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Digital Epidemiological Surveillance Data Utilization for Decision-Making in Disease Control: A Mixed-Methods Evaluation in Riau Province

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Abstract: Digital epidemiological surveillance data forms the foundation of evidence-based public health decision-making, yet data availability does not guarantee optimal utilization in managerial processes. This study aims to evaluate the utilization of digital epidemiological surveillance data in decision-making for disease control programs in Riau Province. The study employed a mixed-methods design with a sequential explanatory approach, involving 156 respondents (decision-makers, surveillance officers, and information system managers) from the Provincial Health Office and 8 District/City Health Offices. Quantitative data were collected through structured questionnaires and analyzed using descriptive, bivariate, and multivariate statistics. Qualitative data were collected through 18 in-depth interviews, 6 FGDs, document review, and observation, then analyzed using thematic content analysis. Although 89.7% of respondents reported routine data availability and 87.5% of locations had implemented web-based surveillance systems, utilization for advanced analysis remained limited: spatial analysis (32.7%), resource allocation planning (45.5%), and forecasting (15.4%). Independent predictors of high data utilization were analytical training (AOR=3.42), satisfactory data quality (AOR=2.87), easy accessibility (AOR=2.64), and adequate supervisory support (AOR=2.31). Major problems included analytical capacity gaps (only 34.6% felt capable), information system fragmentation (31.4% integrated), underutilization of digital infrastructure (only 18.6% routinely using dashboards), and a decision-making culture based on experience rather than data. There is a significant gap between digital surveillance infrastructure availability and its utilization for strategic decision-making. Despite technological investments, digital systems function primarily as digitized manual processes rather than enabling advanced analytics.

Keywords: Data Utilization; Digital Surveillance; Epidemiological Surveillance

Introduction

Digital epidemiological data serve as a critical foundation for evidence-based public health decision-making. The digital transformation of health systems has fundamentally changed how epidemiological data are collected, stored, and potentially utilized for program management. Effective digital epidemiological surveillance systems enable early identification of health threats, appropriate resource allocation, and evaluation of intervention programs through real-time data access and advanced analytics capabilities (Kostkova et al.,

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2021; Talisuna et al., 2019). However, data availability and technological infrastructure alone do not guarantee optimal utilization in managerial processes. Studies in various countries have demonstrated gaps between surveillance data availability and its utilization for strategic decision-making at operational levels, suggesting that digital transformation does not automatically translate into improved decision-making practices (Hung et al., 2020; Mercado et al., 2017).

Surveillance data quality is a critical factor affecting the validity of managerial decisions, particularly in digital systems where data flows rapidly across multiple levels. Costa-Santos et al. (2021) identified various data quality problems in national COVID-19 surveillance, including reporting inconsistencies, incomplete variables, and data delays that were amplified by digital reporting systems. Similar problems have been reported in malaria surveillance systems in the Asia-Pacific region, where limitations in information technology infrastructure and human resource capacity hinder data utilization for malaria elimination planning, despite implementation of digital platforms (Mercado et al., 2017; Ohrt et al., 2015). Howes et al. (2016) emphasized that the operational utility of routine data depends heavily on completeness, timeliness, and information accessibility for decision-makers—qualities that digital systems promise but do not always deliver.

Digital transformation in health systems has opened opportunities for real-time epidemiological data utilization through web-based dashboards and platforms. Ivanković et al. (2021) identified COVID-19 dashboard features that support decision-making, including interactive data visualization, temporal trend analysis, and geographic disaggregation. Kazemi-Kazemi-Arpanahi et al. (2020) demonstrated how web-based registries can improve data accessibility for monitoring and rapid response. However, implementation of these digital technologies faces challenges in developing countries, particularly regarding infrastructure reliability, availability of skilled personnel to manage and analyze digital data, and system integration across fragmented platforms (Hung et al., 2020). The paradox of "data-rich but information-poor" systems, where organizations invest heavily in digital infrastructure yet struggle to transform data into actionable intelligence, has become increasingly recognized as a critical barrier to evidence-based public health practice.

International experience demonstrates the importance of integrating digital epidemiological data with comprehensive health information systems. Van Goethem et al. (2020) reported Belgium's success in building an integrated digital COVID-19 surveillance system with hospitalization data, enabling real-time monitoring of health service capacity through automated data flows and interactive dashboards. Jannot et al. (2017) evaluated a clinical data warehouse in France that has been utilized for 8 years for research and clinical decision-making, demonstrating the potential of well-designed digital repositories. Lin et al. (2013) created protocols that leveraged big data from electronic medical records to enhance cardiovascular services in China, demonstrating their advanced analytics capabilities. These experiences provide valuable lessons about factors influencing successful digital epidemiological data utilization, including the critical importance of system interoperability, user-centered design, and organizational readiness for digital transformation.

In Indonesia, particularly Riau Province, there has been no comprehensive evaluation of digital epidemiological surveillance data utilization in disease control program decision-making. Riau Province faces complex health challenges, including communicable diseases such as malaria, tuberculosis, and dengue, as well as increasing non-communicable diseases. Digital epidemiological surveillance systems have been implemented at various levels, including web-based reporting platforms and information systems, but the effectiveness of these digital tools in supporting managerial decisions has not been systematically documented. Chisha et al. (2015) demonstrated that enhanced digital surveillance with data feedback loops can improve data quality and program responsiveness but requires strong system commitment and capacity to utilize digital infrastructure effectively.

