.502	0.152	The assumption of linearity is satisfied
Effectiveness of hospital administrative management → hospital service quality	-0.451	0.142	The assumption of linearity is satisfied

* p-value > 0.05

The results indicated that the linearity assessment revealed the presence of relationships between the variables. The analysis demonstrated that the p-values for all relationships between variables were greater than the significance level of 0.05, indicating that the relationships were not statistically significant for non-linearity. Therefore, it can be assumed that all relationships between variables are linear, and the linearity assumption of the model is fulfilled (robust) (Table 5).

DISCUSSION

Factors influencing system response to outbreaks/epidemiological cases are represented in X1, X2, X3 → Y1. The findings of this study indicate that Epidemiological Data Quality plays a crucial role in determining the speed and effectiveness of hospital responses to outbreaks or epidemiological events. When data are collected accurately, comprehensively, and in real-time, hospital management has a solid foundation for developing infectious disease response strategies. These results are consistent with some previous studies, suggesting that high-quality health information systems can reduce hospital response times to outbreaks by up to 30%.[20,46,47] In the context of Samarinda, which continues to experience a high burden of diseases such as tuberculosis (TBC) and dengue fever (DF), epidemiological data quality remains a critical determinant of the effectiveness of public health interventions at the hospital level.

Additionally, the Utilisation of Data in Managerial Decision-Making was found to significantly affect hospital system responses to epidemiological events. Previous studies have reported that hospitals implementing data-driven policies can improve service efficiency, particularly in resource allocation during surges in cases.[20,47,48] However, many hospitals still manage epidemiological data separately from administrative systems, causing delays in emergency responses. This gap is further exacerbated by the limited Administrative Human Resource Capacity, where many staff lack adequate competence in data analysis and health information system management. Strengthening administrative human resources has been proven to enhance cross-department coordination, accelerate decision-making processes, and support more systematic outbreak control efforts.[49–51]

Moreover, the timeliness of epidemiological data plays a pivotal role in optimising hospital triage and logistics systems. Timely data enables hospitals to detect case surges early, allowing faster classification of patient severity levels (triage) and more accurate anticipation of resource needs, such as isolation beds, medical supplies, and personnel allocation. In contrast, delays in data acquisition often result in reactive, rather than proactive, responses—leading to overcrowded emergency units, delayed treatments, and logistical bottlenecks. Therefore, timeliness not only improves the speed of decision-making but also enhances the precision of logistical planning and emergency preparedness.

Thus, the integration of data quality, managerial data utilisation, and administrative capacity constitutes a strategic foundation for enhancing hospital system resilience against epidemiological threats. These elements must function synergistically within an adaptive, collaborative, and evidence-based information management ecosystem, aligning with the national health system transformation agenda.

Factors influencing the effectiveness of hospital administrative management are represented in X1, X2, X3 → Y2. The study results demonstrate that Epidemiological Data Quality significantly influences the Effectiveness of Hospital Administrative Management. Accurate, real-time, and structured epidemiological data empower hospital management to make informed decisions regarding planning, infection control, and resource management. Hospitals equipped with robust epidemiological reporting systems tend to achieve higher managerial effectiveness, especially in cost control and operational efficiency.[52,53] In Samarinda, the low integration rate of epidemiological data (only 47%) remains a significant barrier to achieving evidence-based management, ultimately impacting healthcare service quality.

Furthermore, the Utilisation of Data in Managerial Decision-Making plays a critical role in enhancing administrative effectiveness. Hospitals that optimise epidemiological data for program planning, SOP development, and resource allocation tend to be more responsive and efficient. Other studies confirm that data-driven decision-making increases staff compliance with procedures and accelerates policy adaptation.[54–56]

Additionally, the Administrative Human Resource Capacity is a key enabler linking data quality and utilisation to effective managerial practices.[57,58] Hospitals with trained administrative staff in health information management demonstrate superior performance in quality control, internal audits, and continuous service improvement.[57,59] Therefore, the synergy between data quality, managerial data utilisation, and administrative capacity is essential for creating effective hospital management systems that focus on service quality enhancement.

