



Digital Ecosystem Disparities and Interprovincial Educational Quality in Indonesia: Development of the Digital–Education Vulnerability Index and Spatial Analysis Based on BPS Data and the 2025 Education Report Card

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Abstract

Digital transformation has expanded educational opportunities in Indonesia, but the capacity to benefit from digital resources remains territorially unequal. This study develops a Digital–Education Vulnerability Index (DEVI) for all 38 Indonesian provinces using complete 2025 provincial series from Statistics Indonesia. The final specification integrates youth cellular-phone use, computer use, and internet use within the Digital Vulnerability Index (DVI), and the School Participation Rate for ages 16–18 and senior-secondary Net Enrolment Rate within the Educational Vulnerability Index (EVI). Beneficial indicators were reverse-normalized by min–max transformation, weighted within each dimension by the Entropy Weight Method, and combined with equal dimensional contributions. Spatial dependence was tested with a row-standardized four-nearest-neighbor matrix, while DVI–EVI association, OLS regression with HC3 standard errors, and equal-weight sensitivity analysis assessed cross-dimensional consistency and robustness. Highland Papua (DEVI=0.9441), Central Papua (0.8868), and South Papua (0.5738) recorded the highest vulnerability, whereas DI Yogyakarta (0.0004), Bali (0.0320), and Riau Islands (0.0403) recorded the lowest. DVI and EVI were positively associated (Spearman $\rho=0.671$, $p<0.001$), and DEVI displayed significant spatial clustering (Global Moran's $I=0.545$, $p=0.0001$), with significant High–High concentrations across several Papuan provinces. The entropy-weight and equal-weight rankings were highly concordant ($\rho=0.989$). These results show that digital and educational vulnerability is jointly structured but not interchangeable, supporting territorially differentiated intervention rather than uniform connectivity policy.

Keywords: Composite Index, Digital Divide, Educational Inequality, Spatial Analysis, Vulnerability.



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INTRODUCTION

Digital transformation is now embedded in education systems, but expanded connectivity has not produced equivalent opportunities across territories or social groups. The digital divide extends beyond binary internet access to differences in device availability, connection quality, digital competence, patterns of use, and the capacity to convert technological resources into educational benefit (Corkin et al., 2022; Kaarakainen & Saikkonen, 2023; Mascheroni et al., 2022). Digital inequality is therefore better understood as a multidimensional condition in which socioeconomic position, geography, institutional capacity, and digital skills interact rather than as a single infrastructure deficit (Meng et al., 2024; Mirazchiyski, 2025; Ragnedda et al., 2022).

Empirical research links broadband and internet availability with educational participation and achievement, but the relationship is heterogeneous. Educational effects depend on the quality and purpose of technology use, household resources, institutional conditions, and the readiness of schools and students to employ digital resources productively (Caldarulo et al., 2023; Cambini et al., 2024; van de Werfhorst et al., 2022). Differences in adolescents' digital skills and teachers' digital competence further indicate that nominal access does not ensure equivalent instructional capacity or learning opportunity (Lin et al., 2023; Ren et al., 2022; Wang et al., 2024).

Geography adds a distinct dimension because educational resources, digital infrastructure, and social disadvantage are spatially structured. Spatial studies identify territorial clustering, spillovers, and persistent urban–rural gaps that are not visible in national averages (Delprato et al., 2024; Jiang et al., 2022; Sajjad et al., 2022). Indonesia provides a particularly relevant setting because its archipelagic geography, regional development differences, and recent provincial reorganization create substantial variation in digital and educational conditions. Existing Indonesian evidence documents unequal online-learning access, uneven school accessibility, and persistent regional educational inequality (Hidayah, 2022; Muhaimin et al., 2022; Wirandana & Khoirunurrofik, 2024).

The literature nevertheless remains fragmented. Digital-divide studies commonly examine connectivity, device use, or competence separately, while studies of educational inequality usually focus on participation, attainment, resources, or learning outcomes without integrating territorial digital conditions (Barragán Moreno & Guzmán Rincón, 2025; Guo & Wan, 2022; Mikhailov et al., 2024). Composite indicators can summarize multidimensional disadvantage, but their interpretation is sensitive to normalization, direction, weighting, and robustness choices (Alqararah, 2023). Entropy weighting provides a data-driven mechanism for assigning greater influence to indicators with stronger cross-sectional differentiation, and recent work shows that entropy-based indices can be combined with spatial analysis (D’Amario et al., 2026; Libório et al., 2024).

