Original Article

Geospatial patterns and a two-year comparison of outpatient hospital utilization in Indonesia: An ecological analysis of 38 provinces, 2021–2024

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Abstract

Provincial disparities in hospital outpatient utilization remain a concern in Indonesia. The aim of this study was to examine the geographic distribution and provincial correlates of hospital outpatient utilization and compare utilization between 2023 and 2024. Official aggregate data were analyzed for all 38 provinces in 2024 and 34 provinces with comparable 2023–2024 data. Total utilization was defined as the sum of public- and private-hospital outpatient utilization percentages, rather than the unduplicated proportion of residents receiving care. Analyses included paired comparisons, multivariable and Bayesian regression, and global and local spatial autocorrelation statistics. In 2024, median total utilization was 19.01% (interquartile range (IQR): 15.36–23.37; range: 7.85–31.19). Among comparable provinces, utilization was higher in 24 provinces and lower in 10 provinces in 2024 than in 2023. The mean difference was 0.91 percentage points (95% confidence interval (CI): −0.22 to 2.04; paired *t*-test $p=0.110$), whereas the median difference was 1.25 percentage points (Wilcoxon $p=0.026$). Previous-year utilization showed the strongest bivariate correlation with 2024 utilization ($r=0.872$). In the primary multivariable model, prior hospital facility preference was positively associated with utilization ($b=1.28$; 95%CI: 0.70–1.86), while total insurance coverage was not significantly associated. Bayesian estimates supported the relative ordering of adjusted associations. Total utilization showed no significant global spatial autocorrelation (Moran's $I=0.027$; $p=0.600$), whereas public-hospital share ($I=0.503$; $p<0.001$) and poverty ($I=0.629$; $p<0.001$) were spatially clustered. Local analyses identified high public-hospital dependence and poverty clusters in the Papua region and lower public-hospital dependence in Java. Substantial provincial disparities therefore persist, highlighting the need for context-specific investigation of healthcare access, service availability and public-sector dependence. Ecological associations should not be interpreted as individual-level or causal effects.

Keywords: Hospital outpatient utilization, geospatial analysis, National Health Insurance, ecological study, Indonesia

Introduction

Hospital utilization is a core indicator of health-system performance because it reflects the extent to which population needs, insurance entitlement, geographic access, and provider availability translate into actual healthcare use. In a universal health coverage setting, measuring

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utilization is not a simple count of service contacts [1,2]. It signals how financial protection, supply-side readiness, referral rules, and local socioeconomic conditions interact. A province may report broad insurance coverage and still have low hospital use if residents face long travel distances, limited specialist availability, administrative friction, weak referral pathways, or opportunity costs that make outpatient care difficult to obtain [3].

Indonesia is a particularly relevant setting for this question. The National Health Insurance (NHI) program, known locally as *Jaminan Kesehatan Nasional* (JKN), has expanded population financial protection, but the distribution of hospitals, health workers, specialist services, and transport infrastructure remains uneven across provinces [4]. Outpatient hospital care matters because it is often the first hospital-based contact point before advanced diagnostics, specialist consultation, elective procedures, or inpatient admission. Differences in outpatient use therefore give an early signal of provincial service readiness and of how patients move through the referral system [1,2].

Hospital utilization can be interpreted using a demand–supply framework consistent with Andersen-type models of health service use. Predisposing characteristics, enabling resources, and need factors influence individual care-seeking behavior, while provider availability and the organization of the local health system determine whether care can actually be reached [5,6]. In an ecological analysis, these factors are not observed at the individual level but are represented by provincial indicators such as poverty, education, insurance composition, workforce density, public–private service configuration, and previous health-facility preference. This province-level design can identify policy-relevant provincial patterns but cannot recover individual-level relationships, as province-level associations may differ in magnitude or direction from the corresponding individual-level associations [7].

Studies from Indonesia and other health systems suggest that insurance coverage can improve access without removing utilization disparities [8,9]. Hospital utilization among poorer and subsidized populations may remain constrained by geographic access, referral complexity, supply-side capacity, and the effective use of insurance benefits. Evidence from Indonesia also indicates that non-contribution-assistance (in Indonesian, *Non-Penerima Bantuan Iuran* or non-PBI) members may use secondary and tertiary services more often than contribution-assistance (in Indonesian, *Penerima Bantuan Iuran* or PBI) members, which points to the importance of insurance composition rather than coverage totals alone [6].

Geospatial analysis is needed because national averages can hide subnational heterogeneity. Provinces differ in population density, poverty, hospital distribution, public-sector dependence, island geography, and workforce availability, and these characteristics are spatially patterned [10]. Eastern Indonesian and Papua-related provinces tend to combine high poverty, complex geography, and greater public-sector dependence, whereas metropolitan provinces more often have higher workforce density, a stronger private sector, and greater facility choice. A geospatial framework can establish whether high or low values cluster geographically and whether utilization, poverty, and public-hospital dependence follow the same spatial logic [4,10].

Three gaps remain in this study. First, most Indonesian studies analyze individual-level survey data and report national determinants, providing limited insight into how utilization varies across provinces or whether these variations exhibit spatial patterns. Second, studies examining subnational variation typically focus on healthcare facility availability rather than actual outpatient utilization. Third, analyses of insurance effects commonly treat coverage as a single total, which obscures the PBI/non-PBI distinction that Indonesian claims data suggest is consequential [6,7]. A province-level analysis combining descriptive assessments of utilization patterns, global and local spatial statistics, adjusted ecological regression, and a policy-oriented typology can address these gaps while acknowledging the limitations of ecological inference.

This study examined outpatient hospital utilization across 38 Indonesian provinces using ecological aggregate data. The aims of this study were to: (1) describe the 2024 distribution of total, public and private hospital outpatient utilization and its national geospatial pattern; (2) compare provincial characteristics across tertiles of 2024 utilization; (3) quantify the difference in utilization between 2023 and 2024 among the 34 provinces with comparable values; (4) estimate bivariate, mutually adjusted and Bayesian ecological associations between provincial characteristics and 2024 utilization; (5) test global and local spatial autocorrelation of utilization,

public-hospital share and poverty using province-centroid weights; and (6) describe provincial readiness–utilization positions and an exploratory province typology to support policy prioritization.

Methods

Study design and setting

This ecological study used province-level aggregate data, with the province rather than the individual resident as the unit of analysis. All 38 Indonesian provinces were included in the 2024 cross-sectional analysis. Given the aggregated nature of the data, all associations should be interpreted at the ecological level and not extrapolated to individual-level risks or probabilities.

The study period covered 2021–2024 for descriptive national geospatial mapping and 2023–2024 for the two-year comparison. The 2023–2024 comparison was limited to provinces with comparable public- and private-hospital outpatient values in both years. Four newly established provinces in the Papua region (Papua Barat Daya, Papua Selatan, Papua Tengah and Papua Pegunungan) lacked comparable 2023 public- and private-hospital outpatient utilization data in the source file. These provinces were included in the 2024 cross-sectional and geospatial analyses but excluded from the paired comparison, resulting in 34 provinces for this analysis.

Missing data for the other indicators followed the same administrative pattern. Mean education completion from elementary to senior high school was unavailable for three of the four newly established Papua provinces (Papua Barat Daya, Papua Selatan and Papua Pegunungan), because the 2024 provincial education-completion series had not yet been published separately for these jurisdictions at the time of extraction. The corresponding models therefore used 35 provinces. This set of provinces with missing data differed from the 34-province set used for the 2023–2024 comparison. Papua Tengah had a published education-completion value but lacked comparable 2023 outpatient utilization data, whereas Papua Barat Daya, Papua Selatan and Papua Pegunungan had missing data for both variables. No imputed values were used in any hypothesis testing.

Data sources and data management

The analysis used secondary aggregate datasets containing provincial indicators for 2021–2024 [11-13]. These corresponded to official statistical and health survey outputs, including Statistics Indonesia (BPS) publications, provincial statistical publications, the Indonesian Health Profile and the Indonesian Health Survey (*Survei Kesehatan Indonesia*, SKI). The 2024 dataset contained public-hospital outpatient utilization, private-hospital outpatient utilization, total outpatient utilization at public and private hospitals, poverty, NHI coverage by contribution-assistance category, medical workforce counts, population, education completion, and hospital facility preference [13]. Additional socioeconomic indicators were the Gini ratio, open unemployment, and illiteracy by age group.

Data management consisted of harmonizing every province name with the official Indonesian nomenclature published by Statistics Indonesia (e.g., Sumatera Utara, Jawa Tengah, Kepulauan Riau, Maluku Utara and Papua Pegunungan), which was consistently applied throughout the text, tables, figures and supplementary material. Additional procedures included aligning indicators by year, checking for duplicate provincial records, standardizing numerical values as percentages or rates, and verifying the comparability of 2023 and 2024 outpatient utilization measures before the paired analysis. The newly established Papua provinces were explicitly coded to prevent inappropriate imputation. Missing 2023 values were excluded from all paired analyses and median-imputed only for exploratory clustering, which required a complete data matrix.

Outcome variables

The primary outcome was total outpatient hospital utilization in 2024. It was calculated as the arithmetic sum of two separately published percentages: the percentage of residents who reported outpatient care at a public hospital in the preceding month and the percentage who reported outpatient care at a private hospital in the preceding month. The source survey records

the place of treatment for each reported outpatient contact, so a resident who used both a public and a private hospital within the reference month contributes to both component percentages. The summed measure thus represents a province-level utilization indicator rather than an unduplicated proportion of residents receiving care. This definition was applied consistently throughout the abstract, methods, results, and tables. Given the one-month reference period and the relatively small component percentages, the extent of overlap is expected to be limited. However, this overlap cannot be quantified using aggregate data and is therefore acknowledged as a limitation.

Secondary outcomes were public-hospital outpatient utilization, private-hospital outpatient utilization, public-hospital share of total hospital outpatient utilization, total hospital outpatient utilization in 2023, the absolute percentage-point difference between 2023 and 2024, and the relative difference between 2023 and 2024. Public-hospital share was calculated as public-hospital outpatient utilization divided by total hospital outpatient utilization, multiplied by 100, and was used to identify provinces with greater dependence on the public sector for outpatient hospital care. The absolute difference was calculated as 2024 total utilization minus 2023 total utilization, whereas the relative difference was calculated as the absolute difference divided by 2023 utilization, multiplied by 100. Both quantities are two-year differences and are reported as such rather than as trends or rates of change.

Explanatory variables

Explanatory variables were total NHI coverage, PBI coverage, non-PBI coverage, medical workforce density per 100,000 population, poverty, the Gini ratio, open unemployment, illiteracy among persons aged 15 years and older, mean education completion from elementary to senior high school, population size, and hospital facility preference from SKI 2023. Provinces were grouped into broad geographic regions: Sumatera, Jawa–Bali, Nusa Tenggara, Kalimantan, Sulawesi, Maluku and Papua.

Medical workforce density served as a proxy for supply-side readiness. Hospital facility preference served as a behavioral and historical proxy for care-seeking, as it reflects the extent to which residents had previously selected hospitals as their preferred source of care. Poverty and public-hospital share were treated as indicators of contextual vulnerability and public-sector dependence, respectively.

Construction and validation of the readiness index

The readiness index used in the readiness–utilization visualization was constructed from four province-level components, selected because each represents a distinct dimension of the capacity of a province to convert entitlement into hospital outpatient care: medical workforce density per 100,000 population (workforce supply), total NHI coverage (financial protection), hospital facility preference from SKI 2023 (established hospital-based care-seeking), and the complement of the September 2024 poverty headcount, calculated as 100 minus the poverty percentage (absence of material constraint). Indicators of hospital bed supply and specialist availability were considered but not included because they were available only in the exploratory dataset and used variable definitions that were not consistent with the main analytic file.

