ACHSM Asia-Pacific Journal of Health Management

RESEARCH ARTICLE

AN EXPLORATORY CLUSTERING ANALYSIS OF DIGITAL READINESS AND MATURITY FOR ELECTRONIC MEDICAL RECORD IMPLEMENTATION IN INDONESIA

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ABSTRACT

The Satu Sehat platform for Electronic Medical Records (EMR), launched in Indonesia in 2022, represents an important step toward national health data integration. However, variation in hospital digital readiness may affect the implementation of EMR systems across regions. This study aimed to explore digital maturity and EMR readiness profiles among hospitals in Indonesia.

METHODS:

A cross-sectional secondary dataset from 711 hospitals was analyzed using an exploratory, unsupervised machine-learning approach. K-means clustering and Principal Component Analysis (PCA) were used to identify hospital digital maturity profiles and visualize clustering patterns.

RESULTS:

The analysis identified six hospital clusters with heterogeneous digital maturity characteristics across provinces. Information Systems and Infrastructure, Standards and Interoperability, and Human Capital had the highest overall average scores, whereas Data Analytics had the lowest. Hospitals from East Java, Central Java, and Lampung were distributed across multiple clusters, while hospitals from Papua and Maluku were more concentrated in lower digital maturity profiles.

CONCLUSIONS:

Overall, the findings suggest that hospital readiness for EMR implementation in Indonesia is multidimensional and unevenly distributed. Exploratory clustering may help identify distinct readiness profiles and support more targeted planning for digital health implementation.

KEYWORDS

Electronic medical records; digital maturity; digital readiness; K-means clustering; principal component analysis; Satu Sehat

INTRODUCTION

The integration of Electronic Health Records (EHRs), including Electronic Medical Records (EMRs), into healthcare systems has been widely recognized as an important step in modernizing healthcare delivery and improving patient care.[1] EMR systems have the potential to enhance efficiency, improve the quality of care, and strengthen patient safety by reducing errors associated with incomplete, misplaced, or inaccessible medical records.[2–6] In addition, digital health records can facilitate better coordination among healthcare professionals, support more comprehensive patient management, and reduce errors related to data loss.[7,8]

In Indonesia, the government has strengthened efforts to accelerate digital health transformation through regulations introduced in 2022 and the implementation of the Satu Sehat platform, which aims to unify health data across healthcare facilities and improve interoperability in medical data management.[9] Through this platform, patient health information can be accessed more efficiently across locations, supporting continuity of care even when individuals seek services outside their home healthcare facility.

Despite these efforts, the adoption of EHRs, particularly EMRs, remains uneven across Indonesia. Many hospitals and healthcare facilities continue to face substantial barriers to implementation, including limited infrastructure, disparities in information and communication technology capacity, and insufficient human resource readiness. [10–13] Variations in digital capacity across provinces and institutions may affect the transition from paper-based medical records to digital systems, making readiness for EMR implementation an important issue in the Indonesian healthcare context. [10–13]

Assessing digital readiness is essential because successful EMR implementation depends on multiple interrelated factors, including technological infrastructure, institutional support, workforce competency, interoperability, and data governance. [12,14–18] In this context, the Digital Maturity Index provides a useful framework for evaluating the readiness and progress of healthcare institutions in adopting digital systems. Maturity models help identify stages of adoption, measure institutional preparedness, and support the alignment of digital transformation with clinical and operational goals.[19] Previous studies have also shown that the transition from traditional record-keeping to EMR systems requires an adaptation process involving staff training, infrastructure development, and organizational support. [19–21]

Although several studies in Indonesia have described EMR readiness, limited evidence has examined how digital maturity and readiness patterns are distributed across hospitals and regions using a data-driven analytical approach. In particular, few studies have explored whether hospitals can be grouped into distinct readiness and maturity profiles based on key digital health indicators. This represents an important gap in the literature, as identifying such profiles may support more targeted implementation planning and policy development. Therefore, this study aimed to explore digital readiness and maturity profiles for EMR implementation among hospitals in Indonesia using clustering analysis. Specifically, this study addressed the following research questions: **(1)** What digital readiness and maturity profiles can be identified among hospitals in Indonesia? **(2)** Which key digital maturity indicators most strongly characterize these hospital profiles? and **(3)** How may these profiles inform more targeted strategies for EMR implementation and digital health strengthening in Indonesia?

