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Interprovincial Inequality in The Implementation of Hospital Electronic Medical Records in Indonesia

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ABSTRACT

Indonesia's Minister of Health Regulation No. 24 of 2022 (Peraturan Menteri Kesehatan, Permenkes No. 24/2022) required hospitals to implement electronic medical records (EMRs), known in Indonesia as Rekam Medis Elektronik (RME), by December 31, 2023. However, regional disparities in implementation remained insufficiently understood. This study assessed interprovincial inequalities in comprehensive EMR implementation in 2024, examined associated technological, organizational, and environmental factors, and compared implementation levels with SATUSEHAT platform connectivity in 2025. A cross-sectional ecological study was conducted across 38 Indonesian provinces using data from the 2024 and 2025 Indonesian Health Profiles and Statistics Indonesia publications from 2026. The outcome variable was the proportion of hospitals implementing EMRs across six service areas. Data were analyzed using between-region and within-region variance decomposition and multilevel fractional logistic regression with robust standard errors. Among 3,102 hospitals surveyed, 62.83% had fully implemented EMRs, 34.78% had partially implemented them, and 2.39% had not implemented them. Provincial implementation rates ranged from 0% to 88.9%, with a Gini coefficient of 0.228. Approximately 68% of the observed variation occurred between regions, with implementation rates ranging from 72.2% in Java to 28.2% in Maluku–Papua. The lower odds of comprehensive implementation in Maluku–Papua (odds ratio [OR] = 0.21) were no longer statistically significant after adjustment for internet access, the Human Development Index, and hospital characteristics. The proportion of privately owned hospitals was positively associated with comprehensive implementation (OR = 1.17 per 10-percentage-point increase; 95% confidence interval [CI]: 1.07–1.28), but this association was no longer statistically significant after adjustment for the six regional groupings (OR = 1.05; 95% CI: 0.91–1.21). SATUSEHAT connectivity in 2025 was nearly universal but was not significantly associated with the extent of EMR implementation. These findings indicated that interprovincial inequalities in comprehensive EMR implementation were predominantly regional and associated with disparities in digital infrastructure, human development, and hospital ownership composition. Policy monitoring should therefore extend beyond connectivity indicators to assess implementation comprehensiveness at the provincial level, accompanied by targeted support for regions with lower levels of digital health readiness.

INTRODUCTION

Systematic reviews and meta-analyses have demonstrated that electronic medical records (EMRs) can improve adherence to clinical guidelines and reduce medication errors and adverse drug events, although their effects on mortality have not been conclusively established (Campanella et al., 2016). In the United States, hospitals with higher levels of digital maturity have been associated with better patient safety ratings than those with lower levels of digital maturity (Snowdon et al., 2024). These benefits may be enhanced when health information can be exchanged across healthcare facilities, as health information exchange has been associated with fewer duplicate diagnostic tests, lower healthcare costs, and improved patient safety (Menachemi et al., 2018).

Indonesia mandated the implementation of electronic medical records, known locally as Rekam Medis Elektronik (RME), through Minister of Health Regulation No. 24 of 2022 concerning Medical Records. The regulation required all healthcare facilities to implement EMRs by December 31, 2023, alongside integration with the national SATUSEHAT health data platform (Wulyardhi & Udiana, 2025). However, the integration target was subsequently extended to the end of 2025 because of various implementation challenges. Before the initial deadline, hospital readiness varied considerably. According to the Ministry of Health's 2022 digital maturity assessment, the largest proportions of hospitals were classified at maturity levels 3 (31%) and 4 (22%), with Class A and Class B hospitals demonstrating higher digital maturity than hospitals in other classifications (Jayanthi & Lazuardi, 2023). Regional case studies identified recurring barriers, including insufficient computers in clinical units, incomplete system functionalities, the absence of dedicated information system budgets, and limited integration with SATUSEHAT (Jayanthi & Lazuardi, 2023; Pasaribu et al., 2024). A qualitative study involving 12 hospitals in Java and Sulawesi further revealed that unreliable internet connectivity required healthcare personnel to duplicate electronic documentation through manual recording. Hospitals in Java generally demonstrated more proactive implementation practices, whereas those in Sulawesi tended to adopt EMRs primarily to 10208he au regulatory requirements (Hossain et al., 2025).