Each component was rescaled to the 0–1 interval by min–max normalization across the 38 provinces, so that the province with the lowest observed value scored 0 and the province with the highest observed value scored 1. The four rescaled components were then averaged with equal weights and multiplied by 100, giving an index bounded by 0 and 100. Equal weighting was used because no external evidence base exists for assigning differential weights to these four dimensions in the Indonesian setting, and because equal weighting is transparent and reproducible. No component was reverse-coded other than poverty, and no imputation was required because all four components were complete for all 38 provinces. Observed index values ranged from 14.3 (Papua Pegunungan) to 96.4 (DKI Jakarta).

Three checks were performed. Internal consistency across the four rescaled components was acceptable (Cronbach's α=0.742), with corrected item–total correlations of 0.708 for workforce density, 0.551 for NHI coverage, 0.489 for hospital facility preference, and 0.442 for the poverty complement. A principal component analysis of the standardized components showed that the first component explained 58.0% of the total variance, with loadings of similar magnitude and

sign across all four items (0.44 to 0.57 in absolute value). The equal-weight index correlated 0.996 with the first component score, indicating that data-driven weighting would have produced a nearly identical provincial ranking. Leave-one-component-out reconstruction changed provincial rankings only slightly (Spearman's ρ=0.934–0.961 against the full index). The index was used only as a descriptive summary axis in **Figure 5** and was not included in any hypothesis test.

Statistical analysis

Descriptive statistics were reported as medians and interquartile ranges (IQRs) because the number of provinces was small and several indicators were skewed. Provinces were classified into low, moderate, and high utilization tertiles based on 2024 total hospital outpatient utilization (cut-off values: 17.54% and 22.35%), comprising 13, 12, and 13 provinces, respectively. Differences across tertiles were assessed with the Kruskal–Wallis test using tie correction. Because a *p*-value alone does not convey the magnitude of differences in a sample of this size, each Kruskal–Wallis test was accompanied by the epsilon-squared effect size, $\varepsilon^2=(H-k+1)/(N-k)$, where H is the test statistic, k is the number of groups, and N is the total number of observations. A two-sided $p<0.05$ was considered statistically significant.

The 2023–2024 comparison is a two-year paired comparison and is described as such throughout the manuscript. With only two comparable time points, it cannot identify a trend, a growth rate, a joinpoint, or a seasonal pattern, and no such quantities were estimated. The comparison reports the mean and median differences, the 95% confidence interval (CI) for the mean difference based on the paired *t*-distribution, a paired *t*-test, the Wilcoxon signed-rank test, the Hodges–Lehmann pseudomedian, a percentile bootstrap 95%CI for the median difference based on 10,000 resamples, Cohen's *dz* for the standardized mean difference, and the matched-pairs rank-biserial correlation as a non-parametric effect size.

Bivariate ecological associations were estimated using simple linear regression, with 2024 total hospital outpatient utilization as the dependent variable and each predictor entered separately. Each model reports the unstandardized coefficient (*b*), its standard error, the 95%CI, the Pearson and Spearman correlation coefficients, the coefficient of determination (R^2) and the *p*-value. Bivariate estimates are presented first for transparency, but they are not the primary inferential results because unadjusted ecological coefficients may reflect the influence of correlated provincial characteristics [14,15].

Three multivariable models were then fitted. Model 1 regressed 2024 total utilization on the four conceptually distinct predictors available for all 38 provinces: hospital facility preference (behavioral), non-PBI coverage (financial), medical workforce density (supply), and poverty (socioeconomic). Predictors were limited to four to keep at least eight provinces per estimated coefficient in a sample of 38 [15]. Model 2 decomposed insurance coverage by entering PBI and non-PBI coverage separately; total NHI coverage was not entered alongside its own components, because the three quantities are linearly dependent by construction. Model 3 added 2023 utilization to Model 1 for the 34 provinces with comparable values, so that the remaining coefficients describe cross-sectional differences conditional on the previous year. Coefficients are reported unstandardized, with standardized coefficients given for comparability of magnitude.

Model diagnostics comprised the variance inflation factor (VIF) for each predictor, the Breusch–Pagan test for heteroskedasticity, the Shapiro–Wilk test for residual normality, Cook's distance using a 4/n threshold to identify potentially influential provinces, and global Moran's I applied to model residuals using the same four-nearest-neighbor spatial weights as in the main spatial analysis to assess whether unmodelled spatial structure remained. When the Breusch–Pagan test indicated heteroskedasticity, HC3 heteroskedasticity-consistent standard errors and CIs were reported alongside the classical estimates [16]. Internal validation included non-parametric percentile bootstrap resampling with 5,000 resamples to assess regression coefficients and apparent–bootstrap optimism in R^2, repeated five-fold cross-validation (200 repetitions), and leave-one-province-out cross-validation, with the corresponding root mean squared error (RMSE) reported [17]. Models were also refitted after excluding influential provinces as a sensitivity analysis.

Because the analysis included only 38 provinces, Model 1 was re-estimated using a Bayesian framework as a complementary approach to frequentist inference. Predictors were standardized

to have a mean of 0 and a standard deviation of 1. Weakly informative independent normal priors, $N(0, 10^2)$, were assigned to the regression coefficients, and a diffuse inverse-gamma (0.001, 0.001) prior was assigned to the residual variance. Posterior distributions were obtained using Gibbs sampling with four independent chains of 20,000 iterations each, with the first 5,000 iterations of each chain discarded as burn-in, yielding 60,000 retained draws. Convergence was assessed using the Gelman–Rubin statistic ($\hat{R}$) and the effective sample size [18]. Results were summarized as posterior means, posterior standard deviations, 95% equal-tailed credible intervals (CrI), and the posterior probability that each coefficient is greater than zero.

Geospatial visualization, spatial weights and spatial autocorrelation

The geospatial analysis used two complementary strategies. First, thematic maps based on an Indonesia map base showed annual quartile-class distributions of hospital outpatient utilization from 2021 to 2024. The color scale was defined separately for each year, with blue indicating lower utilization and orange-to-red indicating higher utilization. These maps provide a policy-oriented national overview rather than a formal spatial model.

Second, province-centroid plots supported the inferential spatial analysis because official provincial boundary shapefiles were not included in the analytical dataset. Approximate longitude and latitude coordinates were assigned to each provincial centroid and are reported in **Supplementary Table S1** to enable reproduction of the spatial statistics presented in this article. Centroid coordinates were used rather than boundary polygons for two reasons: the boundary files distributed with the source statistical publications did not include the four provinces created from Papua in 2022, and polygon-based contiguity is poorly defined in an archipelagic setting where many provinces share no land border. A k-nearest-neighbor structure avoids the disconnected observations that contiguity-based weights would produce in this setting. Setting k=4 gives each province the same number of neighbors, preventing differences in the number of neighbors assigned to provinces in outer islands and Java (Jawa) solely because of their geographic locations.

Global Moran's I was calculated for selected indicators using the four-nearest-neighbor weights matrix [16,19]. Row-standardized weights and 9,999 random permutations of the observed values were used to assess whether similar provincial values occurred near one another more often than expected under spatial randomness. Both two-sided and upper-tail permutation *p*-values were reported, together with the expected value of Moran's I under the null hypothesis and the permutation *z*-score.

Local spatial structure was then examined, extending the previous version of this analysis. Local Moran's I (LISA) was computed for total utilization, public-hospital share, and poverty using the same four-nearest-neighbor weights, with 9,999 conditional permutations for each province. Each province was classified into a high–high, low–low, high–low, or low–high quadrant based on its standardized value and spatial lag [20]. Getis–Ord Gi* was computed for the same three indicators using self-inclusive, binary four-nearest-neighbor weights, and the resulting *z*-scores were used to identify hotspots and cold spots [21,22]. Because local statistics were calculated for each province, the corresponding local *p*-values were additionally adjusted for multiple comparisons using the Benjamini–Hochberg false discovery rate (FDR) procedure. Both unadjusted and FDR-adjusted *p*-values are reported [23].

The dependence of the global results on the weights specification was assessed by recalculating Global Moran's I under six alternative schemes: k-nearest-neighbor weights with k=3, 4, 5 and 6; inverse great-circle distance weights; and a 1,000-km distance band, with row standardization applied to the weights. Where a distance band left a province without neighbors, its single nearest neighbor was retained to prevent spatial isolation.

Readiness–utilization visualization

A readiness–utilization plot summarized whether provinces with higher readiness tended to report higher hospital outpatient utilization, using the index defined above. Open circles represent 2023 utilization, filled circles represent 2024 utilization, and vertical arrows indicate the direction and magnitude of the two-year difference. A quadratic frontier with a bootstrap 95% confidence band was added as an exploratory visual guide rather than as a fitted model.

The plot was used to identify provinces that deviated from the expected correspondence between higher readiness and higher utilization. Provinces with low readiness but high or increasing utilization, and those with high readiness but stable or declining utilization, were identified as candidates for further investigation. The plot does not identify the reason for a given position, and the explanations offered in the Discussion are hypotheses to be tested with other data rather than findings of this analysis.

Exploratory clustering analysis

Exploratory k-means clustering was performed using standardized indicators: 2024 total hospital outpatient utilization, the 2023–2024 difference, public-hospital share, total NHI coverage, medical workforce density, poverty, and hospital facility preference. Standardization prevented variables measured on larger numeric scales from dominating the clustering solution. Clustering was performed using the Hartigan–Wong algorithm with 500 random starts [24].

The number of clusters was examined quantitatively rather than selected by visual inspection alone. Solutions for k=2 to k=7 were compared using the average silhouette width [16], the Calinski–Harabasz index [25] and the Davies–Bouldin index [26]. Cluster-specific silhouette widths were inspected for the retained solution, and cluster stability was assessed using nonparametric bootstrap resampling with 1,000 resamples. For each original cluster, the maximum Jaccard similarity with any cluster in the resampled solution was recorded [27]. Jaccard values above 0.75 were interpreted as indicating stable clusters, values between 0.60 and 0.75 as indicating a pattern, and values below 0.60 as providing little support for a cluster as a distinct entity.

Cluster analysis was not used to infer causal relationships but to develop policy-oriented provincial typologies. Cluster labels were assigned after reviewing median profiles and provincial membership; therefore, the labels describe dominant patterns rather than statistical classes with fixed meanings.

Software and reproducibility

Data cleaning, descriptive statistics, non-parametric tests, regression, spatial statistics, clustering, and figure preparation were performed in R version 4.6.1 [28] through RStudio Desktop 2026.01.0+392, using the tidyverse, sf [14], ggplot2 [15], spdep [29], classInt, patchwork, scales, and cluster packages. Thematic maps and scatterplots were exported as high-resolution PNG files at 300 dpi. In all figures, panels were labeled (A), (B), (C), and so on, with the same letters repeated in the corresponding figure titles. All in-figure text, including panel titles, axis titles, axis labels, legends, and province names, is set in Georgia, with a font size of at least 75% of the 10-point figure-title size. Global and local Moran's I statistics and the spatial weight structure were cross-checked in GeoDa version 1.22 using the same four-nearest-neighbor province-centroid weights [19].

All results reported in this article were generated using a single R-based analytical pipeline. No outputs from other statistical packages were presented, and no figures were reproduced from other software. The cleaned province-level dataset, the province-centroid coordinate file (**Supplementary Table S1**), the spatial-weights specification, all supplementary tables and figures, and the complete analysis scripts have been deposited in the permanent open-access repository Zenodo (CERN, Geneva, Switzerland) under a Creative Commons Attribution 4.0 International (CC BY 4.0) license. These materials are available without restriction at https://doi.org/10.5281/zenodo.21845594 [30].

Results

Provincial distribution and national geospatial overview

Hospital outpatient utilization varied widely across Indonesian provinces in 2024. Median total hospital outpatient utilization was 19.01% (IQR: 15.36–23.37), ranging from 7.85% to 31.19%. Hospital-based outpatient care was therefore unevenly distributed, with a gap between the lowest- and highest-utilization provinces that may be relevant for policy.