METHODS

STUDY DESIGN AND DATA SOURCES

This study used a cross-sectional secondary data analysis with an exploratory unsupervised machine learning approach to identify digital maturity and EMR readiness profiles among hospitals in Indonesia. An unsupervised approach was selected because it allows the identification of hidden patterns and similarities in multidimensional data without requiring predefined outcome labels. [21,22]

The study used a secondary dataset from the Ministry of Health of Indonesia, based on the Digital Maturity Index assessment for 2024, collected by the Digital Transformation Officer. The final analytic dataset included 711 hospitals from provinces across western, central, and eastern Indonesia. Although this provided broad geographic coverage, the dataset was not treated as a fully nationally representative sample because some provinces, particularly in eastern Indonesia, had more incomplete records. Because this study relied on an existing administrative dataset, the authors did not conduct any additional primary sampling. Hospitals were included if data were available for the selected digital maturity variables used in the analysis; records with incomplete information on these variables were excluded from the final analytic dataset.

The dataset contained hospital-level indicators related to digital readiness and EMR implementation, including Information Systems and Infrastructure, Standards and Interoperability, Human Capital, Data Analytics, Competence and Usage, Security and Privacy, and Electronic Health Records, as well as an overall Maturity Level variable. These indicators were used to characterize hospital digital maturity and readiness for EMR implementation.

VARIABLES AND MEASUREMENT

The analysis used hospital-level digital maturity indicators available in the Ministry of Health dataset, including Information Systems and Infrastructure, Standards and Interoperability, Human Capital, Data Analytics, Competence and Usage, Security and Privacy, and Electronic Health Records. These domains were treated as proxy indicators of hospital digital readiness for EMR implementation.

For descriptive analysis, the available domain-related data were operationalized into aggregated ordinal scores on a 1–5 scale, with higher scores indicating greater digital maturity within each domain. These aggregated scores were used to summarize the distribution of digital maturity indicators across hospitals and to support the descriptive comparisons presented in Table 1.

For the unsupervised analysis, the clustering procedure was conducted using the selected domain-level indicators after preprocessing and standardization. In this step, the variables were used as analytic features to identify data-driven similarity patterns across hospitals rather than as predefined ordinal readiness categories. Accordingly, the cluster labels generated by the K-means analysis were treated as algorithm-generated identifiers rather than as equivalent to the descriptive maturity scores. The overall Maturity Level variable in the source dataset was used only for descriptive comparisons and was conceptually distinct from the clustering-derived hospital profiles.

CLUSTERING AND STATISTICAL ANALYSIS

Before clustering, the selected domain-level digital maturity indicators were organized into a structured analytic dataset and standardized to improve comparability across variables. Feature scaling was applied to reduce the influence of differences in variable magnitude on the clustering results.

K-means clustering was performed in Python using the scikit-learn library to identify groups of hospitals with similar digital maturity and EMR readiness characteristics. Because K-means is a centroid-based clustering method, similarity was assessed in standardized feature space using Euclidean distance. The number of clusters was assessed using the elbow method by examining the reduction in within-cluster sum of squares across different values of K. Based on this exploratory assessment, a six-cluster solution was selected as a reasonable balance between reduction in cluster inertia and interpretability of hospital profiles. The resulting cluster labels (0–5) were treated as algorithm-generated identifiers rather than predefined ordinal readiness scores.

Principal Component Analysis (PCA) was also implemented using scikit-learn to reduce the dimensionality of the dataset and support visualization of the clustering structure. [21,22] PCA projected the multidimensional hospital data into a lower-dimensional space, facilitating interpretation of the relative separation and overlap among the identified clusters. In addition, descriptive statistical analysis was conducted to summarize hospital digital maturity indicators across the original maturity-level categories in the source dataset. Continuous or score-based variables were presented as means and standard deviations, and group differences were assessed using one-way analysis of variance (ANOVA), with p-values < 0.05 considered statistically significant.