Evaluation of digital epidemiological data utilization in Riau Province is important for identifying existing system strengths, revealing barriers to digital technology utilization, and formulating improvement recommendations. van Mourik et al. (2021) emphasized the need for automated digital surveillance integrated with reporting systems to improve the efficiency and accuracy of decision-making. This study is expected to provide empirical insights into digital epidemiological data utilization practices at the provincial level, identify factors influencing utilization of digital surveillance infrastructure, and recommend strategies for enhancing digital surveillance system capacity to support evidence-based decision-making in disease control in Riau Province. Understanding the gap between digital infrastructure investment and actual utilization can inform more effective implementation strategies for digital health transformation in similar resource-constrained settings.

Method

Study Design

This study employed a mixed-methods design with a sequential explanatory approach, combining quantitative and qualitative methods to obtain a comprehensive understanding of digital epidemiological surveillance data utilization (Costa-Santos et al., 2021; Hung et al., 2020). The quantitative approach was used to measure the level of data utilization and identify influencing factors, while the qualitative approach was used to explore barriers, facilitators, and contexts of digital data utilization in managerial decision-making.

Study Location and Duration

The study was conducted in Riau Province, including the Riau Provincial Health Office and selected District/City Health Offices based on criteria of geographic representation and disease burden. Site selection considered heterogeneity of regional characteristics (urban-rural) and existing digital surveillance system capacity, following the approach used by Talisuna et al. (2019) in multi-site surveillance system evaluation. The study was conducted over 6 months to allow observation of complete reporting and decision-making cycles.

Study Population and Sample

The study population consisted of (1) decision-makers at provincial and district/city levels responsible for disease control programs; (2) epidemiological surveillance officers; and (3) health information system data managers. The sampling technique used purposive sampling for quantitative respondents, with inclusion criteria of a minimum of 1 year of work experience and direct involvement in surveillance or program decision-making processes (Van Goethem et al., 2020). For the qualitative component, maximum variation sampling was used to ensure diversity of stakeholder perspectives, with the number of informants determined based on data saturation principles (Mercado et al., 2017).

Research Instruments

The quantitative instrument was a structured questionnaire adapted from the WHO surveillance system evaluation framework and study on routine data utilization (Hung et al., 2020). The questionnaire measured (1) respondent characteristics; (2) data availability and accessibility; (3) surveillance data quality (completeness, timeliness, accuracy); (4) frequency and types of data utilization; (5) data analysis capacity; and (6) supporting and hindering factors for data utilization. Qualitative instruments consisted of in-depth interview and focus group discussion (FGD) guides developed based on Costa-Santos et al. (2021) findings on issues related to the quality of surveillance data and Ivanković et al. (2021) findings on actionable dashboard features. Instruments were validated through expert review and pilot testing.

Data Collection Techniques

Quantitative data collection was conducted through electronic surveys and paper-based questionnaires, adapted to field conditions. Qualitative data were collected through (1) in-depth interviews with key informants (decision-makers at provincial and district/city levels); (2) FGDs with surveillance officers and data managers; (3) document review, including surveillance reports, Standard Operating Procedures (SOPs), meeting minutes, and program planning documents; and (4) observation of data reporting processes, coordination meetings, and information system use, following Chisha et al. (2015) approach in evaluating surveillance data feedback loops. Data triangulation was conducted to enhance the validity of findings.

Data Analysis

Quantitative data were analyzed using descriptive statistics to describe respondent characteristics and level of data utilization. Bivariate (chi-square, t-test) and multivariate (logistic regression) analyses were used to identify factors associated with epidemiological data utilization, following Howes et al. (2016) approach in evaluating operational utility of routine data. Qualitative data were analyzed using thematic content analysis with a framework analysis approach, following these steps:(1) Familiarization with data through verbatim transcripts; (2) Development of a coding framework based on literature and emerging themes; (3) Indexing and charting data; (4) Interpretation and synthesis of findings (Hung et al., 2020; Van Goethem et al., 2020). Analysis was conducted using NVivo software to facilitate qualitative data management and analysis. Integration of quantitative and qualitative findings was performed at the interpretation stage to generate comprehensive understanding.

Ethical Considerations

This study obtained ethical approval from the relevant Health Research Ethics Committee. Informed consent was obtained from all participants after explanation of the study purpose, procedures, benefits, and risks. Principles of confidentiality and anonymity were maintained by using identification codes and secure data storage, following health research data protection standards (Bialke et al., 2015). Participation was voluntary, and respondents could withdraw at any time without consequences.

Result and Discussion

Respondent Characteristics

This study involved 156 respondents consisting of decision-makers (n=45), surveillance officers (n=78), and information system managers (n=33) from the Riau Provincial Health Office and 8 District/City Health Offices. The majority of respondents were aged 31-40 years (48.7%), held bachelor's degrees (62.2%), and had 5-10 years of work experience (41.0%). For the qualitative component, 18 in-depth interviews and 6 FGD sessions were conducted with a total of 42 participants.

Table 1. Respondent Characteristics (n=156)

Characteristics	n	%
Respondent Group		
Decision-makers	45	28.8
Surveillance Officers	78	50.0
Information System Managers	33	21.2
Age		
20-30 years	38	24.4
31-40 years	76	48.7
41-50 years	32	20.5
>50 years	10	6.4
Education		
Diploma	31	19.9
Bachelor's	97	62.2
Master's	28	17.9
Work Experience		
<5 years	42	26.9
5-10 years	64	41.0
>10 years	50	32.1
Location		
Provincial Health Office	35	22.4
District/City Health Office	121	77.6

The availability and Accessibility of Digital Surveillance Data

Study results showed that 89.7% of respondents stated that surveillance data were routinely available, but only 56.4% considered data accessible when needed. The most widely used reporting system was the web-based Disease Information System (SIP) (78.8%), followed by Excel-based manual reports (65.4%). Despite high adoption of digital platforms, real-time access remained limited (34.6%), revealing a gap between digital infrastructure implementation and functional accessibility. These findings align with Costa-Santos et al. (2021), who identified gaps between data availability and its accessibility for decision-making in digital surveillance systems.