The thematic maps (**Figure 1**) show that interprovincial heterogeneity persisted throughout 2021–2024 rather than being limited to 2024. Because each annual map used quartile classes defined within that year, the maps should be interpreted as showing relative provincial positions for the corresponding year. They identify provinces that appeared repeatedly in higher or lower utilization categories and illustrate how national averages can conceal geographic disparities in service use. The four maps represent annual cross-sections presented side by side, rather than a fitted trend surface.

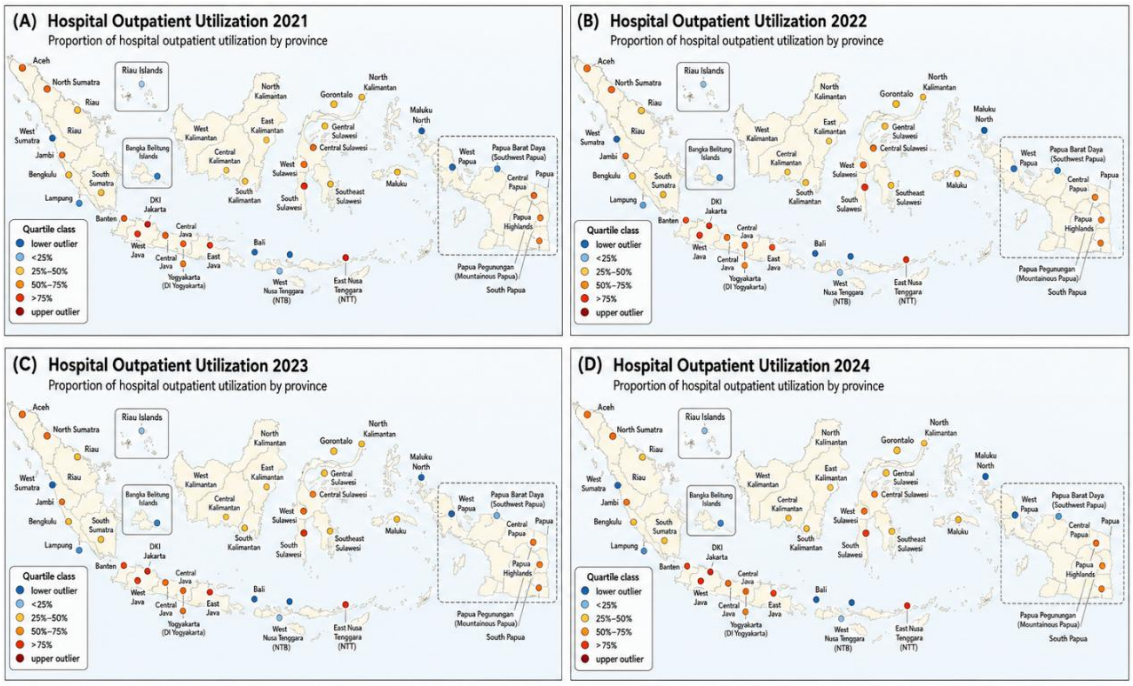


Figure 1. Thematic maps of hospital outpatient utilization across 38 provinces in Indonesia, 2021–2024. (A) 2021; (B) 2022; (C) 2023; (D) 2024. Each panel shows the quartile-class distribution for that year, with blue indicating lower and orange-to-red indicating higher values within the same year, and each panel represents an independent annual cross-section.

Provincial characteristics by utilization tertile

Provincial characteristics were compared across the low, moderate, and high tertiles of 2024 total hospital outpatient utilization (**Table 1**). Utilization tertiles differed on public-hospital outpatient utilization ($p<0.001$, $\varepsilon^2=0.382$), private-hospital utilization ($p=0.030$, $\varepsilon^2=0.144$), non-PBI coverage ($p=0.010$, $\varepsilon^2=0.206$), poverty ($p=0.011$, $\varepsilon^2=0.201$), hospital facility preference ($p<0.001$, $\varepsilon^2=0.341$), and population size ($p=0.034$, $\varepsilon^2=0.137$). Poverty levels differed across tertiles but not monotonically: low-utilization provinces had a higher median poverty level than moderate-utilization provinces, whereas the high-utilization group included both relatively affluent and high-poverty provinces.

Neither the absolute nor the relative 2023–2024 difference between 2023 and 2024 differed significantly across utilization tertiles (absolute difference: $p=0.521$, $\varepsilon^2=-0.022$; relative difference: $p=0.843$, $\varepsilon^2=-0.054$). The median absolute differences across the low-, moderate-, and high-utilization tertiles (0.40, 1.45, and 2.66 percentage points, respectively) should therefore not be interpreted as an ordered gradient. This apparent ordering may reflect sampling variation. The negative epsilon-squared estimates indicate negligible observed between-group effects under this estimator, and the IQRs overlap across all three tertiles. Total NHI coverage, PBI coverage, medical workforce density, the Gini ratio, open unemployment, illiteracy, mean education completion, and public-hospital share also did not differ significantly across tertiles.

Table 1. Provincial characteristics by tertile of 2024 total hospital outpatient utilization

Characteristic	Overall	Tertile of 2024 total hospital outpatient utilization			*p*-value	ε^2
		Low (n=13)	Moderate (n=12)	High (n=13)		
Total hospital outpatient utilization 2024 (%)	19.01 (15.36–23.37)	13.71 (10.99–15.17)	19.01 (18.41–20.56)	25.81 (23.48–26.92)	<0.001	0.883
Public-hospital outpatient utilization 2024 (%)	11.97 (9.11–17.16)	9.06 (7.97–10.71)	11.20 (8.92–16.44)	17.24 (13.41–21.18)	<0.001	0.382
Private-hospital outpatient utilization 2024 (%)	5.48 (3.17–9.43)	4.05 (1.81–5.02)	8.86 (4.02–10.21)	6.21 (4.42–13.86)	0.030	0.144
Total hospital outpatient utilization 2023 (%)	17.85 (16.29–20.51)	12.08 (10.59–15.66)	17.93 (16.90–19.04)	22.42 (19.02–30.54)	<0.001	0.597
Absolute difference 2023–2024 (percentage points)	1.25 (−0.39–2.60)	0.40 (−0.74–2.19)	1.45 (0.49–2.13)	2.66 (−0.95–3.81)	0.521	−0.022
Relative difference 2023–2024 (%)	7.87 (−1.29–16.91)	2.71 (−4.87–19.62)	8.13 (2.81–12.89)	11.48 (−2.95–19.55)	0.843	−0.054
Public-hospital share of hospital outpatient use 2024 (%)	69.65 (50.16–83.08)	69.82 (67.52–83.14)	54.47 (48.32–80.41)	73.01 (49.17–83.09)	0.598	−0.028
NHI coverage 2024 (%)	70.72 (64.37–82.28)	70.34 (63.56–75.59)	68.97 (64.23–74.00)	80.05 (67.11–82.51)	0.327	0.007
NHI PBI coverage 2024 (%)	47.66 (39.26–55.15)	47.87 (46.79–57.15)	41.72 (37.33–48.13)	48.06 (41.53–57.54)	0.335	0.005
NHI non-PBI coverage 2024 (%)	23.82 (18.31–28.35)	18.29 (16.21–20.53)	26.27 (21.14–29.45)	26.05 (20.23–31.99)	0.010	0.206
Medical workforce density 2024 (per 100,000 population)	55.11 (40.67–74.46)	52.53 (36.56–55.85)	56.82 (52.33–77.02)	73.20 (43.35–93.40)	0.220	0.029
Poverty September 2024 (%)	9.57 (5.78–12.61)	11.91 (10.62–15.78)	6.47 (5.59–7.78)	7.77 (5.38–18.09)	0.011	0.201
Gini ratio September 2024	0.345 (0.306–0.364)	0.330 (0.309–0.346)	0.331 (0.302–0.360)	0.360 (0.310–0.405)	0.243	0.024
Open unemployment August 2024 (%)	4.19 (3.22–5.71)	3.13 (2.94–4.48)	4.82 (4.15–5.78)	4.13 (3.70–5.14)	0.112	0.068
Illiteracy aged 15+ (%)	1.89 (1.23–4.72)	2.09 (1.45–4.85)	1.62 (1.19–4.40)	2.11 (1.04–4.35)	0.758	−0.041
Mean education completion, primary to senior secondary (%) (n=35)	84.84 (81.90–86.04)	83.45 (79.54–84.74)	85.56 (83.99–86.84)	85.03 (81.11–89.29)	0.140	0.060
Hospital facility preference, SKI 2023 (%)	5.35 (4.15–7.83)	4.40 (3.50–5.10)	6.35 (4.00–7.75)	7.90 (5.60–9.50)	<0.001	0.341
Population 2024 (million)	3.74 (1.51–6.51)	3.12 (1.50–5.66)	5.63 (3.91–21.16)	2.18 (1.06–4.05)	0.034	0.137

Values are median (interquartile range). Tertiles of 2024 total outpatient hospital utilization: low (n=13), moderate (n=12), high (n=13); cut-off values: 17.54% and 22.35%. *p*-values are from the tie-corrected Kruskal–Wallis test. ε^2: epsilon-squared effect size; negative values arise when the observed H statistic is smaller than its degrees of freedom and indicate no detectable between-group separation. Rows for the 2023–2024 differences are based on 34 provinces and mean education completion on 35 provinces; all other rows use 38 provinces.

Two-year comparison of utilization, 2023–2024

Among the 34 provinces with comparable data, mean total hospital outpatient utilization was 18.63% in 2023 and 19.53% in 2024 (**Figure 2**). The mean difference was +0.91 percentage points (95%CI: −0.22 to +2.04), which was not statistically significant in the paired *t*-test ($t(33)=1.64$, $p=0.110$) and corresponded to a small standardized effect (Cohen's $dz=0.28$). The median difference was +1.25 percentage points, the Hodges–Lehmann pseudomedian was +1.09 percentage points, and the percentile bootstrap 95%CI for the median difference was +0.20 to +2.24. The Wilcoxon signed-rank test was statistically significant (V=168, $p=0.026$; matched-pairs rank-biserial $r=0.435$). The two tests yielded different conclusions, potentially reflecting the asymmetric distribution of provincial differences: most provinces recorded small increases, whereas a few recorded large decreases. Thus, the rank-based test detected a consistent direction of change, whereas the mean-based test did not; the parametric CI for the mean difference also included zero. Utilization was higher in 24 provinces and lower in 10.

The largest increases were observed in Papua (6.85 percentage points), Sulawesi Selatan (6.44), Sulawesi Barat (5.34), Papua Barat (4.04), and Riau (3.57). The largest decreases were observed in Kepulauan Riau (−10.50 percentage points), Kalimantan Selatan (−3.42), Jambi (−3.34), Sulawesi Tengah (−2.49), and Kalimantan Timur (−2.43). The overall mean difference was small and was not statistically significant in the paired *t*-test, whereas provincial differences varied widely. This comparison of two annual cross-sections does not establish a structural or longitudinal trend.