International evidence has consistently demonstrated disparities in electronic health record (I) adoption across healthcare institutions and geographic regions. In the United States, early adoption was concentrated among large, urban, and teaching hospitals, while smaller, nonteaching, and rural hospitals experienced slower implementation (Jha et al., 2009; DesRoches et al., 2012). As basic I adoption became more widespread, disparities increasingly shifted toward the availability and utilization of advanced system functionalities (Adler-Milstein et al., 2017). By 2023, rural critical access hospitals continued to lag behind other hospitals in the adoption of clinical data analytics capabilities (Apathy et al., 2025). In China, I adoption increased from 18.6% in 2007 to 85.3% in 2018, with greater improvements observed in economically developed regions and tertiary (Tier III) hospitals (Liang et al., 2021). In low- and middle-income countries, successful implementation has depended on financial resources, technical infrastructure, organizational readiness, workforce training, and political support (Fritz et al., 2015; Jawhari et al., 2016). Many implementations in low-income countries have remained at preliminary or pilot stages (Woldemariam & Jimma, 2023). Financial and technical constraints have been among the most frequently reported barriers,

particularly high initial investment costs and inadequate technical support (Boonstra & Broekhuis, 2010; Kruse et al., 2016).

Geographic inequality has also presented a persistent challenge to Indonesia's healthcare system. Shortages of intensive care and isolation facilities have been particularly pronounced outside Java. Meanwhile, approximately 22%–26% of specialists in pulmonology, internal medicine, anesthesiology, and radiology have practiced in the Special Capital Region of Jakarta (Daerah Khusus Ibukota Jakarta, DKI Jakarta), despite the region accounting for only approximately 3% of Indonesia's population (Mahendradhata et al., 2021). The substantial contribution of private practice income to physicians' earnings has complicated efforts to achieve equitable specialist distribution, contributing to the continued concentration of medical specialists in Java (Meliala et al., 2013). Similar disparities have been observed in information and communication technology (ICT) development, with Papua, East Nusa Tenggara, West Sulawesi, and North Maluku consistently ranking among the lowest-performing provinces during 2015–2019 (Ramadhanti & Astuti, 2022). Disadvantaged, frontier, and outermost regions, commonly referred to as daerah tertinggal, terdepan, dan terluar (3T regions), have also been concentrated in Nusa Tenggara, Maluku, and Papua (Salsabila & Apriono, 2025). Nevertheless, most Indonesian studies on EMR implementation have relied on case studies involving individual hospitals or small groups of healthcare institutions. National-level evidence quantifying interprovincial disparities in comprehensive EMR implementation following the initial regulatory deadline, the contribution of broader regional differences to these disparities, and their associated determinants has remained limited.

This study adopted the Technology–Organization–Environment (TOE) framework to examine factors associated with disparities in hospital EMR implementation. The framework considers technological conditions, organizational characteristics, and external environmental factors as interconnected dimensions of organizational technology adoption and has previously been applied to hospital information system implementation (Ahmadi et al., 2017). Evidence from a national study in the United States also indicated that organizational and environmental characteristics, including hospital size, network affiliation, and urban location, were associated with EMR adoption (Kazley & Ozcan, 2007). Guided by this framework, the present study aimed to (1) quantify interprovincial and interregional inequalities in comprehensive hospital EMR implementation in 2024, (2) examine the technological, organizational, and environmental factors associated with these disparities, and (3) compare provincial implementation patterns with SATUSEHAT connectivity levels in 2025.

METHOD

Design and unit analysis

This study employed a cross-sectional ecological design using aggregated secondary data from 38 Indonesian provinces, including four newly established provinces in Papua. The outcome variables were measured using 2024 data, representing the first year following the initial regulatory deadline for electronic medical record (EMR) implementation and the most recent year for which provincial EMR implementation status was available. The 2025 Indonesian Health Profile no longer reported provincial EMR implementation status, instead presenting healthcare facility connectivity to the National Health Information System (Sistem

Informasi Kesehatan Nasional, SIKN), which was examined in a complementary analysis. Because the province was the unit of analysis, the observed associations were interpreted at the provincial level and could not be generalized directly to individual hospitals (Morgenstern, 1995).

Data source

Data is taken from three official publications. First, the provincial table in the 2024 Indonesia Health Profile provides the number of hospitals per province according to RME status, ownership, class and beds, and accreditation status. RME data comes from a survey by the Directorate General of Health Services of 3,102 out of 3,228 registered hospitals (96.1%). Second, the provincial table in the 2025 Indonesia Health Profile provides the 2024 Human Development Index (HDI) sourced from BPS, the number of hospitals in 2025, and the number of hospitals connected to the SIKN as of December 2025. Third, Statistics Indonesia 2026 provides the percentage of households accessing the internet in the last three months of 2024 by province, which is sourced from the National Socio-Economic Survey.