Table 2. Digital Surveillance Data Availability and Accessibility

Aspect	Yes (%)	No (%)
Surveillance data routinely available	89.7	10.3
Data easily accessible when needed	56.4	43.6
Electronic data format available	82.7	17.3
Data utilization guidelines available	42.3	57.7
Data downloadable for analysis	51.9	48.1
Real-time access available	34.6	65.4

In-depth interviews revealed that digital data accessibility barriers included limited system access rights (multiple user levels), unstable internet connections in remote areas, lack of training on digital information system use, and inadequate technical support for troubleshooting digital platform issues. A surveillance section head stated: "*We have an online system, but it often has problems. Sometimes data cannot be accessed in real-time due to server or internet issues. We end up still relying on manual reports via WhatsApp for quick decisions. The digital system becomes more of a burden than a help.*" This quote illustrates the paradox of digital transformation, where technology intended to facilitate data access instead creates additional barriers when not supported by adequate infrastructure and capacity.

Digital Surveillance Data Quality

Data quality evaluation showed significant variation across quality dimensions in digital surveillance systems. Data completeness was rated as good by 64.1% of respondents, reporting timeliness was good (58.3%), but data consistency across sources was only rated as good by 38.5% of respondents—a particular concern in digital systems where data from multiple sources should theoretically be easier to reconcile. These findings are consistent with Howes et al. (2016), who found that routine data quality variability affects its operational utility for program planning, even when collected through digital platforms.

Table 3. Digital Surveillance Data Quality Assessment

Quality Dimension	Good (%)	Fair (%)	Poor (%)
Data completeness	64.1	28.2	7.7
Timeliness	58.3	31.4	10.3
Data accuracy	52.6	37.2	10.2
Cross-source consistency	38.5	42.3	19.2
Relevance to needs	71.8	23.7	4.5

Document analysis revealed specific data quality problems in digital systems, including (1) duplication of case reporting from various health facilities despite digital identifiers; (2) inconsistency in operational case definitions among officers entering data into digital platforms; (3) incomplete data, especially for demographic variables and exposure history, with required fields often bypassed; and (4) average reporting delays from community health centers to districts/cities of 7-14 days despite the availability of digital reporting systems. Similar problems were reported by Costa-Santos et al. (2021) in the context of national COVID-19 digital surveillance in Portugal, suggesting that digitalization alone does not resolve fundamental data quality challenges.

Digital Epidemiological Data Utilization for Decision-Making

The level of digital epidemiological data utilization for decision-making varied according to decision type. Surveillance data were most frequently used for routine reporting (92.3%) and disease trend monitoring (78.8%), but utilization for advanced analytics that digital systems theoretically enable remained low: spatial analysis (32.7%), resource allocation planning (45.5%), and forecasting (15.4%). This pattern suggests that digital surveillance systems are primarily used for basic functions rather than leveraging their full analytical potential.

Table 4. Digital Epidemiological Data Utilization by Decision Type

Type of Data Utilization	Frequently (%)	Sometimes (%)	Rarely/Never (%)
Routine reporting to superiors	92.3	6.4	1.3
Disease trend monitoring	78.8	17.3	3.9
Outbreak detection	67.9	24.4	7.7
Program evaluation	48.1	38.5	13.4
Resource allocation planning	45.5	34.6	19.9
Spatial analysis/mapping	32.7	29.5	37.8
Risk factor analysis	29.5	42.3	28.2
Forecasting/prediction	15.4	28.8	55.8

Qualitative findings revealed that program decisions were largely still based on experience and vertical policies at the central level, with digital surveillance data functioning more as justification for decisions already made than as a basis for analysis to formulate them. A leader at the Provincial Health Office of Riau stated: "*Honestly, our program decisions are based more on directives from the Ministry of Health and experience from previous years. We look at the data in the system but don't have time to analyze it in depth. The important thing is whether the numbers go up or down. The digital dashboard looks nice, but we rarely use it for actual decision-making.*" This scenario reflects a fundamental challenge where digital infrastructure exists but organizational practices have not evolved to leverage its capabilities.

Data Analysis and Interpretation capabilities

Capacity evaluation showed a significant gap between needs and actual capabilities in the digital era. Only 34.6% of respondents felt they had adequate data analysis skills, and 28.2% had attended epidemiological analysis training in the past two years. The majority of respondents (71.8%) only used simple descriptive analysis (tabulation, trend graphs), while advanced digital analytics such as spatial analysis (12.8%) and advanced analysis such as time series or modeling (5.1%) were very rarely performed—despite digital systems generating data suitable for these analyses.

Table 5. Respondent Data Analysis Capacity

Capacity Aspect	n	%
Analysis Capability Assessment		
Adequate	54	34.6
Fair	71	45.5
Poor	31	19.9
Analysis Training (past 2 years)		
Attended	44	28.2
Not attended	112	71.8
Types of Analysis Performed		
Simple descriptive analysis	112	71.8
Temporal trend analysis	87	55.8
Stratification analysis	52	33.3
Spatial analysis	20	12.8
Advanced statistical analysis	8	5.1
Software Proficiency		
Microsoft Excel	148	94.9
SPSS/Stata	23	14.7
R/Python	4	2.6
GIS software	12	7.7

This capacity limitation was a major barrier to leveraging digital data for more complex analysis. FGDs with surveillance officers revealed needs for regular training and mentoring in digital data analysis, including how to extract, clean, and analyze data from digital platforms, consistent with Hung et al. (2020) recommendations on the importance of capacity building to enhance routine data utilization in developing countries.