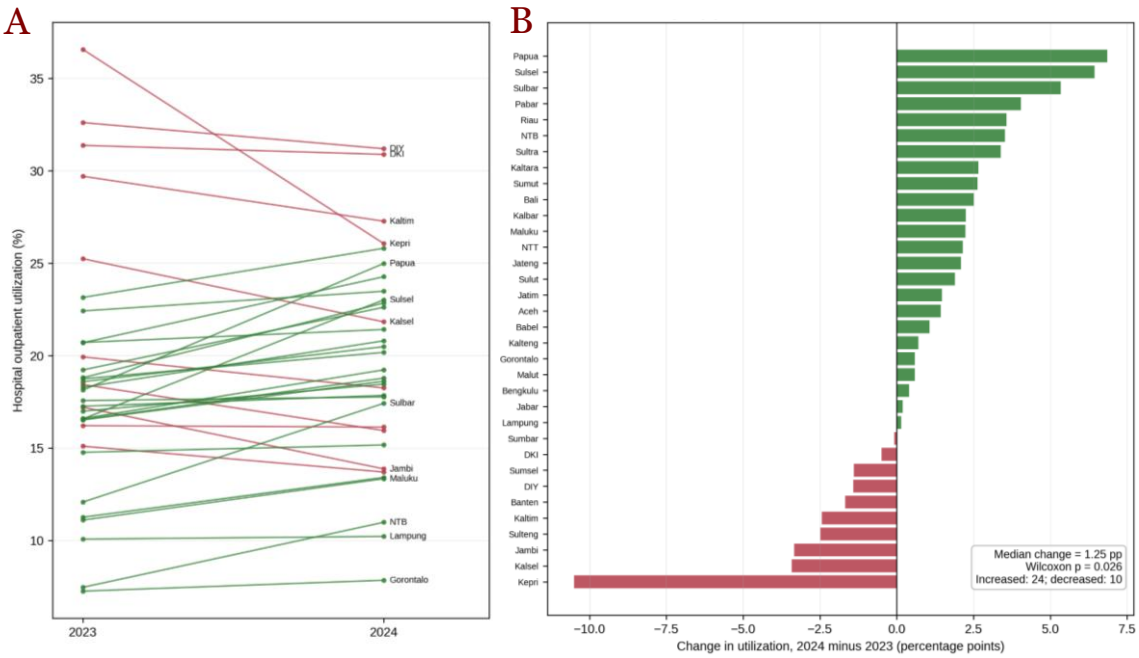


Figure 2. Comparison of hospital outpatient utilization across Indonesian provinces between 2023 and 2024. (A) paired 2023 and 2024 values for the 34 comparable provinces; (B) provinces ranked by the absolute percentage-point difference. Four newly established provinces in the Papua region (Papua Barat Daya, Papua Selatan, Papua Tengah and Papua Pegunungan) had no comparable 2023 values.

Geospatial distribution and global spatial autocorrelation

Province-centroid maps give an inferential spatial view of utilization and contextual indicators. Total hospital outpatient utilization in 2024 did not exhibit a strong national hotspot–coldspot pattern, whereas public-hospital share and poverty showed clearer geographic clustering (**Figure 3**). This contrast is important: utilization reflects the combined effects of demand, supply, referral pathways, and care preferences, whereas poverty and public-sector dependence may be more structurally distributed across geographic areas.

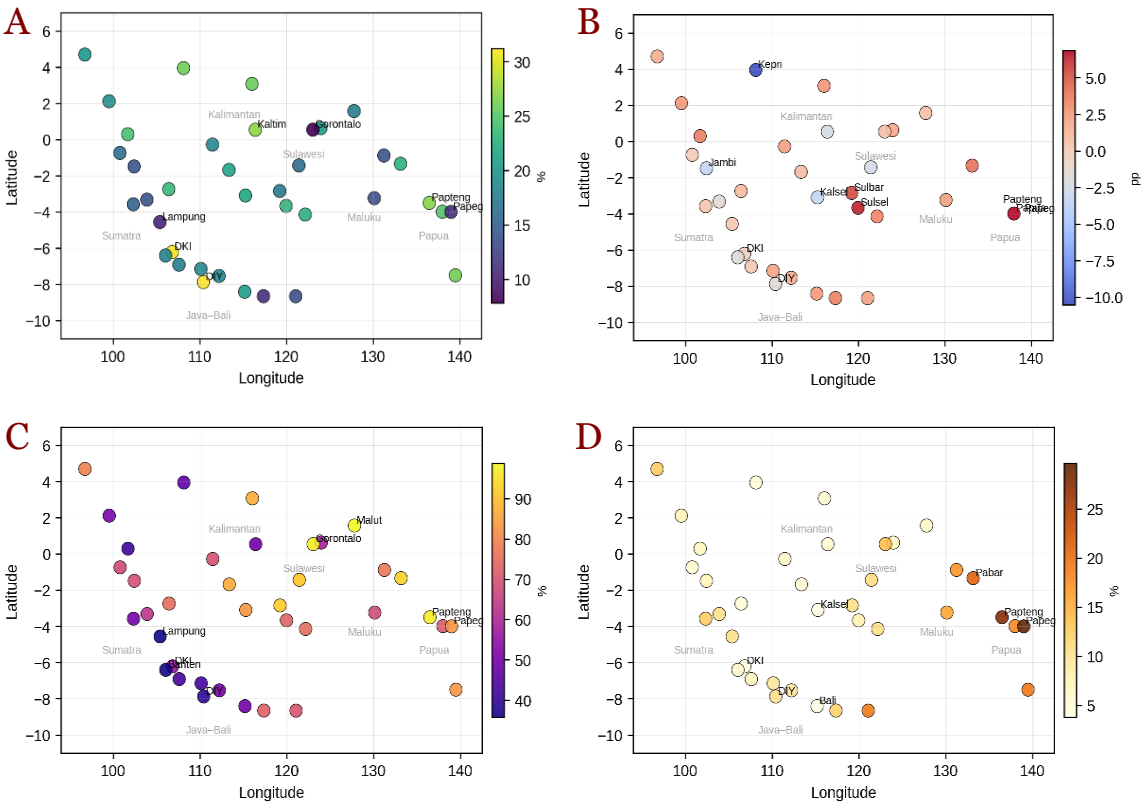


Figure 3. Province-centroid geospatial distribution of hospital outpatient utilization and contextual indicators in Indonesia. (A) total hospital outpatient utilization 2024 (%); (B) absolute difference between 2023 and 2024 (percentage points (pp)); (C) public-hospital share of hospital outpatient utilization (%); (D) poverty in September 2024 (%). Points are approximate provincial centroids (coordinates in Supplementary Table S1), not official boundary-polygon centroids. Change is unavailable for four newly established Papua provinces in 2023 and is displayed as missing.

Total utilization showed weak and non-significant global spatial autocorrelation (Moran's I=0.027, p=0.600), indicating no statistically significant global clustering of hospital outpatient utilization (**Table 2**). Public-hospital share (I=0.503, p<0.001) and poverty (I=0.629, p<0.001) showed strong positive spatial autocorrelation. Total NHI coverage showed a borderline result, reaching conventional statistical significance only in the upper-tail test (I=0.154; two-sided p=0.060; upper-tail p=0.041) and should therefore be interpreted cautiously. Medical workforce density and the 2023–2024 difference showed no statistically significant spatial clustering.

Table 2. Global Moran's I for selected indicators using four-nearest-neighbor province-centroid weights

Indicator	n	Moran's I	E[I]	*z*-score	Two-sided *p*	Greater-tail *p*
Total hospital outpatient utilization 2024	38	0.027	−0.027	0.53	0.600	0.278
Absolute difference 2023–2024	34	0.087	−0.030	1.15	0.246	0.132
Public-hospital share 2024	38	0.503	−0.027	5.17	<0.001	<0.001
NHI coverage 2024	38	0.154	−0.027	1.85	0.060	0.041
Medical workforce density 2024	38	−0.041	−0.027	−0.14	0.892	0.515
Poverty September 2024	38	0.629	−0.027	6.75	<0.001	<0.001

Row-standardized four-nearest-neighbor weights based on province centroids (Supplementary Table S1). Permutation p-values from 9,999 random permutations of the observed values. E[I] is the expected value of Moran's I under spatial randomness, −1/(n−1). Greater-tail p-values test positive spatial autocorrelation only. Sensitivity of these estimates to the weights specification is reported in Supplementary Table S2.

The global results were not sensitive to the choice of spatial weights for the two clearly clustered indicators (**Supplementary Table S2**). Across k-nearest-neighbor weights with k=3 to 6, inverse great-circle distance weights, and a 1,000 km distance band, Moran's I remained

statistically significant ($p \leq 0.001$) for public-hospital share (I=0.237–0.526) and poverty (I=0.294–0.684). Total utilization remained non-significant across all weighting schemes, with I ranging from −0.054 to 0.033 and *p*-values ranging from 0.436 to 0.982, indicating that the lack of significant global spatial autocorrelation in utilization was not specific to the k=4 specification. Two findings were sensitive to the weights specification: NHI coverage reached statistical significance under k=6, inverse-distance and distance-band weights but not under k=3, 4 or 5, whereas the 2023–2024 difference reached significance only under the 1,000 km distance band (p=0.040). Neither finding was considered robust.

Local spatial clusters and hotspot analysis

Global statistics establish whether spatial clustering exists at the national level but did not identify its location. Therefore, local statistics were computed for the three indicators of substantive interest (**Table 3**). For poverty, local Moran's I identified a high–high cluster across the Papua region: Papua Pegunungan (Ii=5.23), Papua Tengah (4.88), Papua Selatan (2.96), and Papua (2.59) remained significant after FDR adjustment ($q \leq 0.002$), whereas Papua Barat and Papua Barat Daya were significant only before adjustment. Getis–Ord Gi* showed consistent results, with z=4.71 (q<0.001) for the four inland and southern Papua provinces and z=2.57 (q=0.064) for Papua Barat and Papua Barat Daya. A low–low poverty cluster in Kalimantan Barat was identified by both statistics but did not remain significant after FDR adjustment.

For public-hospital share, the two statistics revealed a clear spatial dichotomy. Provinces in the Papua region formed a high–high cluster (Papua Barat Daya, Papua Barat, Papua, Papua Selatan, and Papua Pegunungan), whereas provinces in Java formed a low–low cluster in which DKI Jakarta remained significant after FDR adjustment (Ii=0.95, q=0.011), while Jawa Barat, Jawa Tengah, and DI Yogyakarta were significant only before adjustment. Gi* showed a similar pattern, with hotspots in the six Papua provinces, Sulawesi Tengah, and Sulawesi Utara, and coldspots in DKI Jakarta (z=−3.16, q=0.038), Jawa Barat (z=−3.09, q=0.038), Jawa Tengah and DI Yogyakarta (z=−2.74, q=0.058), Banten, Bali, and Jawa Timur. These findings suggest that public-sector dependence in hospital outpatient care was concentrated in eastern Indonesia and relatively lower in Java.

For total utilization, no local cluster remained significant after FDR adjustment. Three provinces showed unadjusted significance (low–low clusters in Bengkulu and Maluku Utara and a low–high outlier in Papua Pegunungan), and Gi* identified Bengkulu and Maluku Utara as unadjusted coldspots. However, all FDR-adjusted q-values exceeded 0.45. These local findings were consistent with the global results, indicating no statistically significant spatial clustering of hospital outpatient utilization after multiple-testing adjustment, despite the significant spatial clustering observed for poverty and public-hospital share.

Ecological associations with 2024 total utilization

Bivariate ecological regression identified several positive correlates of 2024 total hospital outpatient utilization (**Table 4**). The strongest correlate was previous-year hospital outpatient utilization (b=0.735; 95%CI: 0.586 to 0.883; Pearson r=0.872; R^2=0.761; p<0.001), which accounted for approximately three-quarters of the variance in 2024 utilization across the 34 comparable provinces. Hospital facility preference, measured in the 2023 Indonesian Health Survey (SKI), was the second strongest correlate (b=1.375; 95%CI: 0.911 to 1.839; r=0.708; R^2=0.501; p<0.001). These associations are illustrated in **Figure 4**.

Non-PBI coverage was positively associated with utilization (b=0.293; 95%CI: 0.114 to 0.471; r=0.484; R^2=0.235; p=0.002), as was medical workforce density (b=0.067 per additional medical worker per 100,000 population; 95%CI: 0.023 to 0.111; r=0.456; R^2=0.208; p=0.004). Total NHI coverage was not significantly associated with utilization (b=0.094; 95%CI: −0.050 to 0.237; p=0.193), suggesting that overall insurance coverage alone did not account for provincial differences in utilization. PBI coverage, poverty, the Gini ratio, unemployment, illiteracy, education completion, and population size were also not significantly associated with utilization.