ETHICAL CONSIDERATIONS

The study got a letter of ethical clearance (No. KET 180/UN2.F12.D.1.2.1/PPM. 00.02/2024). The study adhered to ethical guidelines concerning data privacy and confidentiality. Since the dataset was anonymized and provided by the Ministry of Health, no personally identifiable information was included in the analysis. The authors are committed to upholding ethical standards in publishing this study's findings by ensuring organizational privacy and data confidentiality throughout the digital health implementation process.

RESULT

Table 1 presents the distribution of 711 hospitals across six clusters by province, showing regional variation in digital maturity profiles. Hospitals from Lampung, East Java, and Central Java were distributed across multiple clusters, indicating heterogeneity in cluster membership within these provinces. East Java was represented in all six clusters, reflecting variation in hospital-level digital maturity characteristics. In contrast, provinces such as Papua and Maluku had fewer hospitals and were more concentrated in clusters with lower digital maturity.

TABLE 1. DIGITAL MATURITY AND READINESS FOR ELECTRONIC MEDICAL RECORDS AMONG HOSPITALS IN INDONESIA

Province	∑ Sample	% Cluster of Digital Maturity						% mean	P Value
		0	1	2	3	4	5		
Aceh	27	1.9	5.0	4.5	3.6	1.7	6.6	3.8	0.001
South Sumatera	21	2.9	5.0	2.3	0	1.7	3.8	3.0	
West Sumatera	26	1.0	4.3	6.0	14.3	1.1	3.8	3.0	
Bengkulu	20	1.9	3.1	2.3	7.1	3.4	1.9	2.8	
Lampung	69	10.5	9.9	3.8	7.1	12.9	11.3	9.7	
Jakarta	54	13.3	5.6	8.3	7.1	7.9	3.8	7.6	
West Java	56	10.5	5.0	6.0		10.1	10.4	7.9	
Central Java	75	9.5	13.0	10.5	3.6	9.0	12.3	10.5	
Jogjakarta	52	4.8	5.6	10.5		10.1	5.7	7.3	
East Java	93	20	9.3	12.8	7.1	15.7	15.7	13.1	
Banten	24	3.8	3.1	1.5	3.6	3.9	4.7	3.4	
Bali	32	2.	4.3	7.5		2.8	6.6	4.5	
West Kalimantan	18	2.9	2.5	4.5		1.7	1.9	2.5	

South Kalimantan	14	2.9	0.6	3.0		0.6	4.7	2.0
Central Sulawesi	11	1.9	3.1	0.8	7.1	0.6		1.5
South Sulawesi	34	6.7	5.6	2.3	3.6	6.2	2.8	4.8
Southeast Sulawesi	25	1.0	5.6	2.3	14.3	3.4	1.9	3.5
Maluku	1	0.1						0.1
North Maluku	15	1.0	3.1	0.8	10.7	2.2	0.9	2.1
Jambi	2		0.6			0.6		0.3
South Sumatera	4		0.6	0.8		0.6	0.9	0.6
Babel	3		0.6			0.6	0.9	0.4
NTB	13		1.9	3.0	3.	1.7	1.9	1.8
NTT	5		0.6	0.8			2.8	0.7
North Kalimantan	1		0.6					0.1
North Sulawesi	1		0.6					0.1
Gorontalo	5		0.6	2.3			0.9	0.7
Riau	3			2.3				0.4
Riau Island	3			1.5	3.6			0.4
Central Papua	1				3.			0.1
North Kalimantan	1					0.6		0.1
Papua Barat Daya	1					0.6		0.1

Note: Cluster 0 or 1 means ready to EMR/digitalization; 2 or 3 moderately ready, 4 or 5 not ready

Table 2 presents the average scores of the digital maturity indicators on a 1–5 scale across the hospital clusters. Information Systems and Infrastructure, Standards and Interoperability, and Human Capital had the highest overall mean scores, each at 3.5. In contrast, Data Analytics had the lowest overall mean score at 2.4. Differences in mean scores across clusters were also observed, indicating variation in digital maturity characteristics among the identified hospital groups.