Digital Health Information System Infrastructure

The majority of study locations (87.5%) had implemented web-based information systems, representing substantial investment in digital infrastructure. However, integration across digital systems remained a major challenge, with only 31.4% of respondents stating that the surveillance system was integrated with other health information systems (SIMPUS, SIKDA). Digital data visualization dashboards were available in 43.6% of locations, but only 18.6% utilized them routinely for monitoring—indicating severe underutilization of available digital tools.

Table 6. Digital Health Information System Infrastructure

Infrastructure Component	Available (%)	Utilized (%)
Web-based reporting system	87.5	78.2
Cross-system integration	31.4	22.4
Visualization dashboard	43.6	18.6
Adequate computer equipment	67.3	67.3
Stable internet connection	52.6	52.6
Local server	28.2	24.4
Mobile application	19.2	12.2
Automated reporting	15.4	8.3

Field observations showed that although digital technology infrastructure was available, its utilization was not yet optimal due to limited technical support for digital systems, irregular system maintenance, and resistance to change from officers accustomed to manual systems. These findings align with Kazemi-Arpanahi et al. (2020), who identified implementation challenges for web-based registry systems in developing countries, where digital infrastructure does not automatically translate into improved practices.

Factors Affecting Digital Data Utilization

Bivariate analysis showed several factors significantly associated with the level of digital epidemiological data utilization: education (p=0.012), data analysis training (p<0.001), data quality (p<0.001), data accessibility (p<0.001), guideline availability (p=0.003), and supervisory support (p<0.001).

Table 7. Factors Associated with Digital Data Utilization

Factor	High Utilization (%)	Low Utilization (%)	p-value
Education			0.012
Master's	71.4	28.6	
Bachelor's	54.6	45.4	
Diploma	38.7	61.3	
Analysis Training			<0.001
Attended	77.3	22.7	
Not attended	42.9	57.1	
Data Quality			<0.001
Good	73.8	26.2	
Fair/Poor	35.4	64.6	
Data Accessibility			<0.001
Easy	68.2	31.8	
Difficult	33.8	66.2	
Guideline Availability			0.003
Available	66.7	33.3	
Not available	45.5	54.5	
Supervisory Support			<0.001
Good	71.6	28.4	
Poor	38.2	61.8	

Multivariate logistic regression analysis identified four independent predictors of high digital data utilization: data analysis training (AOR=3.42; 95% CI: 1.65-7.09), satisfactory data quality (AOR=2.87; 95% CI: 1.48-5.56), easy data accessibility (AOR=2.64; 95% 95%CI: 1.35-5.16), and satisfactory supervisory support (AOR=2.31; 95% CI: 1.18-4.52). These findings suggest that successful digital surveillance implementation requires not only technological infrastructure but also capacity building, quality assurance, and organizational support.

Barriers to Digital Epidemiological Data Utilization

Thematic analysis of qualitative data identified six major themes of barriers to digital data utilization:(1) Capacity Barriers—limitations in analytical, interpretation, and digital data visualization capabilities, with officers trained in manual systems struggling to adapt to digital platforms; (2) Technical Barriers—information system problems, internet connectivity, software compatibility, and inadequate technical support for digital systems; (3) Organizational Barriers—high workload, officer turnover, and lack of time for in-depth analysis, with digital systems sometimes adding to rather than reducing workload; (4) Data Quality Barriers—incomplete, inaccurate, and inconsistent data persisting despite digital platforms; (5) Cultural Barriers—decision-making habits based on experience and intuition rather than data, with digital dashboards viewed as "nice to have" rather than essential decision-support tools; (6) Policy Barriers—lack of regulations mandating digital data use in decision-making and inadequate investment in digital infrastructure maintenance.

Representative quotes from key informants: "*Our main problem is not that we don't have data or digital systems, but that we don't have time and ability to process digital data into useful information. Every day we're busy inputting data into the system, generating reports here and there. When do we analyze? The digital system should make things easier, but it feels like double work.*" (Surveillance Officer, District A)
"*Sometimes the same data shows different numbers between the digital system, Excel reports, and paper records. We become confused about which one to use for planning. The digital system should solve this, but it created new problems.*" (Section Head, District B Health Office)
"*Program decisions are mostly top-down from the central level. Local data from our digital system rarely becomes the main consideration. At most, we export data from the system to justify activity proposals to the province or central level. The dashboard has all these fancy features, but decision-makers don't look at it.*" (Division Head, Riau Provincial Health Office)

These findings are consistent with Hung et al. (2020), who identified multi-level barriers to routine data utilization in low- and middle-income countries, suggesting that digital transformation alone is insufficient without addressing organizational and cultural factors, Mercado et al. (2017), who found surveillance system capacity gaps in Asia-Pacific even with digital infrastructure investments.

Digital Data Utilization Model for Decision-Making

Based on the integration of quantitative and qualitative findings, this study identified a digital data utilization model encompassing four levels:(1) Basic Level—routine digital reporting and simple monitoring using basic system features; (2) Intermediate Level—trend analysis and outbreak detection using standard digital dashboard functions; (3) Advanced Level—program evaluation and evidence-based planning leveraging integrated digital data sources; (4) Optimal Level—predictive analysis and strategic decision-making utilizing advanced analytics, machine learning, and AI capabilities of modern digital systems. The majority of study locations (68.7%) remained at basic to intermediate levels despite having digital infrastructure theoretically capable of supporting advanced functions, consistent with Van Goethem et al. (2020) findings on surveillance system maturity variability and suggesting that digital infrastructure alone does not ensure progression to higher utilization levels.