Table 3. Local indicators of spatial association and Getis–Ord Gi* hotspot analysis (four-nearest-neighbor weights)

Indicator and province	Local I	Quadrant	LISA *p*	LISA q	Gi* *z*	Gi* *p*	Gi* q
Poverty, September 2024							
Papua Pegunungan	5.23	High–high	<0.001	0.001	4.71	<0.001	<0.001
Papua Tengah	4.88	High–high	<0.001	0.001	4.71	<0.001	<0.001
Papua Selatan	2.96	High–high	<0.001	0.001	4.71	<0.001	<0.001
Papua	2.59	High–high	<0.001	0.002	4.71	<0.001	<0.001
Papua Barat	1.57	High–high	0.032	0.202	2.57	0.010	0.064
Papua Barat Daya	1.11	High–high	0.019	0.147	2.57	0.010	0.064
Kalimantan Barat	0.64	Low–low	0.048	0.263	−2.05	0.040	0.202
Public-hospital share, 2024							
DKI Jakarta	0.95	Low–low	<0.001	0.011	−3.16	0.002	0.038
Jawa Barat	1.72	Low–low	0.003	0.057	−3.09	0.002	0.038
Jawa Tengah	1.50	Low–low	0.013	0.087	−2.74	0.006	0.058
DI Yogyakarta	1.65	Low–low	0.020	0.109	−2.74	0.006	0.058
Papua Barat Daya	0.60	High–high	0.013	0.087	2.42	0.016	0.076
Papua	0.24	High–high	0.014	0.087	2.26	0.024	0.076
Papua Barat	1.26	High–high	0.042	0.133	2.42	0.016	0.076
Papua Pegunungan	0.81	High–high	0.037	0.127	2.26	0.024	0.076
Papua Selatan	0.81	High–high	0.037	0.127	2.26	0.024	0.076
Sulawesi Utara	−0.60	Low–high	0.007	0.087	2.06	0.039	0.099
Total utilization, 2024							
Bengkulu	0.82	Low–low	0.026	0.472	−2.38	0.017	0.598
Maluku Utara	0.29	Low–low	0.038	0.472	−2.02	0.043	0.598
Papua Pegunungan	−1.56	Low–high	0.029	0.472	−0.13	0.899	0.899

LISA: local indicator of spatial association; q: Benjamini–Hochberg false discovery rate–adjusted *p*-value computed across all 38 provinces within each indicator.
Provinces reaching $p<0.05$ on local Moran's I are listed. LISA *p*-values from 9,999 conditional permutations; Gi* *p*-values from the standard normal distribution of the Gi* *z*-score. Quadrant refers to the province value relative to its spatial lag. Gi* used self-inclusive four-nearest-neighbor binary weights, so neighboring provinces sharing the same neighbor set return identical *z*-scores.

Table 4. Bivariate ecological associations with total outpatient hospital utilization in 2024

Predictor	n	*b* (SE)	95%CI	Pearson *r*	Spearman ρ	R^2	*p*-value
NHI coverage 2024 (%)	38	0.094 (0.071)	−0.050 to 0.237	0.216	0.312	0.047	0.193
NHI PBI coverage 2024 (%)	38	−0.068 (0.078)	−0.225 to 0.090	−0.144	−0.084	0.021	0.389
NHI non-PBI coverage 2024 (%)	38	0.293 (0.088)	0.114 to 0.471	0.484	0.498	0.235	0.002
Medical workforce density 2024 (per 100,000)	38	0.067 (0.022)	0.023 to 0.111	0.456	0.409	0.208	0.004
Poverty September 2024 (%)	38	−0.199 (0.147)	−0.497 to 0.099	−0.221	−0.352	0.049	0.183
Gini ratio September 2024	38	23.864 (19.664)	−16.017 to 63.745	0.198	0.193	0.039	0.233
Open unemployment August 2024 (%)	38	0.830 (0.663)	−0.516 to 2.175	0.204	0.167	0.042	0.219
Illiteracy aged 15+ (%)	38	−0.191 (0.180)	−0.557 to 0.174	−0.174	−0.081	0.030	0.296
Mean education completion (%)	35	0.187 (0.148)	−0.114 to 0.487	0.215	0.249	0.046	0.216
Hospital facility preference, SKI 2023 (%)	38	1.375 (0.229)	0.911 to 1.839	0.708	0.643	0.501	<0.001
Population 2024 (million)	38	−0.037 (0.084)	−0.208 to 0.134	−0.074	−0.102	0.005	0.660
Total hospital outpatient utilization 2023 (%)	34	0.735 (0.073)	0.586 to 0.883	0.872	0.863	0.761	<0.001

b: unstandardized linear regression coefficient; CI: confidence interval; R^2: coefficient of determination; SE: standard error.
Each predictor was entered in a separate model with 2024 total outpatient hospital utilization as the dependent variable. Models are bivariate and ecological and should not be read as individual-level or causal effects. The 2023 utilization row uses 34 provinces and the education row 35 provinces; all other rows use 38.

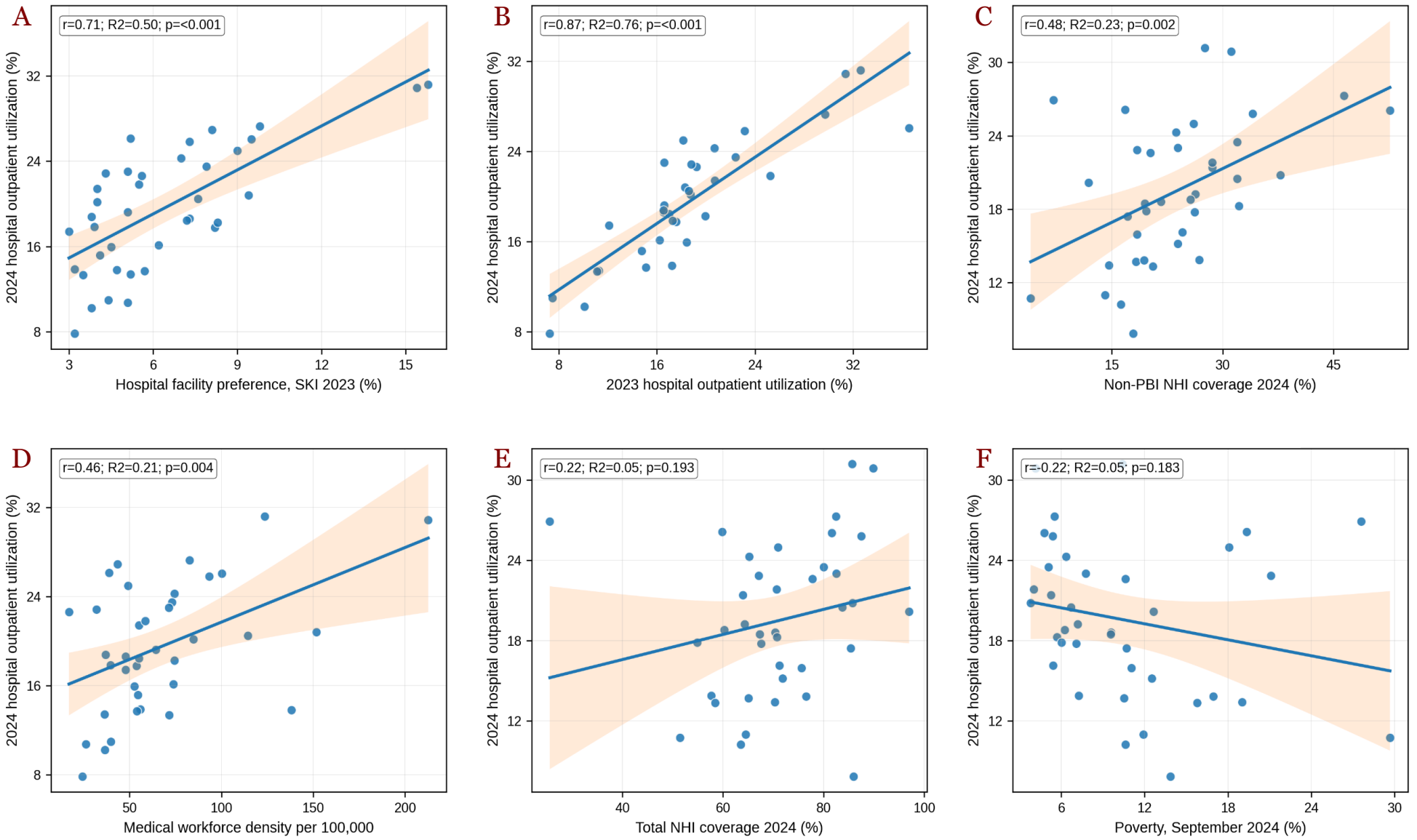


Figure 4. Scatter plots of key ecological associations with total hospital outpatient utilization in 2024. (A) Prior hospital facility preference, SKI 2023; (B) previous-year (2023) hospital outpatient utilization; (C) NHI non-PBI coverage 2024; (D) medical workforce density 2024; (E) total NHI coverage 2024; (F) poverty, September 2024. Lines are fitted linear regressions with 95% confidence bands.

The clearest gradients in **Figure 4** were observed for previous-year utilization and hospital facility preference, followed by non-PBI coverage and medical workforce density. The non-significant association between total NHI coverage and utilization suggests that insurance enrolment did not necessarily translate into effective outpatient care use. The stronger association with non-PBI coverage may reflect differences in socioeconomic position, urban access, employment-linked coverage and capacity to complete referrals. However, the present study cannot distinguish among these explanations, none of which was directly tested.

Mutually adjusted and Bayesian ecological models

Because provincial characteristics are correlated with one another, the bivariate associations were further examined with mutually adjusted regression models (**Table 5**). In Model 1, which included the four predictors available for all 38 provinces, only hospital facility preference remained significantly associated with 2024 utilization (b=1.278; 95%CI: 0.596 to 1.960; p=0.0006; standardized β=0.658). The coefficients for non-PBI coverage (b=0.168; 95%CI: −0.072 to 0.408; p=0.164; β=0.278) and medical workforce density (b=−0.014; 95%CI: −0.065 to 0.037; p=0.582; β=−0.095) were attenuated and no longer statistically significant; the workforce coefficient also changed sign. The model explained 53.6% of the variance in provincial utilization (adjusted R^2=0.480; $F(4,33)$=9.54; p<0.001). Collinearity was not a major concern, as all VIF values were below 2.8.