Each table is extracted from official documents, then the number of 38 provinces is matched to the national total row and the number of hospitals per province is matched between tables; all 2024 tables pass this check. The accreditation percentages for South Papua, Central Papua, Mountainous Papua, and Southwest Papua are not included in the source, so it is calculated from the number of accredited hospitals divided by the number of hospitals. In the 2025 connectivity table, the national total row (3,221 hospitals) turns out to be the same as the number of 37 provinces without Aceh, so this study uses the sum of provincial rows (3,307 hospitals).

Variable

The outcome variable is the proportion of hospitals that are running a full RME, i.e. RME in six services: 10210he autho, outpatient, inpatient, emergency installation, support unit, and pharmacy. The denominator is the number of hospitals surveyed in the province. Following the data source, hospitals with RME in at least three of the six services are categorized as partial RMEs. Explanatory variables are grouped according to the TOE framework (Table 1). Since RME data are not available by type of ownership, ownership is measured as the composition of hospitals at the provincial level. Provinces are also grouped into six archipelago regions: Sumatra (10 provinces), Java (6), Bali-Nusa Tenggara (3), Kalimantan (5), Sulawesi (6), and Maluku-Papua (8).

Data analysis

The analysis in this study was carried out in four stages. First, the implementation of RME was described per province and per archipelagic region. Interprovincial inequality was measured by the coefficient of variation and the Gini coefficient without weighting. The magnitude of regional inequality was measured by eta squared, which is the part of the interprovincial diversity located between the six regions. Second, the bivariate relationship was tested with Spearman correlation.

Table 1. Operational definitions of variables and data sources

Dimensions	Variable	Operational definition	Source
Results	Full RME	Hospitals with RME in six services divided into surveyed hospitals, 2024	Indonesia Health Profile 2024
Technology	Internet access	Percentage of households accessing the internet in the last three months, 2024	Indonesia Statistics 2026 (Susenas)
Organization	Private ownership	Private hospitals divided into all hospitals, 2024	Indonesia Health Profile 2024
Organization	Accreditation	Accredited hospitals divided into all hospitals, 2024	Indonesia Health Profile 2024
Organization	Hospital size	Number of beds divided by number of hospitals, 2024	Indonesia Health Profile 2024
Environment	IPM	Provincial Human Development Index, 2024	Indonesia's Health Profile 2025 (BPS data)
Environment	Region	Maluku-Papua indicators (Maluku, North Maluku, and six provinces of Papua = 1; others = 0) and six archipelago regions	Researcher grouping
Complements	Connectivity 2025	SIKN-connected hospitals as of December 2025 will be divided into registered hospitals in 2025	Indonesia's Health Profile 2025

Third, because the outcome variables are proportional with values of 0 to 1, including a value of 0 in one province, multivariable analysis uses *logit fractional regression* (Papke & Wooldridge, 1996). This model estimates the conditional average of proportions through a logit function using *the quasi-likelihood method*, so that values 0 and 1 can be analyzed without transformation or deletion (Ramalho et al., 2011). Four models are arranged in tiers. Model 1 contains only the Maluku-Papua indicator. Model 2 adds internet access and HDI. Model 3 adds three hospital characteristics. The weakening of the regional coefficient from Model 1 to Model 3 shows how far the regional gap is related to other factors. Model 4 replaces the Maluku-Papua indicator with a fixed effect of six regions (comparator: Java) to test whether the relationship in Model 3 persists within the same region. As a complement, the Pearson correlation is calculated between the proportion of the full RME and the proportion of private hospitals after both are subtracted by the average of their regions (31 degrees of freedom). The standard error uses the robust HC3 estimator recommended for small samples (Long & Ervin, 2000). The results are presented as the ratio of odds and the average marginal effect between provinces in percentage points; R^2 is calculated as the square of the correlation between the observed value and the predicted value.