Discussion

The Digital Paradox: Gap Between Infrastructure and Utilization

This study reveals a significant paradox in digital epidemiological surveillance: although 89.7% of respondents reported routine data availability and 87.5% of locations had implemented web-based surveillance systems representing substantial digital infrastructure investment, utilization for strategic decision-making remained limited, especially for advanced analytics that digital systems theoretically enable—spatial analysis (32.7%), resource allocation planning (45.5%), and forecasting (15.4%). This digital paradox is consistent with Hung et al. (2020) findings in a systematic review on routine data utilization in low- and middle-income countries, which identified that data availability and digital infrastructure do not automatically guarantee utilization for decision-making. Mercado et al. (2017) found similar patterns in evaluating malaria surveillance systems in Asia-Pacific, where digital data were collected extensively but rarely analyzed for informed strategic planning.

This phenomenon exemplifies what Kostkova et al. (2021) termed "data-rich but information-poor syndrome," where health organizations invest heavily in digital infrastructure yet fail to transform data into actionable intelligence. In the Riau Province context, this digital paradox is exacerbated by the perception that digital surveillance data function more as administrative requirements for reporting to higher levels rather than as analytical tools for local decision-making. The finding that only 18.6% of locations with digital dashboards actually utilize them routinely is particularly striking, representing a severe case of digital infrastructure underutilization. Qualitative findings confirm that program decisions remain dominated by vertical policies from the central level and subjective experience, with digital data playing more of a retrospective justification role than a prospective basis for formulating strategies. This indicates that evidence-based public health principles have not yet been integrated into managerial practice at operational levels, despite digital transformation investments, as emphasized by Talisuna et al. (2019) in the context of surveillance systems in Africa.

The digital divide in utilization—where systems are implemented but not leveraged—suggests that technological solutions alone are insufficient without addressing the socio-technical dimensions of digital health implementation. Digital surveillance systems in Riau Province appear to have become digitized versions of manual processes rather than transformative tools enabling new capabilities. This pattern reflects broader challenges in digital health transformation, where technology deployment outpaces organizational readiness, capacity development, and cultural change necessary to realize digital benefits.

Data Quality in Digital Systems: Persistent Challenges

This study found that data quality is a significant independent predictor of digital data utilization (AOR=2.87; 95% CI: 1.48-5.56), but quality problems persist despite digital platforms. The most problematic quality dimension was cross-source consistency (only 38.5% of respondents rated it as good), reflecting fragmentation of unintegrated digital health information systems—a particularly concerning finding given that digital systems theoretically should facilitate data reconciliation and consistency. Costa-Santos et al. (2021), in evaluating COVID-19 surveillance data quality in Portugal, identified similar problems: reporting inconsistencies, incomplete variables, and data duplication that persist in digital systems, suggesting that digitalization alone does not resolve fundamental data quality challenges.

Specific problems found in Riau Province—case reporting duplication despite digital identifiers, operational definition inconsistencies among officers entering data, and 7-14 days reporting delays despite digital reporting systems—have serious implications for outbreak detection and response. These findings challenge the assumption that digital systems automatically improve data quality and timeliness. Howes et al. (2016) emphasized that the operational utility of routine data for malaria control planning depends heavily on completeness and timeliness; the 7-14 days reporting delays found in this study far exceed WHO standards for reportable diseases requiring reporting within 24-48 hours for diseases with outbreak potential, indicating that digital infrastructure has not achieved expected improvements in timeliness.

The persistence of data quality problems in digital systems suggests several underlying issues: inadequate data validation rules in digital platforms allowing incomplete or inaccurate entries; insufficient training on proper data entry procedures; lack of feedback mechanisms to correct errors; and fragmented systems requiring duplicate data entry. Van Goethem et al. (2020) demonstrated that Belgium's integrated digital COVID-19 hospitalization surveillance system enabling real-time health service capacity monitoring succeeded precisely because it addressed these issues through automated validation, integrated data flows, and real-time feedback—elements largely absent in Riau Province's digital infrastructure.

Operational definition inconsistencies among officers found in this study reflect weak standardization of surveillance terminology and procedures, even in digital systems that could theoretically enforce standardization. De Quirós et al. (2018) argued for the importance of terminology services to control health vocabulary and ensure data interoperability in digital systems. Implementation of standard terminologies such as ICD-10, SNOMED-CT, or LOINC embedded in digital platforms needs strengthening in Riau Province to improve data consistency and comparability across time and locations, leveraging digital systems' capability to enforce standards rather than merely digitizing inconsistent manual processes.

Analytical Capacity Gap in the Digital Era

The finding that only 34.6% of respondents felt they had adequate analytical capabilities and 71.8% had never attended epidemiological analysis training in the past 2 years reveals a critical capacity gap that undermines digital surveillance investments. Data analysis training proved to be the strongest independent predictor of digital data utilization (AOR=3.42; 95% CI: 1.65-7.09), confirming that human capacity is the critical bottleneck in digital health transformation. Hung et al. (2020), in a systematic review, identified analytical capacity as one of the main barriers to routine data utilization in low- and middle-income countries, with recommendations for implementing sustainable training programs and mentorship—challenges amplified in the digital era, where required skills extend beyond traditional epidemiology to include data science, programming, and digital literacy.

The dominance of simple descriptive analysis use (71.8%) with minimal advanced analysis such as spatial analysis (12.8%) or time series modeling (5.1%) represents a severe underutilization of digital systems' analytical potential. Digital surveillance platforms generate rich, granular data suitable for sophisticated analyses, yet capacity limitations prevent leveraging these capabilities. Pfeiffer & Stevens (2015) argued that the big data era requires sophisticated spatial and temporal epidemiological analysis capacity to identify clusters, predict outbreaks, and optimize resource allocation—precisely the advanced analytics that digital systems enable but that Riau Province personnel cannot perform. Jain et al. (2019) demonstrated how combining disease surveillance data with meteorological and socio-economic data using machine learning can improve dengue outbreak prediction accuracy—an approach entirely dependent on analytical capacity that remains largely absent in Riau Province despite digital data availability.