Table 5. Multivariable ecological regression models for total outpatient hospital utilization in 2024

Model and predictor	*b* (SE)	95%CI	Standardized β	VIF	*p*-value
Model 1: Four-predictor adjusted model (n=38)					
Intercept	7.464 (3.930)	−0.531 to 15.458	–	–	0.066
Hospital facility preference, SKI 2023 (%)	1.278 (0.335)	0.596 to 1.960	0.658	2.12	0.0006
NHI non-PBI coverage 2024 (%)	0.168 (0.118)	−0.072 to 0.408	0.278	2.71	0.164
Medical workforce density 2024 (per 100,000)	−0.014 (0.025)	−0.065 to 0.037	−0.095	2.09	0.582
Poverty September 2024 (%)	0.084 (0.161)	−0.243 to 0.411	0.093	2.26	0.605
Model 2: Insurance coverage decomposed (n=38)					
Intercept	8.206 (5.946)	−3.906 to 20.318	–	–	0.177
Hospital facility preference, SKI 2023 (%)	1.273 (0.341)	0.578 to 1.968	0.655	2.13	0.0007
NHI PBI coverage 2024 (%)	−0.011 (0.066)	−0.145 to 0.123	−0.026	1.35	0.867
NHI non-PBI coverage 2024 (%)	0.158 (0.132)	−0.111 to 0.428	0.262	3.31	0.240
Medical workforce density 2024 (per 100,000)	−0.012 (0.027)	−0.068 to 0.043	−0.084	2.38	0.652
Poverty September 2024 (%)	0.078 (0.167)	−0.263 to 0.419	0.086	2.37	0.645
Model 3: Conditional on 2023 utilization (n=34)					
Intercept	4.991 (2.877)	−0.902 to 10.885	–	–	0.094
Total hospital outpatient utilization 2023 (%)	0.701 (0.137)	0.422 to 0.981	0.750	3.56	<0.001
Hospital facility preference, SKI 2023 (%)	0.299 (0.294)	−0.303 to 0.901	0.152	3.62	0.317
NHI non-PBI coverage 2024 (%)	−0.071 (0.091)	−0.258 to 0.116	−0.117	2.83	0.445
Medical workforce density 2024 (per 100,000)	0.008 (0.021)	−0.034 to 0.050	0.058	2.75	0.698
Poverty September 2024 (%)	0.088 (0.143)	−0.204 to 0.380	0.101	1.79	0.543

b: unstandardized coefficient; CI: confidence interval; SE: standard error; VIF: variance inflation factor. Model 1 R^2=0.536, adjusted R^2=0.480, $F(4,33)$=9.54, p<0.001. Model 2 R^2=0.537, adjusted R^2=0.464, $F(5,32)$=7.41, p<0.001. Model 3 R^2=0.793, adjusted R^2=0.756, $F(5,28)$=21.44, p<0.001. Total NHI coverage was not entered together with its PBI and non-PBI components because the three are linearly dependent. Diagnostics and internal validation are given in Supplementary Table S3.

Model 2 separated insurance coverage into its two components. PBI coverage was not significantly associated with utilization (b=−0.011; 95%CI: −0.145 to 0.123; p=0.867), and non-PBI coverage remained non-significant after adjustment (b=0.158; p=0.240), whereas the association with hospital facility preference remained largely unchanged. In Model 3, which

additionally adjusted for 2023 utilization among the 34 comparable provinces, previous-year utilization was the strongest correlate (b=0.701; 95%CI: 0.422 to 0.981; p<0.001), and no other predictor reached statistical significance, including hospital facility preference (b=0.299; p=0.317). This model explained 79.3% of the variance in utilization (adjusted R^2=0.756). These findings suggest that hospital facility preference and previous-year utilization capture overlapping information about established provincial care-seeking patterns. Once either was accounted for, the remaining provincial indicators contributed little additional explanatory information.

Model 1 satisfied most diagnostic criteria, although some concerns remained (**Supplementary Table S3**). Residuals were normally distributed (Shapiro–Wilk W=0.976; p=0.589) and showed no statistically significant residual spatial autocorrelation (Moran's I=0.128; p=0.128). However, this non-significant result did not establish that the four covariates fully accounted for the spatial structure in the outcome. The Breusch–Pagan test indicated heteroskedasticity (LM=12.43; p=0.014), so HC3 standard errors were also calculated. These strengthened the main finding for hospital facility preference (b=1.278; HC3 95%CI: 0.701 to 1.855; p<0.001), while the association with non-PBI coverage remained non-significant (95%CI: −0.020 to 0.356; p=0.078). Two provinces exceeded the Cook's distance threshold of 4/n=0.105 (Papua Tengah, D=0.225; Papua Pegunungan, D=0.146). Refitting the model after excluding these provinces left the hospital facility preference coefficient essentially unchanged (b=1.188; 95%CI: 0.656 to 1.720; p<0.001).

Internal validation indicated that the model's apparent explanatory power should be interpreted cautiously. The bootstrap percentile 95%CI for hospital facility preference excluded zero (0.505 to 1.779) across 5,000 resamples, whereas the bootstrap CI for non-PBI coverage only narrowly excluded zero (0.002 to 0.446). The intervals for workforce density and poverty included zero. Bootstrap optimism in R^2 was small (+0.033), but out-of-sample performance was weaker than the apparent fit: repeated five-fold cross-validated R^2 was 0.362 (SD 0.073), and leave-one-province-out R^2 was 0.392, with an RMSE of 4.42 percentage points. Thus, the model explained variation in the observed 38 provinces better than it predicted utilization in held-out observations, a distinction that is important given the small sample size. These results caution against overinterpreting the apparent R^2 of 0.536.

Bayesian re-estimation of Model 1 using weakly informative priors yielded broadly similar conclusions (**Table 6**). All four chains converged, with $\hat{R}$=1.000 for every parameter and an effective sample size of approximately 15,000 per chain. The posterior distribution for hospital facility preference was clearly positive (posterior mean: 3.747 percentage points per standard deviation; 95%CrI: 1.773 to 5.728; posterior probability of a positive coefficient: 1.000). For non-PBI coverage, the posterior distribution was predominantly positive but retained considerable uncertainty (posterior mean: 1.577; 95%CrI: −0.667 to 3.824; P(β>0)=0.918). The posterior distributions for workforce density (P(β>0)=0.299) and poverty (P(β>0)=0.695) were centered relatively close to zero. The Bayesian R^2 was 0.530, consistent with the frequentist estimate.

Readiness–utilization trajectories

The readiness–utilization plot gives a combined view of provincial readiness and the two-year difference in hospital outpatient utilization (**Figure 5**). Several provinces with low readiness scores nevertheless recorded high or increasing utilization, whereas several high-readiness provinces showed stable or declining utilization. High utilization may therefore reflect different circumstances: broad provider availability and easier access in some provinces, and pressure on limited hospital alternatives in others. Across all 38 provinces, the readiness index was moderately correlated with 2024 utilization (Pearson r=0.536; p<0.001), so readiness accounted for under a third of the observed variation.

Table 6. Bayesian linear regression for total outpatient hospital utilization in 2024, standardized predictors (n=38)

Parameter	Posterior mean	Posterior SD	95%CrI	P(β>0)	$\hat{R}$
Intercept	19.427	0.696	18.042 to 20.785	–	1.000
Hospital facility preference, SKI 2023	3.747	1.006	1.773 to 5.728	1.000	1.000

Parameter	Posterior mean	Posterior SD	95%CrI	P(β>0)	R^
NHI non-PBI coverage 2024	1.577	1.143	−0.667 to 3.824	0.918	1.000
Medical workforce density 2024	−0.519	1.007	−2.517 to 1.451	0.299	1.000
Poverty September 2024	0.521	1.049	−1.542 to 2.585	0.695	1.000
Residual variance σ^2	18.291	4.797	11.175 to 29.814	–	1.000

CrI: equal-tailed credible interval; R^: Gelman–Rubin convergence statistic; SD: standard deviation. Predictors were standardized to mean 0 and unit standard deviation, so coefficients are percentage-point changes in utilization per one standard deviation of the predictor. Priors: $\beta \sim N(0, 10^2)$ independently; $\sigma^2 \sim$inverse-gamma(0.001, 0.001). Gibbs sampling, four chains of 20,000 iterations with 5,000 burn-in (60,000 retained draws). Bayesian R^2=0.530.

Positions relative to the fitted frontier are descriptive. Above-frontier, high-readiness may reflect mature hospital markets and wider facility choice, whereas above-frontier, low-readiness provinces may indicate pressure on a limited number of public facilities. Provinces below the frontier with moderate readiness warrant further investigation of referral completion, primary-care substitution, or service acceptability. These interpretations cannot be confirmed with the present data and are presented as a hypothesis for future studies incorporating facility-level or individual-level information.

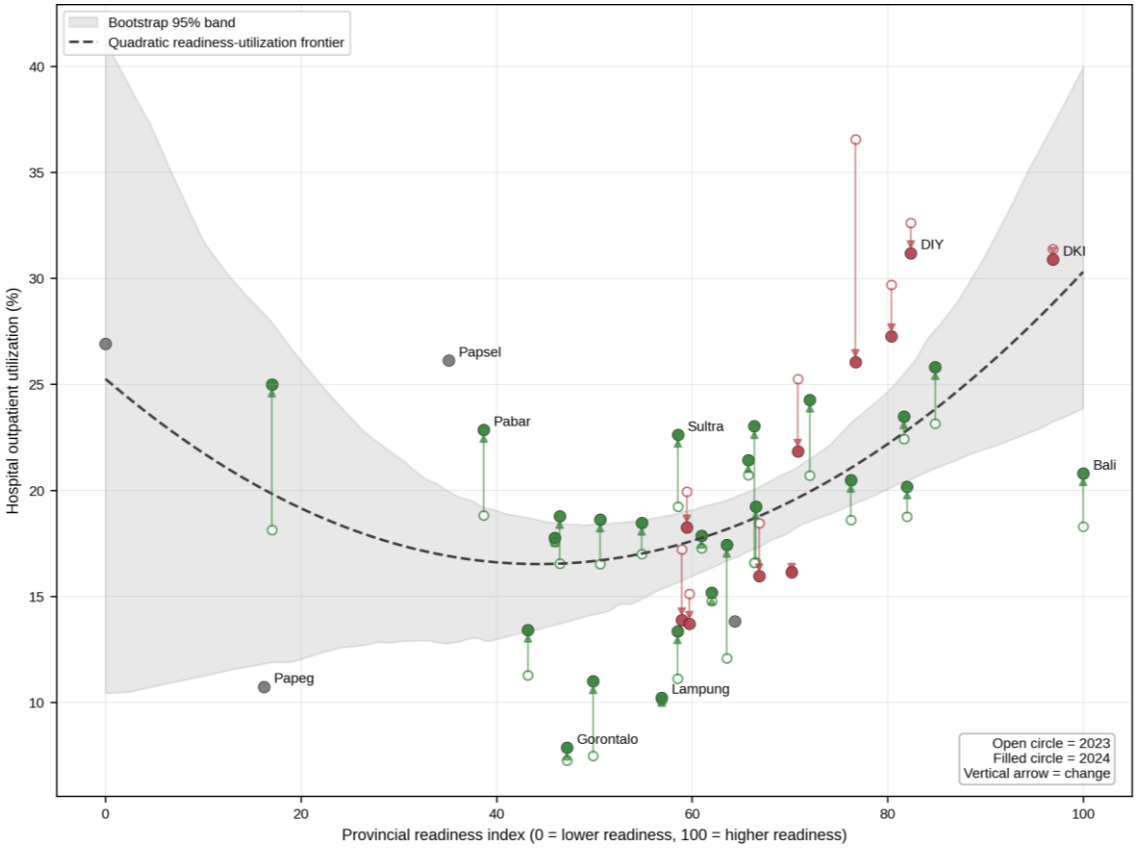


Figure 5. Readiness–utilization trajectories, 2023–2024. The figure has a single panel and therefore carries no panel letter. Open circles indicate 2023 values, filled circles 2024 values, and vertical arrows indicate the difference between the two years. The dashed curve is an exploratory quadratic frontier with a bootstrap 95% band. The readiness index is the equal-weighted mean of four min–max scaled components (medical workforce density, total NHI coverage, hospital facility preference, and 100 minus the poverty headcount), scaled 0–100; construction and validation are described in the Methods. Province names follow the official Indonesian nomenclature used throughout the manuscript.

Exploratory province typology

The clustering diagnostics did not identify a single optimal number of clusters (**Table 7**). The average silhouette width was identical for k=2 and k=3 (0.268) and fell for larger k. The Calinski–Harabasz index was highest at k=2 (13.92) and declined monotonically thereafter, whereas the Davies–Bouldin index favored k=3 (1.222) over k=2 (1.313). The three-cluster solution was

retained because it performed comparably to the two-cluster solution on the silhouette criterion, was favored by the Davies-Bouldin index, and distinguished two groups of provinces with different policy implications that would otherwise have been merged (**Figure 6**). This choice prioritizes interpretability over a claim of optimal statistical separation.