The Digital–Education Vulnerability Index (DEVI) differs from a conventional single-domain composite measure in three respects. First, it retains Digital Vulnerability (DVI) and Educational Vulnerability (EVI) as separate dimensions before integration, permitting direct identification of concordance and mismatch between the two processes. Second, entropy weights are estimated within each dimension and the two dimensions enter DEVI equally, preventing a domain from dominating merely because it contains more indicators. Third, the index is evaluated spatially and statistically, allowing the analysis to determine whether high vulnerability forms geographic concentrations and whether educational vulnerability varies systematically with digital conditions. The theoretical value therefore lies not in mechanically combining established indicators, but in testing whether digital and educational disadvantage operate as a co-located territorial process or diverge across provinces.

The final empirical specification uses only indicators with verified 2025 values for all 38 provinces under the current administrative structure. Digital vulnerability is represented by youth cellular-phone use, computer use, and internet use, while educational vulnerability is represented by participation among persons aged 16–18 years and age-appropriate senior-secondary enrolment. This restricted core avoids introducing indicators with non-equivalent provincial coverage or definitions into the weighting procedure and yields a fully reproducible index from observed provincial data.

The study aims to measure DVI, EVI, and DEVI across Indonesian provinces; identify the spatial distribution and local clustering of the integrated index; and evaluate the statistical relationship between digital and educational vulnerability while identifying provinces that depart from the dominant national pattern. Its contribution is an empirically completed provincial typology that combines objective within-dimension weighting, balanced cross-dimensional integration, spatial diagnostics, regression analysis, and weighting sensitivity in a single framework.

RESEARCH METHODS

This study employed a quantitative, cross-sectional ecological design with the province as the unit of analysis. The analytical population comprised all 38 Indonesian provinces under the current administrative structure. The final index used 2025 provincial observations from Statistics Indonesia, principally the 2025 Indonesian Youth Statistics and 2025 Education Statistics, both of which draw on the March 2025 National Socioeconomic Survey (Susenas). The use of a single reference year and a common territorial structure was intended to prevent temporal and administrative-boundary inconsistencies in the composite index.

Each candidate variable was audited for definition, unit, reference year, territorial coverage, direction of association with vulnerability, missingness, and reproducibility. The final inclusion rule was fixed before index calculation: an indicator entered the core DEVI only when a comparable 2025 value was available for every province under the 38-province structure. Five indicators met this requirement in the assembled analytical database. Planned variables with incomplete or non-equivalent provincial coverage were excluded from the core index rather than imputed, thereby keeping the weighting procedure based entirely on observed and definitionally aligned values.

The final framework contained two dimensions. Digital Vulnerability comprised youth cellular-phone use, computer use, and internet use; Educational Vulnerability comprised the School Participation Rate (APS) for ages 16–18 and the Net Enrolment Rate (APM) at senior-secondary level. All five indicators are beneficial in their original form, so each was reverse-normalized to ensure that higher normalized values consistently represented greater vulnerability. The operational specification is reported in Table 1.

Table 1. Operational Framework of the Digital–Education Vulnerability Indicators

Dimension	Indicator	Measurement	Original Interpretation	Vulnerability Direction
Digital Vulnerability	Youth cellular-phone use	Percentage of youth aged 16–30	Higher value indicates broader mobile access	Reversed
Digital Vulnerability	Youth computer use	Percentage of youth aged 16–30	Higher value indicates broader advanced-device use	Reversed
Digital Vulnerability	Youth internet use	Percentage of youth aged 16–30	Higher value indicates broader online access	Reversed
Educational Vulnerability	School Participation Rate (APS), age 16–18	Percentage	Higher value indicates stronger participation	Reversed
Educational Vulnerability	Net Enrolment Rate (APM), senior-secondary	Percentage	Higher value indicates stronger age-appropriate enrolment	Reversed

Note: The final core index contains only indicators with complete 2025 observations for all 38 provinces. All retained indicators are beneficial in their original direction and were reverse-normalized so that higher values denote greater vulnerability.