TABLE 2. MEAN (SD) OF DIGITAL MATURITY INDICATORS BY ORIGINAL MATURITY LEVEL AMONG HOSPITALS IN INDONESIA

Key indicator	Cluster 0 Mean (SD)	Cluster 1 Mean (SD)	Cluster 2 Mean (SD)	Cluster 3 Mean (SD)	Cluster 4 Mean (SD)	Cluster 5 Mean (SD)	Overall Mean (SD)	P-value
Information Systems & Infrastructure	4.4 (0.4)	2.9 (0.5)	3.4 (0.5)	1.9 (0.4)	3.9 (0.4)	3.4 (0.5)	3.5 (0.7)	<0.001
Standards & Interoperability	4.5 (0.5)	2.5 (0.6)	3.9 (0.5)	1.9 (0.7)	4.0 (0.6)	3.0 (0.7)	3.5 (1.0)	<0.001
Human Capital	4.6 (0.7)	1.9 (0.6)	2.4 (0.7)	1.1 (0.5)	3.8 (0.6)	3.0 (0.6)	3.0 (1.2)	<0.001
Data Analytics	4.0 (0.7)	1.3 (0.3)	1.9 (0.6)	0.3 (0.3)	2.9 (0.5)	2.5 (0.5)	2.4 (1.1)	<0.001
Competence and Usage	4.6 (0.3)	2.4 (0.5)	3.1 (0.1)	1.2 (0.5)	4.0 (0.4)	3.5 (0.5)	3.4 (1.0)	<0.001
Security & Privacy	4.3 (0.5)	1.8 (0.6)	2.1 (0.7)	1.0 (0.4)	3.3 (0.7)	3.1 (0.1)	2.7 (1.1)	<0.001
Electronic Medical Records	4.4 (0.4)	2.8 (0.6)	3.6 (0.5)	1.3 (0.8)	3.8 (0.4)	3.4 (0.5)	3.4 (0.5)	<0.001
Overall Maturity Level	4.4 (0.5)	2.8 (0.4)	3.2 (0.4)	1.9 (0.4)	4.0 (0.1)	3.4 (0.5)	3.5 (0.8)	<0.001

Note: Values are presented as mean (SD), where SD = standard deviation. P-values were calculated using one-way analysis of variance (ANOVA).

Figure 1 presents a pair plot of the key digital maturity indicators, providing an overview of their distributions and pairwise relationships. The diagonal density plots show the distribution of each variable, while the off-diagonal scatterplots illustrate the relationships between indicators. Information Systems and Infrastructure showed a slightly left-skewed distribution, indicating that most hospitals had relatively high scores, with fewer hospitals showing lower values. In contrast, Security and Privacy displayed a broader distribution, suggesting greater variability across hospitals.

The scatterplots show generally positive relationships among several indicators. Stronger positive associations were observed between Information Systems and Infrastructure and Human Capital, and between Competence and Usage and Electronic Health Records. By comparison, Security and Privacy showed weaker visual associations with several other indicators. Overall, the figure indicates that digital maturity domains were related to each other, although the strength of these relationships varied across indicators.