Table 7. Internal validation of the k-means solutions

Number of clusters	Average silhouette width	Calinski–Harabasz index	Davies–Bouldin index	Within-cluster sum of squares
2	0.268	13.92	1.313	186.80
3 (retained)	0.268	12.47	1.222	151.21
4	0.196	11.74	1.458	127.19
5	0.186	11.33	1.309	109.11
6	0.197	10.50	1.195	98.09
7	0.202	10.18	1.090	87.22

Higher silhouette and Calinski–Harabasz values and lower Davies–Bouldin values indicate better-separated clusters. k-means with the Hartigan–Wong algorithm and 500 random starts on seven standardized indicators. Cluster-wise silhouette widths for the retained three-cluster solution were 0.288 (general/mixed), 0.235 (high-capacity metropolitan), and 0.187 (Papua high-need); bootstrap mean maximum Jaccard similarities were 0.456, 0.515, and 0.398, respectively.

Cluster-specific silhouette widths for the retained solution were modest (general/mixed: 0.288; high-capacity metropolitan: 0.235; Papua high-need: 0.187), and bootstrap stability was low to moderate. The mean maximum Jaccard similarity across 1,000 resamples was 0.515 (SD=0.243) for the high-capacity metropolitan cluster, 0.456 (SD=0.122) for the general/mixed cluster, and 0.398 (SD=0.280) for the Papua high-need cluster. All three values were below the 0.60 threshold conventionally used to indicate cluster stability [27]. The typology should therefore be treated as a descriptive summary of the province profiles presented in **Table 8**, useful for organizing policy discussion rather than as a validated classification of provinces. The individual indicators in **Tables 1** and **5** provide the primary basis for statistical inference in this study.

The three-cluster solution may help prioritize policy responses by distinguishing high-utilization metropolitan provinces from high-need, public-sector-dependent provinces in the Papua region, a distinction that may be obscured by a uniform national approach. The Papua cluster highlights potential priorities such as strengthening public hospitals, supporting referral transport, and redistributing the health workforce. The metropolitan cluster suggests priorities related to managing high-volume care, improving public–private coordination, and monitoring declining utilization. The general/mixed cluster requires province-specific assessment rather than a uniform response. Given the modest silhouette widths and low bootstrap stability reported above, these groupings should inform policy discussions rather than determine resource allocation.

Two exploratory scatterplot panels included in the submitted version, showing hospital outpatient utilization against insurance coverage, hospital-room availability, general practitioner supply, specialist supply, nurse supply, perceived difficulty accessing hospital care, and bed availability, have been moved from the main text. These plots were produced outside the R-based analytical pipeline used for the other results, were of lower resolution, and used variable definitions that were not consistent with those in **Tables 4** and **5**. They are provided as **Supplementary Figures S1** and **S2** for interested readers; no findings reported in the main article depend on them.

Discussion

This ecological analysis produced five main findings. First, hospital outpatient utilization varied substantially across Indonesian provinces in 2024. Second, utilization was higher in 2024 than in 2023 in most comparable provinces, but the mean difference was small and its confidence interval included zero. Third, previous-year utilization and prior hospital facility preference were the strongest correlates of 2024 utilization, followed by non-PBI coverage and medical workforce density, while total NHI coverage was unrelated to utilization; after mutual adjustment, only facility preference remained associated with utilization.

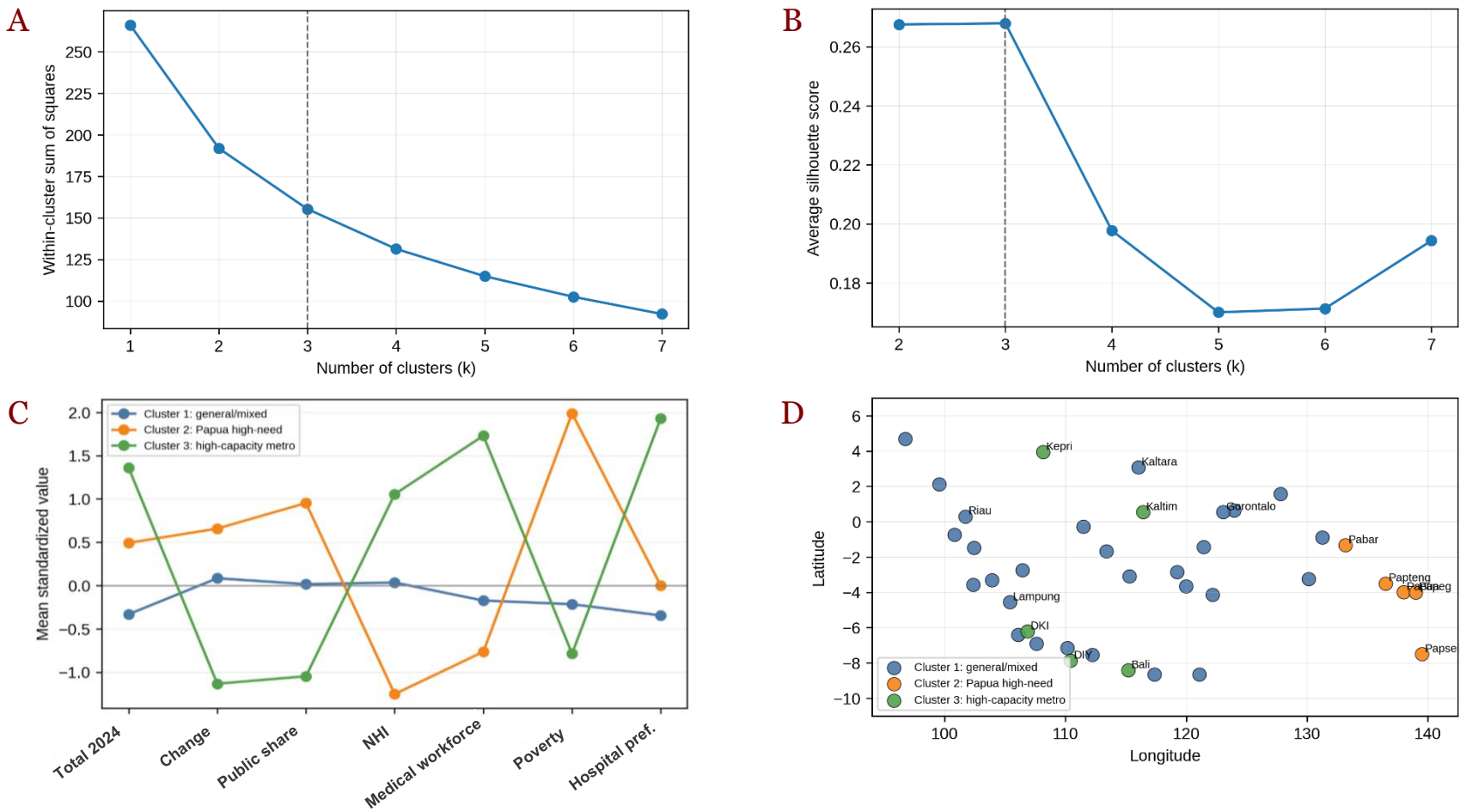


Figure 6. Exploratory k-means typology of provincial hospital outpatient utilization. (A) elbow plot; (B) silhouette plot; (C) standardized cluster profiles; (D) province-centroid cluster map. Province names follow the official Indonesian nomenclature used throughout the manuscript.

Table 8. Exploratory k-means cluster profiles

Cluster profile	n	2024 utilization, median (IQR)	Public-hospital share, median	NHI coverage, median	Medical workforce density, median	Poverty, median	Mean silhouette	Bootstrap Jaccard
General/mixed profile	28	18.05 (13.86–20.72)	69.65	70.53	55.11	8.66	0.288	0.456
Papua high-need and public-dependent profile	5	24.99 (22.85–26.12)	83.14	59.84	38.85	21.09	0.187	0.398
High-capacity metropolitan profile	5	27.27 (26.06–30.88)	49.17	85.67	123.66	4.78	0.235	0.515

IQR: interquartile range; NHI: National Health Insurance. Clustering used the standardized indicators listed in the Methods. Missing 2023 difference values were median-imputed for clustering only. Cluster labels are interpretive and policy-oriented, not causal classifications.

Fourth, total utilization showed no significant global or local spatial clustering, whereas public-hospital dependence and poverty were strongly clustered, with local statistics locating that clustering in the Papua region and, for public-hospital share, an opposing low–low cluster in Java. Fifth, exploratory clustering separated provinces into general/mixed, Papua high-need public-dependent and high-capacity metropolitan profiles, though internal validation was weak.

The weak association between total NHI coverage and hospital outpatient utilization does not indicate that insurance is unimportant. Rather, it suggests that formal entitlement alone may not translate into effective service use. This distinction is central to universal health coverage: coverage on paper must be converted into accessible services, timely referrals, and acceptable care. Andersen-type models similarly conceptualize enabling resources, such as insurance, as operating alongside need, provider availability, geographic accessibility, income, information, and health-system organization [7,31,32].

The stronger bivariate association between non-PBI coverage and hospital outpatient utilization is consistent with Indonesian evidence that non-subsidized groups and those with higher socioeconomic status use secondary and tertiary healthcare services more often than the subsidized groups [6,7]. Several mechanisms could contribute to this pattern: non-PBI members may be more concentrated in urban employment sectors, live closer to hospitals, have greater flexibility to complete referrals, or face lower non-medical costs. However, these mechanisms were not measured in the present study. The attenuation of the non-PBI coefficient after adjustment for hospital facility preference (**Table 5**) suggests that the bivariate association partly reflects information shared with established provincial care-seeking patterns. Nevertheless, the Bayesian posterior assigned a 92% probability to a positive coefficient for non-PBI coverage, suggesting that the evidence for a positive association remains plausible, although uncertain. Recent evidence on JKN underutilization also indicates that non-use of outpatient insurance benefits remains substantial and is associated with labor-market constraints, rural residence, and local service capacity [5].

The policy implications are clear. Expanding NHI coverage remains necessary, but improving hospital outpatient utilization also requires ensuring that insured residents can reach facilities, obtain referral authorization, access available specialists, and afford non-medical costs. Provincial insurance coverage should therefore be monitored alongside hospital density, workforce distribution, referral completion, waiting times, transport barriers, and public-hospital workload.

The most consequential change from the unadjusted to the adjusted analysis is that hospital facility preference was the only provincial characteristic that retained an association with 2024 utilization once the other indicators were held constant, and that previous-year utilization displaced even that association when it was available. Both variables may capture overlapping aspects of the same underlying pattern: how far hospital-based outpatient care is already the established route to care in a province. This design cannot separate two readings of their dominance. One is substantive persistence, in which referral networks, provider distribution, household expectations, and local practice patterns change slowly, so a province's utilization level is largely inherited from its own recent history. The other is measurement overlap, since facility preference and utilization are both derived from household reports of hospital use and may share reporting behavior as well as underlying behavior. Distinguishing these would require individual-level panel data linking reported preference at one time point to verified utilization at another.

This has a practical consequence for interpreting the workforce result. Medical workforce density was positively associated with utilization in the bivariate model (b=0.067; p=0.004) but not after adjustment, where the point estimate was slightly negative. The unadjusted coefficient should therefore not be read as an estimate of what adding health workers to a province would do to outpatient utilization. Workforce density is correlated with insurance composition, poverty, and established hospital use, and in these data it showed no statistically significant independent association with provincial utilization once those factors were accounted for.

The unadjusted positive association between workforce density and utilization is consistent with health-system frameworks that treat the workforce as a core building block of service delivery, and with studies linking hospital capacity, primary-care organization and provider supply to utilization patterns [33-36]. It also fits Roemer-type arguments that available capacity

can generate utilization by increasing service opportunity, referral acceptance, appointment slots and diagnostic throughput [33]. In this dataset, however, that association did not survive mutual adjustment, so the present analysis provides only limited support for this framework and cannot be cited as provincial-level evidence for a Roemer effect in Indonesia.