Fourth, the resilience of the results was tested in six ways: (1) a weighted model of the number of hospitals surveyed, so that each hospital contributes equally; (2) *the percentile bootstrap interval* of 2,000 provincial retakes; (3) the expenditure of one province in turn; (4) the expenditure of Central Papua and Mountainous Papua, whose household internet access (36.1% and 12.2%) is far below that of other provinces (65.7% or more); (5) the breakdown of government ownership into hospitals owned by local governments as well as hospitals owned by the Ministry of Health, the TNI/Polri, SOEs, and other ministries; and (6) the replacement of the Maluku-Papua indicator with the indicator of the Eastern Region of Indonesia (all

provinces outside Sumatra, Java, and Bali). Multicollinearity was checked with *variance inflation factor* (VIF). The analysis was carried out with Python 3.13 (statsmodels 0.15 and SciPy 1.18); the HC3 standard error was calculated directly from the leverage matrix. The significance level used was 0.05.

Research ethics

This study only uses aggregate data that is publicly published and does not contain individual data, so it does not require ethical approval.

RESULTS AND DISCUSSION

Of the 3,102 hospitals surveyed by 2024 (96.1% of the 3,228 registered hospitals), 1,949 (62.83%) have implemented full RME across six services, 1,079 (34.78%) have implemented it partially, and 74 (2.39%) have not implemented it. This means that one year after the initial deadline of December 31, 2023, more than a third of hospitals have not met full implementation.

Overview of interprovincial RME implementation

Table 2. Descriptive statistics of research variables (n = 38 provinces)

Variable	Average	SB	Minimum	Median	Maximum
Hospitals with full RME (%)	50,6	20,8	0,0	52,1	88,9
Private hospitals (%)	44,2	21,9	5,9	47,7	81,7
Accredited hospitals (%)	92,9	7,6	60,0	94,7	100,0
Average beds per hospital	108,8	18,5	63,6	110,8	148,5
Households with access to the internet (%)	86,3	16,0	12,2	90,4	98,2
Human Development Index	73,50	5,13	54,43	74,08	84,15
RME survey coverage (%)	96,6	3,5	86,7	96,6	101,3

Note. SB = standard deviation. Statistics are calculated between provinces without weighting, so that the average full RME (50.6%) is different from the national achievement (62.83%). The proportion of full RME is calculated against the hospitals surveyed. Survey coverage above 100% in one province (DI Yogyakarta: 80 hospitals surveyed, 79 registered) comes from data sources.

The proportion of hospitals with full RME varies greatly between provinces (Figure 1). The median is 52.1%, with a range from 0% in mountainous Papua to 88.9% in the Bangka Belitung Islands. A total of 15 out of 38 provinces are below 50%, while only 7 provinces reach 70% or more. The coefficient of variation of 0.41 and the Gini coefficient between provinces of 0.228 show a marked inequality.

Inequality between regions

Full implementation was highest in Java (72.2%) and lowest in Maluku-Papua (28.2%), a difference of 43.9 percentage points or 2.6 times (Table 3). Maluku-Papua covered only 4.0% of the hospitals surveyed, but accounted for 17 out of 74 (23.0%) hospitals that had not implemented RMEs. In this region, partial implementation (58.1%) was more common than full implementation. The disparity was largely regional: 68% of full interprovincial RME diversity occurred between archipelagos (eta squared = 0.68). The proportion of private

hospitals clustered more strongly (76% of the diversity occurred between regions); in Maluku-Papua the proportion (18.9%) was less than one-third of the proportion in Java (74.2%).