FIGURE 1. PAIRWISE RELATIONSHIPS AMONG DIGITAL MATURITY INDICATORS IN HOSPITALS IN INDONESIA

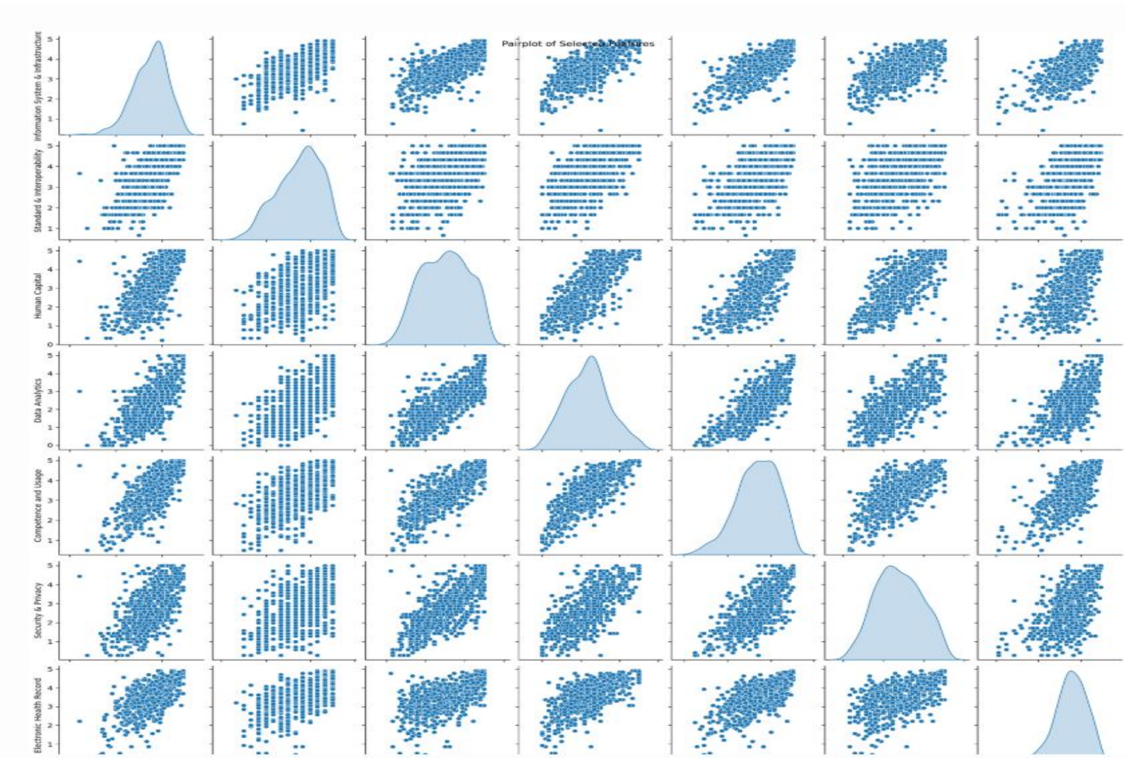


Figure 2 presents the elbow plot used to assess the number of clusters in the K-means analysis. The within-cluster sum of squares decreased substantially from K = 1 to K = 3, after which the rate of reduction became more gradual. This pattern indicates diminishing gains in compactness as additional clusters were added. For this exploratory analysis, a six-cluster solution was retained to provide more detailed differentiation of hospital digital maturity profiles. The resulting labels 0–5 were used as cluster identifiers only and were not interpreted as direct readiness scores.