The gap in analytical software proficiency—with only 14.7% proficient in SPSS/Stata, 7.7% in GIS software, and 2.6% in R/Python—is particularly problematic in the digital era, where these tools are essential for extracting value from digital surveillance data. While 94.9% of respondents were proficient in Microsoft Excel, this basic tool is insufficient for the complex analyses that digital surveillance systems enable. Lin et al. (2013) in the CHERRY study protocol in China emphasized the importance of integrating big data analytics capacity into electronic health record systems to improve cardiovascular care, demonstrating that digital infrastructure investments must be matched by capacity development investments. Adaptation of successful capacity-building models from China, including establishment of data science units and partnerships with universities for technical support, could address Riau Province's capacity gaps.

The digital divide in analytical capacity creates a two-tiered system where digital infrastructure exists, but only those with advanced skills can leverage its full potential—a situation that perpetuates rather than reduces health inequities. Training programs must evolve from traditional epidemiology curricula to include digital literacy, data science fundamentals, and hands-on experience with analytical tools commonly used in digital health systems. Moreover, training must be continuous rather than one-time events, given the rapid evolution of digital technologies and analytical methods.

Digital Infrastructure Fragmentation and Integration Challenges

Although 87.5% of locations had implemented web-based systems representing substantial digital infrastructure investment, the low cross-system integration (31.4%) and dashboard utilization (18.6%) indicate severe digital infrastructure fragmentation and underutilization. These findings align with Kazemi-Kazemi-Arpanahi et al. (2020), who identified web-based registry implementation challenges in Iran, including limited technical support and resistance to change—problems amplified when multiple unintegrated digital systems coexist. Ivanković et al. (2021), in assessing 158 COVID-19 dashboards, found that actionable dashboards must have features including interactivity, multi-level data disaggregation, temporal trend visualization, and integration with other data sources—features that Riau Province's digital dashboards possess but that remain unutilized.

The digital health information system fragmentation found in Riau Province—with surveillance systems, SIMPUS, and SIKDA operating as separate digital silos—creates significant barriers to comprehensive analysis despite all being digital platforms. This fragmentation forces users to navigate multiple systems, manually reconcile data discrepancies, and duplicate data entry—defeating the efficiency promises of digital transformation. Jannot et al. (2017), in an 8-year evaluation of Georges Pompidou Hospital's clinical data warehouse, emphasized the importance of integrated data repositories enabling cross-sectional and longitudinal analysis through unified digital platforms. Bauer et al. (2016) developed the Integrated Data Repository Toolkit (IDRT), facilitating health analytics on heterogeneous medical data, which could serve as a model for addressing Riau Province's digital fragmentation through middleware solutions enabling interoperability without requiring complete system replacement.

The digital interoperability challenge extends beyond technical integration to include semantic interoperability—ensuring that data from different digital systems can be meaningfully combined and compared. The finding that 38.5% of respondents rated cross-source consistency as good reflects not only technical fragmentation but also a lack of standardized terminologies and data definitions across digital platforms. Implementing FHIR (Fast Healthcare Interoperability Resources) standards or similar interoperability frameworks could enable digital systems to communicate effectively while maintaining their specialized functions.

Low implementation of automated surveillance (15.4%) and mobile applications (19.2%) shows missed opportunities for digital innovation to improve timeliness and coverage. Van Mourik et al. (2018) argued that automated surveillance can reduce workload, improve accuracy, and enable real-time monitoring—benefits that require sophisticated digital infrastructure beyond basic web-based reporting. Rajvanshi et al. (2020) demonstrated the success of comprehensive mobile applications for disease surveillance, workforce management, and supply chain management in India's Malaria Elimination Project, showcasing how mobile-first digital strategies can overcome connectivity limitations while enabling field-level data collection—an approach highly relevant for Riau Province's remote areas where internet connectivity remains unstable (only 52.6% reported stable connections).

The underutilization of available digital infrastructure, particularly dashboards, suggests fundamental problems in user-centered design and change management. Digital dashboards that looked "nice" according to informants but were rarely used for decision-making indicate a disconnect between system design and user needs. Successful digital health implementation requires iterative design processes involving end-users, continuous feedback mechanisms, and ongoing optimization based on actual usage patterns elements apparently absent in Riau Province's digital system deployment.

Organizational and Cultural Barriers to Digital Transformation

Qualitative findings revealed that barriers to digital data utilization are not only technical but fundamentally organizational and cultural. High workload, officer turnover, and lack of time for in-depth analysis reflect structural constraints that digital systems sometimes exacerbate rather than alleviate—with officers reporting "double work" of maintaining both digital and manual systems during transitions. Chisha et al. (2015) showed that enhanced surveillance with feedback loops can improve data quality and program responsiveness but requires dedicated personnel and protected time for analysis—resources often not allocated when digital systems are implemented.

The decision-making culture based on experience and intuition rather than data, with digital dashboards viewed as "nice to have" rather than essential decision-support tools, reflects what Talmage et al. (2020) called "experiential decision-making culture" that resists transformation toward "evidence-informed decision-making culture." This cultural resistance is particularly problematic in digital contexts where investments in technology create expectations for rapid transformation that organizational culture cannot support. The international expert Delphi consensus emphasized the importance of leadership commitment, organizational learning systems, and performance feedback mechanisms to drive cultural transformation—elements requiring deliberate change management strategies often overlooked in digital health implementations focused on technology deployment.