Specifically, we highlighted both technical and organisational barriers, such as the lack of interoperability between units, inconsistent data standards across departments, and limited staff training in the use of integrated digital systems. These factors continue to hinder the seamless flow of data and contribute to delays in managerial responsiveness. In addition, we have clarified that managerial effectiveness in this study is not solely defined by time or cost efficiency. It also encompasses compliance with Standard Operating Procedures (SOPs), alignment with quality indicators, and improvements in service outcomes. This addition emphasises that the integration of epidemiological data not only supports operational efficiency but also strengthens quality standardisation and safety within hospital management.

The mediating roles of system responses to outbreaks on hospital administrative management are represented in X1, X2, X3 → Y1 → Y2. The analysis reveals that Epidemiological Data Quality, Data Utilisation, and Administrative Human Resource Capacity indirectly influence hospital administrative effectiveness through the mediating role of the System Response to Outbreaks/Epidemiological Cases. High-quality data enables early detection and rapid reporting, strengthening system responsiveness to epidemiological events. When the response system operates optimally, administrative decision-making becomes more evidence-based and targeted, resulting in improved governance and service management across hospitals.

Moreover, strategic data utilisation in managerial processes and competent administrative personnel further reinforce this mediation process. Recent studies have shown that hospitals with robust epidemiological response systems can maintain operational continuity while upholding service quality standards during infectious disease surges.[60–62] Therefore, the system response acts as a crucial link connecting managerial inputs (data and human resources) to administrative effectiveness, resulting in more adaptive, efficient, and high-quality hospital services.

Furthermore, the system response functions as a feedback loop that supports continuous managerial improvement. For instance, in several hospitals in Samarinda, the early detection of rising dengue cases through the SIMRS-triggered surveillance system prompted immediate adjustments in triage protocols and temporary reallocation of isolation units. These changes were monitored in real time, and the resulting data—such as reduced patient wait times and increased treatment adherence—were fed back into the management dashboard. This feedback loop enabled hospital administrators to evaluate the effectiveness of their response strategies and refine standard operating procedures (SOPs) accordingly. As a result, system responsiveness not only facilitates rapid reaction but also promotes adaptive learning and evidence-based policy adjustments within hospital governance.

The mediating roles of system response to outbreaks on hospital service quality are represented in X1, X2, X3 → Y1 → Z. The findings also reveal that Epidemiological Data Quality, Data Utilisation, and Administrative Human Resource Capacity indirectly affect Hospital Service Quality through the mediation of the System Response to Outbreaks/Epidemiological Cases. When epidemiological data are accurate and relevant, and optimally utilised in managerial decision-making processes, hospitals are better equipped to respond rapidly, precisely, and systematically to epidemiological events, thereby enhancing reliability and public trust in their services.[63–65]

Additionally, a competent administrative workforce strengthens the system's adaptive capacity to dynamic epidemiological scenarios, ensuring the continuity of safe and high-quality services even during crises. An effective response system serves as a critical bridge, ensuring the efficiency and quality of key service aspects, including triage, care delivery, and referral management. Thus, the synergy between managerial inputs and system responsiveness contributes directly to the overall improvement of hospital service quality.

Specifically, we have elaborated that a timely and structured system response—supported by high-quality epidemiological data and competent administrative capacity—contributes to continuity of care by minimising service disruptions during outbreak events. It also enhances patient safety by enabling early intervention and efficient triage, and improves patient satisfaction through responsive and well-coordinated service delivery. These connections reinforce the argument that data-driven hospital management systems are essential for sustaining high-quality care in dynamic public health contexts.