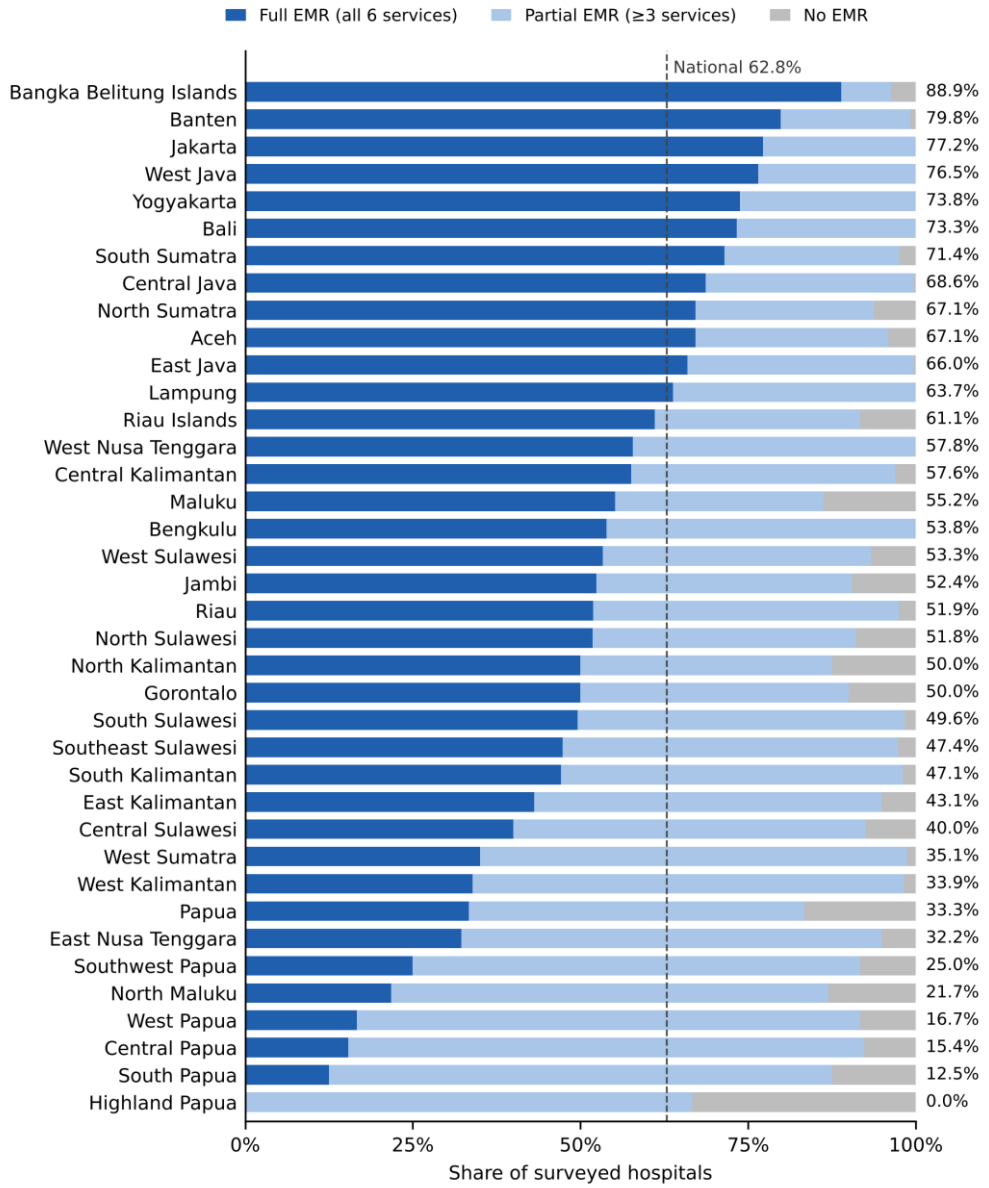


Figure 1. Proportion of hospitals with full, partial, and unattended RME by province, 2024 (sorted by proportion of full RME; dotted line = national achievement of 62.8%)
Source: Indonesia Health Profile 2024, processed.

Table 3. RME implementation and hospital characteristics by region, 2024

Region	Prov.	Hospitals surveyed	Full RME (%)	Partial RME (%)	Not yet RME (%)	Private hospitals (%)	Accredited hospitals (%)	RT internet access (%)	IPM
Javanese	6	1.566	72,2	27,7	0,2	74,2	96,9	91,2	77,7
Sumatra	10	731	61,4	34,6	4,0	59,3	95,1	92,1	75,4
Bali & Nusa Tenggara	3	179	55,9	42,5	1,7	53,6	92,8	87,0	73,6
Sulawesi	6	288	48,6	46,5	4,9	40,3	93,3	90,2	73,2
Kalimantan	5	214	44,4	51,9	3,7	41,6	94,1	92,8	74,6
Maluku-Papua	8	124	28,2	58,1	13,7	18,9	86,6	68,1	67,5

Note. Prov. = number of provinces; Hospitals = hospitals; RT = households. The percentage of RMEs, private hospitals, and accredited hospitals is calculated from the combined number of hospitals in the region. Internet access and HDI are the average of the provinces without weighting.

Factors related to full implementation

Bivariately, the proportion of full RME was positively correlated with the proportion of private hospitals ($\rho = 0.74$), HDI ($\rho = 0.64$), proportion of accredited hospitals ($\rho = 0.53$), household internet access ($\rho = 0.48$), and average beds per hospital ($\rho = 0.45$); all were significant at $p < 0.01$. Since these variables are interrelated, the contribution of each was tested with a stratified model (Table 4).