Data preprocessing began with verification of province names and administrative codes, duplicate detection, missing-value assessment, range validation, and exploratory examination of potential outliers. Particular attention was given to the harmonization of the current 38-province administrative structure because the use of indicators based on earlier provincial boundaries could generate artificial differences between observations. Consequently, only data that could be reconciled with the contemporary provincial structure were retained for the principal analysis.

Because the selected indicators were expressed in different measurement units, min–max normalization was applied to transform them onto a comparable scale ranging from 0 to 1. For an adverse indicator, in which a higher original value represented greater vulnerability, the normalized value was calculated using Equation (1).

Equation (1). Normalization of an adverse indicator

$$z_{ij} = (x_{ij} - \min x_j) / (\max x_j - \min x_j)$$

where x_{ij} denotes the observed value of indicator j in province i , and z_{ij} represents its normalized value.

For a beneficial indicator, in which a higher original value represented a more favorable condition, the direction was reversed using Equation (2).

Equation (2). Reverse normalization of a beneficial indicator

$$z_{ij} = (\max x_j - x_{ij}) / (\max x_j - \min x_j)$$

This transformation ensured a uniform interpretation across all components of the index. Normalized values approaching 1 represented greater vulnerability, whereas values approaching 0 represented lower vulnerability.

Indicator weights were subsequently estimated using the Entropy Weight Method (EWM) rather than predetermined subjective weights. This approach assigns greater weight to indicators displaying stronger cross-provincial differentiation and therefore containing greater discriminatory information

(D'Amario et al., 2026; Libório et al., 2024). The proportional contribution of province i to indicator j was calculated using Equation (3).

Equation (3). Proportional contribution of each observation

$$p_{ij} = z_{ij} / \sum z_{ij}$$

The entropy value of indicator j was then calculated using Equation (4).

Equation (4). Entropy value

$$e_j = -k \sum [p_{ij} \ln(p_{ij})]$$

where the entropy constant was defined as:

Equation (5). Entropy constant

$$k = 1 / \ln(n)$$

where n represents the number of provinces included in the analysis. For zero-probability observations, the conventional assumption $p_{ij} \ln(p_{ij}) = 0$ was applied.

The degree of diversification for each indicator was subsequently calculated as:

Equation (6). Degree of diversification

$$d_j = 1 - e_j$$

The final entropy weight was obtained using Equation (7).

Equation (7). Final indicator weight

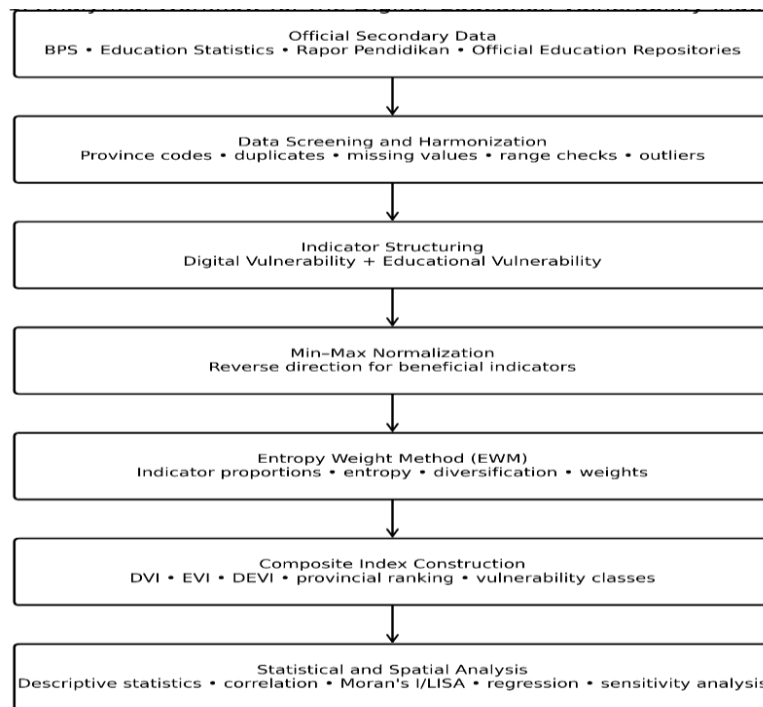
$$w_j = d_j / \sum d_j$$

Accordingly, indicators exhibiting greater variation across provinces received proportionately greater weights, whereas indicators with relatively limited discriminatory variation contributed less strongly to the composite index.