FIGURE 2. ELBOW PLOT FOR CLUSTER SELECTION IN THE K-MEANS ANALYSIS

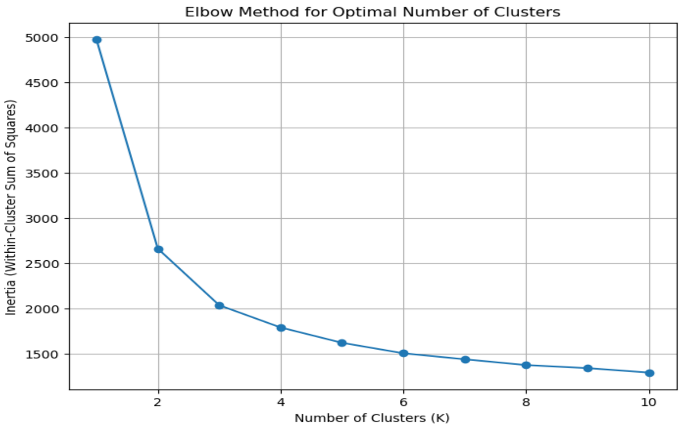
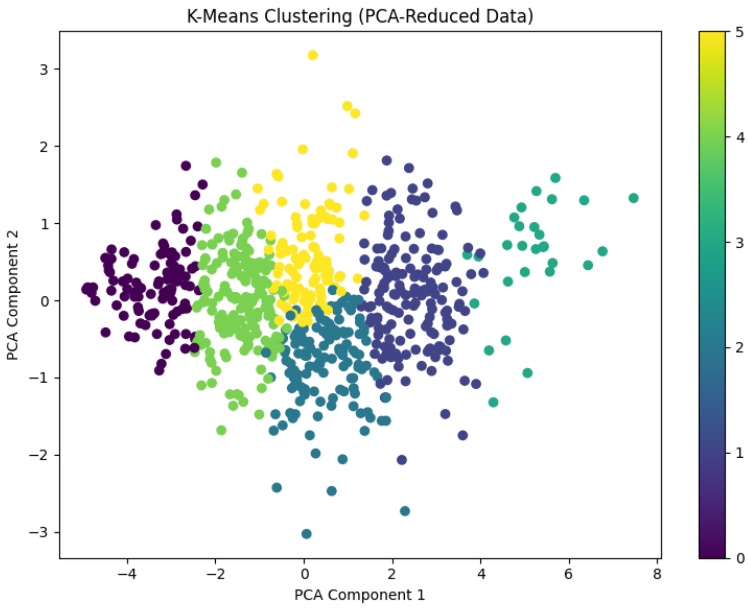


Figure 3 presents the PCA-based visualization of the six-cluster solution derived from the K-means analysis. The plot shows that the clusters were distinguishable in the reduced-dimensional space, although partial overlap was observed among several groups. Cluster 2 and Cluster 3 were located near the central region of the plot, whereas clusters with relatively different digital maturity patterns appeared more separated along the first principal component.

The PCA plot also shows that Cluster 2 was positioned close to Cluster 3, while the other clusters were more distinctly distributed across the reduced-dimensional space. Hospitals in Cluster 2 and Cluster 3 showed lower scores across several domain indicators, including Human Capital, Data Analytics, and Security and Privacy, compared with clusters characterized by relatively higher domain scores. These two clusters included hospitals from both urban and non-urban provinces, including West Sumatra, Maluku, Central Papua, and Jakarta.

FIGURE 3. PCA-BASED VISUALIZATION OF THE SIX-CLUSTER SOLUTION



DISCUSSIONS

Digital transformation in healthcare has been widely recognized as an important strategy for improving service quality, coordination, and system efficiency.[23–25] However, successful implementation of EMR systems depends not only on the availability of digital tools but also on institutional readiness across multiple domains, including infrastructure, human resources, interoperability, and governance.[24,25] In this study, the clustering analysis showed that hospital digital maturity in Indonesia was heterogeneous, with variation observed not only across provinces but also within the same province. This finding suggests that EMR readiness should not be understood as a uniform regional characteristic, but rather as a multidimensional institutional condition that differs across hospitals.

The study also showed that some domains of digital maturity were relatively stronger than others. Information Systems and Infrastructure, Standards and Interoperability, and Human Capital had higher average scores, whereas Data Analytics showed the lowest overall score. This pattern is consistent with broader international literature showing that many health systems reach the stage of basic digital documentation before developing more advanced capacities for data use, analytics, and decision support. In this sense, digital maturity is not simply defined by the existence of EMR systems, but by the extent to which digital information can be integrated, interpreted, and translated into better clinical and managerial decision-making. The low score in Data Analytics suggests that digital maturity in many hospitals may still be limited to system adoption rather than effective data utilization. This is important because the value of EMR systems depends not only on whether records are digitized, but also on whether digital data can be translated into meaningful clinical, managerial, and policy insights.