Table 4. Odds ratio (IK 95%) of the full RME implementation of the *tiered* logit fractional model

Variable	Model 1	Model 2	Model 3	Model 4
Maluku-Papua Region (ref.: other regions)	0,21*** (0,10-0,43)	0,44* (0,23-0,87)	0,69 (0,31-1,52)	—
Household internet access (per 10 percentage points)	—	1,08 (0,78-1,50)	1,17 (0,78-1,78)	1,24 (0,79-1,97)
IPM (per 1 point)	—	1,10*** (1,05-1,16)	1,03 (0,96-1,12)	1,03 (0,95-1,12)
Proportion of private hospitals (per 10 points%)	—	—	1,17*** (1,07-1,28)	1,05 (0,91-1,21)
Proportion of accredited hospitals (per 10 percentage points)	—	—	1,23 (0,72-2,08)	1,15 (0,64-2,06)
Average TT per RS (per 10 TT)	—	—	1,01 (0,84-1,21)	1,01 (0,84-1,20)
Six-region fixed effect	No	No	No	Yes
R^2 (observed-predicted correlation)	0,501	0,654	0,732	0,770

Note. N = 38 provinces; each province is treated as a single unit. Model 4 replaces the Maluku-Papua indicator with a fixed effect of six archipelago regions (comparator: Java); the regional

coefficient is reported in the text. HC3 robust standard error. Hospital = hospital; TT = bed. * p < 0.05; ** p < 0.01; p < 0.001.

Without other variables, *the* odds of full implementation in Maluku-Papua province were only 0.21 times *the odds* of other provinces (Model 1). This gap narrowed to 0.44 after internet access and HDI were included (Model 2); in this model HDI was positively related (odds ratio per point 1.10; 95% IK 1.05-1.16), while internet access was not. The gap then narrowed to 0.69 and was no longer meaningful after hospital characteristics were added (Model 3; p = 0.35). In Model 3, only the proportion of private hospitals associated is meaningful: every 10 percentage point increase is associated with a 1.17 times higher probability of full implementation (95% IK 1.07-1.28), or an average of 3.4 percentage points higher.

The relationship did not persist when differences between regions were controlled in more detail. With a fixed effect of six regions (Model 4), the ratio of the proportion odds of private hospitals dropped to 1.05 (95% IK 0.91-1.21) and was meaningless, also in the weighted model (1.11; 95% IK 0.91-1.34). There were no meaningful technological, organizational, or environmental variables in this model. After subtracting the average of their respective regions, the correlation between the proportion of private hospitals and the proportion of full RME was only 0.17 (p = 0.34). Meanwhile, all regions remained with lower full implementation odds than Java (odds ratio 0.30-0.68), with a significant difference in Kalimantan (0.41; IK 95% 0.19-0.89; p = 0.025). Model 4 explains about 77% of the variation between provinces, while the model that contains only the six regions explains 68%.

Endurance test

In the Model 3 specification, the relationship between the proportion of private hospitals was consistent in the weighted model (odds ratio 1.23; 95% IK 1.13-1.35), *percentile bootstrap* interval of 2,000 retakes (1.08-1.30), expenditure of one province alternately (odds ratio 1.15-1.20; highest p 0.002), and expenditure of Central Papua and Mountainous Papua (odds ratio 1.16; IK 95% 1.07-1.26). When ownership was broken down in more detail with private hospitals as a comparator, the proportion of local government-owned hospitals was associated with lower *odds* (odds ratio per 10 percentage points 0.86; IK 95% 0.76-0.98; p = 0.019), while the proportion of hospitals belonging to the Ministry of Health, TNI/Polri, SOEs, and other ministries was meaningless (p = 0.46).

The results are sensitive to the way the region is controlled, if the Maluku-Papua indicator is replaced with the indicator of the Eastern Region of Indonesia (all provinces outside Sumatra, Java, and Bali), the ratio of the proportion odds of private hospitals to 1.12 (95% IK 1.00-1.25; p = 0.052) in the unweighted model and 1.12 (95% IK 0.96-1.31; p = 0.14) in the weighted model. Thus, the relationship between the proportion of private hospitals is only meaningful when the region is controlled with a single Maluku-Papua indicator, and then weakens when the regional control is made more detailed. The highest VIF value in Model 3 is 5.7 (HDI), below the threshold of 10. The Pearson dispersion in the weighted model of 2.82 indicates overdispersion, so a robust standard error is used.