Some provinces with relatively low workforce density reported high or rising utilization. One explanation is public-hospital dependence combined with limited availability of alternative services, so that high utilization reflects pressure on a small number of facilities rather than good access. The local spatial results support the first part of this interpretation, since public-hospital share is significantly clustered in the provinces concerned, but the data contain no measure of unmet need, waiting time, or referral completion, so the pressure interpretation itself remains untested. In high-capacity provinces, high utilization may instead reflect the availability of multiple hospitals, specialist access and a stronger private sector.

The geospatial results are central to the interpretation. Total utilization was not globally autocorrelated and, once local statistics and multiple-comparison adjustment were applied, no individual province emerged as a significant utilization hotspot or coldspot. Public-hospital share and poverty, by contrast, were strongly clustered at both global and local scales. Utilization may reflect several local mechanisms acting together, while vulnerability and public-sector dependence showed a clearer spatial structure.

The local statistics add information that the global tests could not provide. The high–high poverty cluster is confined to the Papua region and is strong enough to survive false discovery rate adjustment in four provinces, while the public-hospital share results show an explicit east–west dichotomy: a high–high cluster across the six Papua provinces and Sulawesi, and a low–low cluster across Java where private outpatient hospital capacity is greatest. Because these two structures overlap geographically but the utilization surface does not, spatial targeting should be based on poverty and public-sector dependence rather than on utilization levels. A province is not adequately served simply because its utilization is high, and Papua Pegunungan illustrates the point directly: it appeared as a low–high local outlier for utilization while also falling within the strongest high–high poverty cluster in the country.

The Papua high-need public-dependent cluster makes the same point in profile terms. These provinces combined high poverty, high public-hospital share, lower workforce density, and high or rising utilization, suggesting a need for a different policy approach from that used in high-utilization metropolitan provinces such as DKI Jakarta, DI Yogyakarta, Bali, Kalimantan Timur and Kepulauan Riau. These profile descriptions rest on the observed medians in **Table 8** rather than on the cluster assignment itself, which was only weakly supported by the validation metrics.

These findings are consistent with the wider literature on geographic inequality in healthcare access in Indonesia. Work on hospital distribution has emphasized that archipelagic geography, uneven population density, and uneven hospital distribution create accessibility problems across provinces and island clusters [1]. The present study extends that argument from facility distribution to realized outpatient hospital use and shows that spatially clustered poverty and public-sector dependence are relevant considerations for utilization planning.

The median increase of 1.25 percentage points between 2023 and 2024 is a difference between two annual cross-sections. It is not a trend, a growth rate, or evidence of a structural shift, and it is not described as one anywhere in this article. The mean difference of +0.91 percentage points had a 95%CI of −0.22 to +2.04 and a small standardized effect size, so the national-level increase was not statistically significant in the paired *t*-test; the significant Wilcoxon result reflects the consistency of direction across provinces rather than the magnitude of the mean difference. Provincial differences were heterogeneous, ranging from +6.85 to −10.50 percentage points.

Recovery of delayed care after the pandemic, changes in referral behavior, local service expansion, shifting patient preference, and substitution between hospital and non-hospital outpatient pathways are all plausible contributors to this heterogeneity. None of these factors was measured in this dataset, and with only two annual observations per province, the design cannot distinguish between them or exclude measurement variation in the underlying household surveys. These explanations are presented as candidate hypotheses for future research using

longer time series and facility-level data, rather than as findings of this study. Claims about post-pandemic recovery, in particular, should not be inferred from these results.

The typology is useful because it converts several indicators into policy-readable provincial groups. The general/mixed cluster contains most provinces and should not receive a uniform policy label, because the same utilization level can arise from different combinations of workforce readiness, poverty, insurance composition, public–private supply, and referral behavior.

The Papua high-need public-dependent cluster is the clearest candidate for targeted intervention. Priorities include strengthening public hospital outpatient capacity, improving referral transport, expanding specialist outreach, supporting telemedicine where clinically appropriate, improving health-worker retention and reducing non-medical access costs. Financial coverage alone is unlikely to be sufficient if practical access and supply-side readiness are the main constraints. This reading is supported by the local spatial results, which place the strongest poverty and public-sector-dependence clusters in these provinces, rather than by the cluster assignment alone.

The high-capacity metropolitan cluster requires a different mix of interventions: demand management, continuity of care, coordination between primary care and hospitals, monitoring of private-sector utilization, and management of high-volume outpatient services. Declining utilization in a high-capacity province should not automatically be interpreted as deterioration, since it may reflect substitution to primary care, changes in private-sector use, or normalization after unusually high prior utilization; these explanations cannot be determined from the present data. Utilization decline should therefore be assessed alongside waiting times, referral completion, quality, and unmet-need indicators before any conclusions are drawn.

This study contributes to the Indonesian health-services literature in three ways. First, it focuses on hospital outpatient utilization rather than general healthcare utilization or inpatient care alone; hospital outpatient use is a key interface between primary care, referral systems, specialist services, and hospital financing. Second, it combines distributional, ecological, geospatial, and typological approaches in a single province-level analysis. Third, it distinguishes total utilization from contextual dependence on public hospitals, showing that the same utilization level can have different policy implications across provinces.

Methodologically, the study sets out a transparent approach to province-level geospatial analysis when official boundary shapefiles are unavailable. Province-centroid weights are not a substitute for boundary-polygon analysis, but they support a reproducible assessment of whether values are spatially patterned. Reporting the centroid coordinates (**Supplementary Table S1**), together with a sensitivity analysis across six weighting schemes (**Supplementary Table S2**), allows readers to judge the extent to which the spatial conclusions depend on that choice. The combination of global and local spatial statistics, adjusted and Bayesian regression, and internally validated clustering follows established practice in spatial epidemiology and health services research [20,37-42].

This study has both strengths and limitations. Its strengths were that it used all 38 provinces for the 2024 cross-sectional analysis, combined multiple provincial indicators, and applied descriptive statistics, nonparametric testing with effect sizes, bivariate and adjusted regression, Bayesian estimation, a two-year comparison, geospatial visualization, global and local spatial statistics, readiness trajectories, and clustering with internal validation within a single analytical pipeline. Its limitations are substantial and constrain the interpretation of the findings. First, the design is ecological, so the results describe provinces rather than individuals. Associations observed between province-level aggregates need not hold at the individual level and may even run in the opposite direction, a phenomenon known as ecological fallacy. Thus, the non-PBI and poverty coefficients describe provincial patterns rather than associations among individual members or poor households. Second, the two-year comparison included only two comparable years and only 34 provinces, while mean education completion was unavailable for three of the four newly established Papua provinces; consequently, models including this variable used 35 provinces. Third, the inferential spatial analysis used approximate province centroids rather than official boundary-based centroids. Although the global results were stable across six weighting schemes for the two clearly clustered indicators, the borderline results for NHI coverage and the 2023–2024 difference were specification-dependent. Local statistics based on only 38 units also

have limited power, which is why FDR-adjusted results are reported alongside unadjusted results. Fourth, several variables were proxies rather than direct measures of hospital readiness, and the primary outcome was the sum of two separately published percentages rather than an unduplicated proportion of residents. Residents who used both a public and a private hospital during the reference month therefore contributed to both component percentages, and the extent of this overlap cannot be estimated from aggregate data. Fifth, unmeasured confounding by morbidity burden, urbanization, travel time, hospital quality, referral rules, private-sector prices, and patient preference remains possible. With only 38 units, the adjusted models could accommodate four to five covariates, leaving potential for residual confounding. Sixth, out-of-sample performance was appreciably weaker than the apparent fit (cross-validated R^2=0.362 versus apparent R^2=0.536), and the cluster solution did not meet conventional stability thresholds. Therefore, neither the regression R^2 nor the typology should be treated as a predictive tool.

Future research should use district-level or individual-level data, official boundary shapefiles, longer time series, facility supply indicators, morbidity profiles, travel-time metrics, and multilevel or spatial regression models. Linking JKN claims, SUSENAS, SKI, hospital information system records, and geospatial travel-time data would enable a stronger assessment of whether insurance coverage translates into effective hospital outpatient access. District-level data, covering approximately 514 administrative units, could also support spatial regression, Bayesian hierarchical spatial models with conditional autoregressive priors, and formal mediation analysis, approaches that are not feasible with only 38 provincial units.

Conclusion

Hospital outpatient utilization in Indonesia varies substantially between provinces. Utilization was higher in 2024 than in 2023 in most of the 34 comparable provinces, but the mean difference was small and its confidence interval included zero; therefore, the two-year comparison does not establish a national increase. Total NHI coverage was not significantly associated with provincial differences in utilization. The strongest correlates were previous-year utilization and prior hospital facility preference, followed by non-PBI coverage and medical workforce density. After mutual adjustment, only prior facility preference remained significantly associated with utilization, while Bayesian estimation provided broadly consistent evidence. Public-hospital dependence and poverty showed strong spatial clustering, concentrated in the Papua region, with a contrasting low public-hospital share cluster in Java, whereas total utilization showed no statistically significant clustering at either the global or local scale. Policy should therefore go beyond aggregate insurance expansion and combine financial protection with workforce distribution, public-hospital strengthening, regional referral planning, transport support and targeted interventions in high-poverty, public-sector-dependent provinces. Because the analysis is ecological, these conclusions describe provinces rather than individuals and identify priorities for further investigation rather than established causal effects.

Ethics approval

Ethical review was not required for this study. The analysis used only aggregate, province-level secondary data that are officially published and publicly available, contain no individual identifiers, and cannot be used to re-identify any person or household. No primary data were collected, no human participants were contacted, and no individual-level records were accessed, so the study falls outside the categories requiring review under the Regulation of the Minister of Health of the Republic of Indonesia concerning health research ethics and under the national guidelines of the Indonesian Health Research Ethics Committee. The study was nevertheless conducted in accordance with the principles of the Declaration of Helsinki as they apply to research using existing anonymous data, and all source datasets were used within the terms of use published by Statistics Indonesia and the Ministry of Health.

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Competing interests

All authors declare that they have no competing interests.

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Underlying data

All source data are aggregate provincial indicators published by Statistics Indonesia (*Statistik Indonesia* 2024; Provinces in Figures 2024) and the Ministry of Health of the Republic of Indonesia (Indonesian Health Profile 2023; Indonesian Health Survey 2023), as cited in references 11 to 13. The cleaned province-level analytic dataset, the province-centroid coordinate file reproduced in Supplementary Table S1, the spatial weights specification, all supplementary material, and the R scripts that generate every table and figure in this article have been deposited in the permanent open-access repository Zenodo (CERN, Geneva, Switzerland) under a Creative Commons Attribution 4.0 license and are available without restriction at https://doi.org/10.5281/zenodo.21845594 [30].

Supplementary Table S1. Approximate province-centroid coordinates used to construct the spatial weights matrix. Supplementary Table S2. Global Moran's I for six indicators under six alternative spatial weighting schemes. Supplementary Table S3. Diagnostics and internal validation for Model 1. Supplementary Figures S1 and S2. Exploratory scatterplots of hospital outpatient utilization against insurance coverage and provider-availability indicators, removed from the main text. All supplementary tables and figures listed here have been deposited in the permanent open-access repository Zenodo (CERN, Geneva, Switzerland) under a Creative Commons Attribution 4.0 license and are available without restriction at https://doi.org/10.5281/zenodo.21845594.

Declaration of the use of artificial intelligence

Artificial intelligence–assisted writing tools were used to assist with language editing, structuring of the manuscript, and formatting of tables and captions. The specific tools used were Grammarly (Grammarly Inc., San Francisco, CA, USA) and the AJE Grammar Check, together with the AJE academic writing rubric (American Journal Experts, Durham, NC, USA). No artificial intelligence tool was used to generate data, to conduct or interpret any statistical analysis, or to produce any figure. All scientific content, statistical output, figures, tables, software version details, and references were reviewed and verified by the authors, who take full responsibility for the accuracy and integrity of the work as published.

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