The dominance of top-down policy from the central level with minimal consideration of local digital data indicates not only cultural resistance but also structural barriers to decentralization. Digital surveillance systems theoretically enable local decision-making by providing local stakeholders with real-time access to local data, yet governance structures have not evolved to leverage this capability. Premaratne et al. (2019), in evaluating Sri Lanka's malaria elimination, identified that strong technical and operational underpinnings at the local level, including empowerment for local decision-making based on local data, are key success factors enabled by digital systems but requiring deliberate policy decisions to grant local decision space.

Resistance to change from officers accustomed to manual systems, identified in field observations, represents a significant organizational barrier requiring change management strategies. Digital transformation literature emphasizes that technology adoption follows S-curves with early adopters, early majority, late majority, and laggards—requiring differentiated strategies for different groups. Training alone is insufficient; successful digital transformation requires champions who demonstrate benefits, peer-to-peer learning opportunities, ongoing technical support reducing frustration with digital systems, and recognition/incentives for effective digital tool utilization.

The perception that digital systems add to rather than reduce workload reflects poor implementation processes where new digital requirements are layered onto existing manual processes rather than replacing them. Digital transformation should include business process reengineering, eliminating redundant manual steps once digital systems are functional, but this requires careful planning and phased implementation, often absent in rushed digital deployments.

Digital Maturity Model and Transformation Pathway

The four-level digital data utilization model identified in this study—from basic reporting to optimal predictive analytics—is consistent with digital maturity models in health informatics literature. Van Goethem et al. (2020) described progression from simple notification systems to sophisticated integrated surveillance platforms, a journey that Riau Province has begun through digital infrastructure deployment but has not yet completed in terms of actual utilization. The majority of locations (68.7%) remaining at basic-intermediate levels despite advanced digital infrastructure indicates that technological readiness far exceeds organizational readiness, a common pattern in digital health transformation.

For progression from basic to intermediate level, priorities include not just having digital systems but actually using their core features: improving data quality through digital validation rules, ensuring timeliness through real-time digital reporting, and building basic analytical capacity to extract and visualize digital data. Shretta et al. (2020) recommended standardized data collection tools, regular data quality audits, and refresher trainings—all of which can be enhanced through digital automation but require human capacity to implement and monitor.

For progression to advanced level, investment in advanced analytical capacity, GIS infrastructure, and integration across digital data sources is needed. Li & Mackaness (2015) demonstrated a multi-agent-based, semantic-driven system for epidemic management decision support that could serve as a model for advanced-level utilization, but implementing such systems requires not just software but also personnel capable of configuring, maintaining, and using these advanced digital tools.

To achieve optimal level with predictive analytics and strategic decision-making, fundamental transformation in infrastructure, capacity, and culture is required alongside emerging digital technologies. MacIntyre et al. (2023) argued for artificial intelligence's role in epidemic monitoring and alerts, including machine learning for pattern recognition, natural language processing for social media surveillance, and predictive modeling for outbreak forecasting—capabilities entirely dependent on digital data but requiring sophisticated data science expertise. Zhang et al. (2020) developed interpretable deep-learning models for early sepsis prediction that could be adapted for infectious disease surveillance, showcasing the potential of AI-enhanced digital surveillance.

However, AI-based surveillance implementation requires critical prerequisites largely absent in Riau Province: high-quality big data (undermined by current data quality problems), computational infrastructure (limited by connectivity issues), data science expertise (only 2.6% proficient in R/Python), and ethical frameworks for algorithmic accountability. Delgado et al. (2020) warned about bias in AI systems for COVID-19, emphasizing that AI amplifies existing data quality problems and biases—making foundational improvements in data quality and analytical capacity essential prerequisites for AI adoption rather than shortcuts around capacity limitations.

The digital transformation pathway for Riau Province must therefore be sequential and systematic: first stabilizing basic digital infrastructure and improving data quality; then building intermediate analytical capacity and integration; subsequently implementing advanced analytics and decision-support tools; and only then exploring AI and predictive analytics. Attempting to leapfrog to advanced capabilities without foundational elements risks creating sophisticated digital systems that remain as unutilized as current dashboards.

Implications for Digital Health Policy and Practice in Riau Province

Based on research findings, several policy and practice recommendations can be formulated specifically addressing digital health transformation in Riau Province: First, optimizing digital data quality through technology-enabled solutions:(a) Implementing automated data validation rules in digital platforms preventing incomplete or inconsistent entries at the point of data capture; (b) Establishing real-time data quality monitoring dashboards with automated alerts for anomalies, duplicates, or delays; (c) Developing standardized digital terminologies and code sets embedded in entry forms ensuring consistency; (d) Creating automated cross-system data reconciliation processes identifying and flagging discrepancies between digital platforms. Costa-Santos et al. (2021) emphasized systematic approaches to data quality integrating technical solutions with procedural improvements—approaches particularly powerful when leveraging digital automation capabilities.

Second, digital capacity building through blended learning approaches: (a) Developing online learning modules for self-paced digital literacy and basic analytics accessible to all personnel; (b) Implementing hands-on training in extracting, cleaning, and analyzing data from existing digital platforms; (c) Creating peer learning networks where digitally proficient officers mentor others; (d) Establishing a provincial digital health support unit providing ongoing technical assistance and advanced analytical services; (e) Partnering with universities to provide data science training and embed graduate students as digital health fellows. Hung et al. (2020) recommended tiered capacity building with differentiated training—an approach enhanced by digital learning technologies enabling scalable, personalized learning paths.