SATUSEHAT Connectivity 2025

In December 2025, the sum of 38 provinces resulted in 3,307 hospitals connected to SIKN, while the number of registered hospitals was 3,288. The ratio of the two per province

ranged from 0.97-1.08 and did not correlate with the proportion of the full RME in 2024 (ρ = 0.09; p = 0.60).

One year after the initial deadline of the Minister of Health Regulation 24/2022, the RME obligations are formally almost met, but the depth has not yet been met. Only 2.39% of hospitals have not implemented RME, but more than a third have only implemented it in some services. This shift in the gap from "there or nothing" to "superficial or thorough" is in line with the experience of the United States, where the gap shifted to the use of advanced functions after widespread basic adoption (Adler-Milstein et al., 2017).

Inequality that is mainly regional

The gap between provinces in this study is wide, from 0% to 88.9%, and about two-thirds of them are located between the archipelago. The pattern is Java in the top position and Maluku and Papua in the bottom position. The Maluku-Papua gap is no longer meaningful once internet access, HDI, and hospital characteristics are controlled. This means that the backwardness of the eastern region is present along with a weaker digital ecosystem, lower human development, and a government-dominated hospital market. However, Model 4 shows that these factors cannot be separated from the region itself, as none remain meaningful once all six regions are controlled. With 38 provinces, the study could not determine whether the regions only represent a combination of these factors or also contain other barriers, such as geographical conditions, logistics costs, and the availability of information technology personnel.

This pattern is in line with the literature of low- and middle-income countries that place infrastructure, funding, and human resource capacity as a condition for the success of RMEs (Fritz et al., 2015; Jawhari et al., 2016; Woldemariam & Jimma, 2023). Three of the four provinces with the lowest ICT development in 2015-2019, namely Papua (before expansion), East Nusa Tenggara, and North Maluku, were also among the provinces with the lowest full RMEs in the study (Ramadhanti & Astuti, 2022). Disadvantaged, frontier, and outermost regions are concentrated there and difficult to reach by land infrastructure programs (Salsabila & Apriono, 2025), while unstable networks force officers to record twice (Hossain et al., 2025). However, lagging is not only in the east. Kalimantan remains significantly behind Java after other factors are controlled, while West Sumatra (35.1%) and West Kalimantan (33.9%) are well below the national average. Interventions therefore need to be based on provincial data, not just based on the eastern region.

Ownership composition as a marker of regional disparities

The proportion of private hospitals had the strongest bivariate correlation and was the only meaningful factor in Model 3. This relationship persisted in weighted, *boottrap*, and provincial spending models, but weakened with the Indonesian Eastern Region indicator and disappeared after the six regions were controlled. The proportion of private hospitals was also the most robust variable grouped by region. Therefore, ownership composition is more accurately read as a marker of regional disparities than a stand-alone determinant, in line with the finding that private sector growth goes hand in hand with the concentration of specialist doctors in more developed regions (Meliala et al., 2013). The Model 4 confidence interval is still wide (0.91-1.21), so weak relationships within the region cannot be ruled out either.

The finding that the proportion of local government-owned hospitals related to lower achievement remains worthy of study, with the same limitations. Two mechanisms may play a

role. First, some regional hospitals depend on the local government budget cycle; in a hospital, the information system budget is still combined with public goods and services spending (Jayanthi & Lazuardi, 2023). Second, the acceptance of hospital information systems in Indonesia is determined more by organizational factors, such as management support, facility conditions, and user involvement, than by technology factors (Handayani et al., 2017). The relationship between ownership and adoption of RME is not universal: in Hebron, public hospitals are more successful (Najjar et al., 2021), whereas in the United States, ownership is meaningless once the size and affiliation of the network are controlled (Kazley & Ozcan, 2007). Since the analysis was conducted at the provincial level, this finding also does not mean that every private hospital is better prepared than a government hospital (Morgenstern, 1995).

Accreditation, size, and digital environment

Accreditation was positively directional but meaningless, likely because the diversity was small: the provincial median was 94.7%. Hospital size was also meaningless, in contrast to the United States literature that places size as an important determinant (Jha et al., 2009; DesRoches et al., 2012; Kazley & Ozcan, 2007). The national obligations that apply to all hospital classes may reduce the superiority of large hospitals, and the average bed per province is a rough measure. Internet access and HDI are positively bivariately correlated, but intersect with region and ownership composition, making their contributions difficult to separate in the 38 observations. The experience of other countries paints an optimistic picture: in China, regions and hospitals that were initially left behind are growing faster (Liang et al., 2021), and in the United States critical access hospitals narrowed the gap in advanced functioning in 2018-2023 even though they have not closed them yet (Apathy et al., 2025).