The mediating roles of system response and administrative management effectiveness on hospital service quality are represented in X1, X2, X3 → Y1 → Y2 → Z. The results further indicate that Epidemiological Data Quality, Data Utilisation, and Administrative Human Resource Capacity significantly influence Hospital Service Quality through a dual mediation pathway: first via the System Response to Outbreaks/Epidemiological Cases, and second through the Effectiveness of Hospital Administrative Management. This finding highlights the importance of integrating high-quality epidemiological information systems, data-driven decision-making, and competent administrative human resources to create a responsive, efficient, and quality-oriented hospital service system.[66–68]

A strong system response ensures hospital preparedness and service resilience during emergencies. This swift and accurate responsiveness depends on both accurate data and the administrative staff's ability to execute policies effectively.[69,70] Subsequently, an effective system response enhances administrative management performance, particularly in resource allocation, operational control, and inter-unit coordination, providing a stable organisational foundation even under pressure. As a result, the hospital service quality improves significantly, benefiting both patients and the wider community.

Thus, improvements in hospital service quality are not determined solely by medical and clinical aspects, but are heavily influenced by the administrative system's capability, underpinned by data quality, informed decision-making, and skilled administrative personnel. This layered approach reinforces the necessity of hospital management transformation based on data integration and systemic responsiveness as a key strategy for improving healthcare service quality.

This study points out the critical need for national and regional health authorities to prioritise the integration of epidemiological surveillance systems with hospital information systems (SIMRS) as part of a broader digital health transformation strategy. Policymakers are also encouraged to invest in strengthening the capacity of administrative human resources, particularly in health informatics and data-driven decision-making.

However, the study acknowledges several potential confounding factors that may influence the findings. These include variations in hospital accreditation status, disparities in information system infrastructure, and differing levels of leadership commitment at the local level. These factors, which were not fully controlled in the study design, may affect both system responsiveness and the quality of administrative management.

This study also has certain limitations. The cross-sectional design limits the ability to infer causality, and the reliance on self-reported data may introduce response bias. Future studies employing longitudinal or mixed-methods designs are recommended to validate and extend the current findings, particularly in diverse healthcare settings.

CONCLUSION

This study highlights the critical role of integrated epidemiological data in improving hospital administrative management and service quality. Hospitals, with high-quality data, strong managerial use of that data, and competent administrative personnel, demonstrate greater responsiveness to epidemiological events and more effective internal management. These organisational capabilities serve as a foundation for improved healthcare service delivery.

The findings suggest that policy-makers and hospital leaders should prioritise strengthening data integration systems, investing in administrative human resources, and building responsive mechanisms to health crises. Such strategies are essential not only for addressing current epidemiological challenges but also for ensuring the delivery of resilient and high-quality hospital services in the future.

CONFLICT OF INTEREST

The authors declare that there are no conflicts of interest during this study.

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DATA AVAILABILITY

All data generated or analyzed during this study are included in this published article. Additional datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

SUPPLEMENTAL DATA

No additional supplemnental data areprovided for this study. All relevant data supporting the findings of this research are included within the main article.

AUTHOR CONTRIBUTIONS

MA played a primary role in developing the research concept, formulating the intellectual manuscript, conducting the literature review, collecting and analysing the data, and drafting the research manuscript. KF contributed to the editing and review processes and assisted in preparing the draft for publication.

DECLARATION OF USING AI IN THE WRITING PROCESS

Artificial Intelligence (AI) tools were utilized during the preparation of this manuscript to assist in language editing and clarity improvement. Specifically, generative AI tools (e.g., OpenAI's ChatGPT) were used to help rephrase and refine parts of the text under the supervision of the authors. All intellectual content, data interpretation, and final conclusions remain the responsibility of the authors. No AI tools were used to generate, analyze, or interpret the research data presented in this study.

LIST OF ABBREVIATIONS

SIRS: Hospital Information System; SIMRS: Hospital Management Information System; DF: Dengue Fever; TBC: Tuberculosis; PLS-SEM: Partial Least Squares Structural Equation Modelling

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