The relationships observed across domains further support the view that digital maturity is a multidimensional construct. The pair-plot analysis showed stronger positive associations between infrastructure and human capital, and between competence and EMR use, indicating that technical capacity and workforce readiness often develop together. At the same time, Security and Privacy showed weaker alignment with several other domains, suggesting that progress in digital adoption does not automatically ensure progress in data protection and confidentiality. This is important because international EMR readiness frameworks generally emphasize that digital maturity requires balanced development across technological, organizational, and governance domains, rather than progress in a single area alone. From this perspective, the findings of this study reinforce the need to evaluate digital readiness as a staged and multidimensional process.

Another important finding is that lower-readiness hospital profiles were identified in both urban and non-urban settings. Although hospitals in provinces such as Jakarta and East Java are often assumed to benefit from stronger infrastructure and greater workforce availability, some hospitals in these areas were still classified as lower-maturity profiles. Conversely, hospitals in provinces such as Central Papua and Maluku also appeared in lower-readiness clusters, reflecting continuing structural limitations. This pattern suggests that geography alone does not fully explain digital readiness. Institutional governance, local implementation capacity, staff competence, and organizational support may also play major roles in shaping EMR adoption. This interpretation is aligned with previous studies emphasizing that human competency, training, infrastructure readiness, and organizational support are central determinants of EMR implementation success. [7,11,12,28–30]

From a health information systems perspective, this study contributes by showing the value of exploratory clustering for identifying hospital digital maturity profiles beyond simple descriptive categorization. Rather than treating hospitals as belonging to a single linear level of readiness, the clustering approach enabled identification of groups with distinct patterns of strengths and weaknesses across domains. This has implications not only for Indonesia but also for broader digital health systems research, particularly in settings where digital transformation is progressing unevenly across institutions. Profiling hospitals in this way may support more targeted implementation strategies, allowing policymakers to tailor interventions according to dominant readiness barriers, such as workforce development, security and privacy, or data analytics capacity.

LIMITATIONS

This study was exploratory and relied on secondary administrative data, so the identified clusters should be interpreted as empirical profiles rather than definitive or validated readiness categories. Although the dataset covered hospitals from provinces across Indonesia, the analytic sample was not treated as fully nationally representative because some provinces, particularly in eastern Indonesia, had more incomplete records. In addition, the digital maturity domains were operationalized as proxy indicators from the available dataset and may not fully capture institutional readiness for EMR implementation. Finally, cluster evaluation in the original analysis relied on the elbow method and PCA-based visualization, and additional clustering validity indices were not available. Even so, the study provides useful early evidence on variation in hospital digital maturity and highlights the need for more context-sensitive approaches to digital health implementation in Indonesia.

CONCLUSION

This study identified heterogeneous profiles of digital maturity and EMR readiness among hospitals in Indonesia using an exploratory clustering approach. Digital maturity was not distributed uniformly across provinces or hospitals, with substantial variation observed both across and within regions. Hospitals from East Java, Central Java, and Lampung were distributed across multiple clusters, whereas hospitals from Papua and Maluku were more concentrated in lower digital maturity profiles.

Across the domains of Information Systems and Infrastructure, Standards and Interoperability, and Human Capital, average scores were relatively higher, while Data Analytics had the lowest overall score. Differences in Human Capital, Data Analytics, Security and Privacy, and other domain-level indicators helped characterize the hospital profiles identified in the clustering analysis.

Overall, these findings suggest that hospital readiness for EMR implementation in Indonesia is multidimensional and cannot be captured by a single uniform level. The identified profiles may support more targeted digital health strategies by highlighting areas of need, including infrastructure development, workforce strengthening, data analytics capacity, and improvements in security and privacy. Further studies using stronger validation methods and broader longitudinal assessment are needed to refine these readiness profiles.

ACKNOWLEDGMENTS:

Thank you to all the participants, facilitators, the DTO Ministry of Health, the Information and Data Center Ministry of Health, the Team Working Group Ministry of Health, and all the teams that supported this study.

COMPETING INTERESTS:

No competing interests were disclosed.

GRANT INFORMATION:

This work was supported by a PUTI H-I-2024 (NKB-09/UN2.RST/HKP.05.00 grant from Universitas Indonesia.

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