Third, digital infrastructure integration and optimization: (a) Implementing interoperability standards (HL7 FHIR or similar) enabling data exchange across SIMPUS, SIKDA, and surveillance systems without requiring complete system replacement; (b) Developing a master patient index and unique identifiers preventing duplication across digital systems; (c) Creating integrated data warehouses consolidating surveillance, clinical, and administrative data for comprehensive analysis; (d) Redesigning digital dashboards based on user feedback and actual decision-making workflows rather than technical capabilities; (e) Implementing progressive web applications providing offline capability for areas with unstable connectivity; (f) Establishing service-level agreements for digital system maintenance and technical support ensuring reliability. Ivanković et al. (2021) identified dashboard features supporting decision-making—principles that should guide dashboard redesign focused on usability and actionability rather than aesthetic appeal.

Fourth, digital transformation change management: (a) Developing digital health champions at each site who receive advanced training and provide peer support; (b) Creating feedback mechanisms where users can report digital system problems and see responsive improvements; (c) Implementing phased transitions where manual processes are eliminated only after digital systems prove reliable, reducing "double work"; (d) Establishing performance metrics explicitly measuring digital data utilization in decision-making, not just data entry completion; (e) Creating incentive structures recognizing and rewarding effective digital tool utilization and data-driven decisions; (f) Conducting regular digital maturity assessments tracking progress and identifying barriers. Talmage et al. (2020) identified organizational culture as critical for evidence-based practice—culture change requiring sustained leadership commitment and deliberate strategies beyond technology deployment.

Fifth, governance structures enabling digital-enabled decentralization: (a) Establishing policies mandating that program decisions be documented with supporting digital data analysis; (b) Creating local decision spaces where districts can adapt programs based on local digital surveillance data rather than only following top-down directives; (c) Implementing regular data review meetings using digital dashboards as the primary information source; (d) Developing standard operating procedures for data sharing across levels and programs through digital platforms; (e) Creating provincial-district-facility coordination mechanisms enabled by shared access to digital surveillance data. Talisuna et al. (2019) emphasized governance structures for effective surveillance—structures that digital systems can enable through transparent data sharing but that require policy decisions granting authority to act on local data.

Sixth, sustainable digital health financing: Current findings suggest that digital infrastructure investments have not been matched by investments in capacity building, maintenance, and ongoing support—creating underutilized systems. Sustainable digital health requires: (a) Budget allocations for ongoing digital system maintenance, not just initial deployment; (b) Dedicated positions for digital health specialists and data analysts; (c) Funding for continuous capacity building as digital technologies evolve; (d) Resources for internet connectivity improvements in remote areas; (e) Investment in user-centered design and iterative system improvements based on usage data.

Conclusion

This study reveals a significant digital paradox in epidemiological surveillance in Riau Province: substantial investment in digital infrastructure (87.5% with web-based systems, 43.6% with dashboards) has not translated into commensurate improvements in data utilization for strategic decision-making. Although the majority of respondents reported routine digital data availability (89.7%), utilization for advanced analytics that digital systems theoretically enable remains very limited—spatial analysis (32.7%), resource allocation planning (45.5%), and forecasting (15.4%). This gap represents underrealization of digital transformation investments and missed opportunities for evidence-based disease control. Factors independently influencing digital data utilization are data analysis training (AOR=3.42), data quality (AOR=2.87), data accessibility (AOR=2.64), and supervisory support (AOR=2.31)—suggesting that human and organizational factors, not technology alone, determine digital health success. Persistent data quality problems despite digital platforms—especially cross-source consistency (only 38.5% rated good), variable completeness, and 7 - 14 days delays despite real-time reporting capability—indicate that digitalization alone does not resolve fundamental surveillance challenges and may introduce new complexities. The widespread analytical capacity gap, with the majority of officers only capable of simple descriptive analysis (71.8%) and minimal proficiency in advanced analytical software (2.6% in R/Python, 7.7% in GIS), limits the ability to leverage digital surveillance data for early warning and predictive analytics. Digital infrastructure fragmentation with minimal cross-system integration (31.4%) and severe dashboard underutilization (only 18.6% routinely using available dashboards) reflects both technical interoperability challenges and organizational barriers to digital adoption. More fundamentally, organizational culture dominated by experience-based decision-making and top-down policies rather than data-driven approaches, combined with the perception of digital systems as administrative burdens rather than decision-support tools, indicates the need for cultural and structural transformation alongside technological improvements. The majority of study locations (68.7%) remain at basic-intermediate levels in the digital data utilization maturity model despite having infrastructure theoretically capable of advanced functions—demonstrating that technological readiness far exceeds organizational readiness. Strengthening digital epidemiological surveillance data utilization in Riau Province requires comprehensive, multi-level interventions addressing technical, organizational, and cultural dimensions of digital health transformation. Priority actions include systematic improvement of digital data quality through automated validation and monitoring; structured digital capacity building programs with differentiated training; digital infrastructure integration using interoperability standards; user-centered dashboard redesign focused on actionability; deliberate change management addressing resistance and building digital champions; governance reforms enabling digital-enabled decentralization; and sustainable financing for digital system maintenance and support, not just deployment. These improvements will transform digital surveillance systems from underutilized digitized versions of manual processes into powerful tools enabling advanced analytics, predictive modeling, and evidence-based decision-making. Success requires recognizing that digital transformation is fundamentally an organizational and cultural change process enabled by technology, not a technological solution to organizational problems.

Sustained leadership commitment, adequate resource allocation beyond initial infrastructure costs, multi-sectoral collaboration, continuous learning and adaptation, and explicit focus on digital equity will determine whether digital surveillance investments realize their transformative potential for disease control in Riau Province and similar settings.

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