From connectivity to implementation depth

The latest national data shows progress. As of October 2025, 3,138 out of 3,239 hospitals have implemented RMEs, but 495 of them do not yet cover all six core services. This means that about 82% of hospitals have implemented RMEs across six services, up from 62.83% in 2024. These two figures are not fully comparable because the sources and denominators are different, and the breakdown per province has not been published, so it is not yet certain whether inequality between provinces has narrowed.

Meanwhile, SATUSEHAT's connectivity is saturated and no longer distinguishes between hospitals that send complete data and those that are only connected. The problems behind the connection are not yet resolved: system developers connected to SATUSEHAT most often report server outages, followed by difficulties mapping RME data to standard terminology (Heryawan et al., 2025). The benefits of health information exchange only arise if the data is exchanged completely and regularly (Menachemi et al., 2018), and the benefits of patient safety are related to digital maturity, not just the existence of the system (Snowdon et al., 2024). National monitoring needs to shift from the number of connected facilities to the depth of implementation, for example the proportion of hospitals with RME across the six services and the completeness of the data sent, which is published per province each year.

Policy implications

These findings lead to three priorities. First, because inequality is primarily regional, support needs to be provided as a regional package for low-income provinces, especially in Maluku-Papua, Kalimantan, and East Nusa Tenggara. This package includes separate

information systems budgets, hardware in service units, and information technology personnel, with local government-owned hospitals as the initial target. Second, the expansion of connectivity in disadvantaged, frontier, and outermost regions needs to be linked to the needs of hospitals, including non-terrestrial alternatives for archipelagic and mountainous areas (Salsabila & Apriono, 2025). Third, because costs and technical support are major barriers (Boonstra & Broekhuis, 2010; Kruse et al., 2016), joint assistance between hospitals within a single province can reduce implementation costs for small hospitals.

Limitations

This study has several limitations. First, the *cross-sectional ecological* design does not allow for causal conclusions or conclusions at the hospital level. Second, RME surveys measure the scope of services, not the quality or intensity of use. Third, 38 provinces limit the power of the test, while the region, internet access, HDI, and ownership composition overlap. Fourth, some Papuan provinces only have 8-18 hospitals, so the proportion is sensitive to changes in one hospital. Fifth, RME data is not available by ownership, so ownership can only be tested through provincial composition. Sixth, the data source does not explain the grouping of hospitals that run RME in only one or two services. Seventh, the outcome and connectivity variables were measured in different years (2024 and 2025). Follow-up research with hospital-level data and several years of data is needed to test the proposed mechanism.

CONCLUSION

One year after the initial regulatory deadline, nearly all hospitals in Indonesia had implemented electronic medical records (EMRs), known locally as Rekam Medis Elektronik (RME), to some extent; however, only 62.83% had achieved comprehensive implementation across six service areas. Substantial interprovincial disparities were observed, with implementation rates ranging from 0% to 88.9%. Approximately two-thirds of the observed variation occurred between major geographic regions, with Maluku–Papua exhibiting the lowest implementation rates. These regional disparities were associated with less-developed digital infrastructure, lower levels of human development, and a higher proportion of government-owned hospitals. Although the proportion of privately owned hospitals was positively associated with comprehensive EMR implementation, this association was no longer statistically significant after adjustment for regional differences. Therefore, hospital ownership composition was more appropriately interpreted as a marker of broader regional disparities rather than an independent determinant of implementation.

These findings highlighted the need for coordinated interventions by central and regional governments to reduce inequalities in comprehensive EMR implementation. Targeted support should prioritize provinces with limited implementation capacity through integrated funding, technological infrastructure, and information technology workforce development, with regional government-owned hospitals serving as initial intervention priorities. Furthermore, monitoring frameworks should extend beyond SATUSEHAT connectivity to include the proportion of hospitals implementing EMRs across all six service areas and the completeness of data transmitted through the platform. Publishing these indicators at the provincial level would strengthen transparency, facilitate the identification of implementation gaps, and support more equitable, evidence-informed digital health policies across Indonesia.

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