Entropy weights were estimated separately within the digital and educational dimensions so that the weights in each dimension summed to 1. DVI was the entropy-weighted sum of the three normalized digital indicators and EVI was the entropy-weighted sum of the two normalized educational indicators. The integrated index was fixed as $DEVI = 0.5(DVI) + 0.5(EVI)$. Equal contribution of the two dimensions prevented the digital domain from receiving greater aggregate influence merely because it contained more retained indicators. Higher DVI, EVI, and DEVI values uniformly represent greater vulnerability.

Provinces were ranked from the highest to the lowest DEVI score. Vulnerability classes were defined by the empirical quintiles of the final DEVI distribution: very low at or below the 20th percentile, low above the 20th through the 40th percentile, moderate above the 40th through the 60th percentile, high above the 60th through the 80th percentile, and very high above the 80th percentile. The resulting cut-off values were 0.1263, 0.1698, 0.2032, and 0.2395, respectively.

The complete analytical procedure is summarized in Figure 1. The sequence begins with the acquisition of official secondary data, followed by screening and harmonization, indicator structuring, normalization, entropy weighting, composite-index construction, and statistical and spatial analyses.



Source: Authors' research framework

Figure 1. Analytical Workflow for the Construction and Analysis of the Digital-Education Vulnerability Index (DEVI)

Descriptive statistics were calculated for the original indicators and the three composite indices, including mean, median, standard deviation, minimum, maximum, interquartile range, and coefficient of variation. These statistics were used to identify the magnitude and distribution of interprovincial disparities before the inferential and spatial analyses.

The relationship between digital and educational vulnerability was evaluated using both Pearson correlation and Spearman rank correlation. Reporting both statistics allowed the analysis to distinguish linear association from rank-order concordance. All inferential tests used a two-sided significance threshold of $\alpha = 0.05$, and the ecological design precludes interpreting province-level associations as individual-level causal effects.

Spatial dependence in DEVI was evaluated with Global Moran's I using a row-standardized four-nearest-neighbor ($k=4$) spatial-weights matrix constructed from representative provincial geographic locations under the current 38-province structure. A k -nearest-neighbor specification was selected because a pure land-contiguity matrix would produce isolated observations in an archipelagic country. Statistical significance was assessed with 9,999 random permutations, with the null expectation defined as $-1/(n-1)$.

Local Moran's I (LISA) was calculated using the same row-standardized $k=4$ matrix. Local significance was evaluated with 9,999 conditional permutations at $\alpha = 0.05$. Significant observations were classified as High-High, Low-Low, High-Low, or Low-High according to the sign of the province's centered DEVI value and the sign of its spatial lag. The spatial specification was fixed before interpretation and applied uniformly to all provinces.

Regression analysis used EVI as the dependent variable and DVI as the explanatory variable. Ordinary Least Squares provided the baseline province-level association, and HC3 heteroskedasticity-robust standard errors were used for inference because of the small cross-sectional sample and the possibility of influential observations. With a single explanatory variable, the variance inflation factor is 1 by construction.

Regression diagnostics included the Shapiro-Wilk test of residual normality, the Breusch-Pagan test of heteroskedasticity, and Cook's distance for influence. Externally studentized residuals were examined to identify provinces whose educational vulnerability differed materially from the value predicted by their digital vulnerability. Because Highland Papua had the largest Cook's distance, the

DVI coefficient was additionally estimated after excluding that observation as an influence sensitivity check.

Weighting robustness was assessed by reconstructing DVI and EVI with equal indicator weights within each dimension while retaining the 0.5/0.5 dimensional integration rule. Rank concordance between the entropy-weight and equal-weight DEVI specifications was measured using Spearman correlation, and the maximum absolute provincial rank shift and changes in vulnerability class were recorded.

All calculations were executed in Python 3.13.5 using pandas 2.2.3, NumPy 2.3.5, SciPy 1.17.0, and statsmodels 0.14.6. Spatial weights, permutation tests, ranking, and sensitivity routines used deterministic random seeds to ensure computational reproducibility.

RESULTS AND DISCUSSION

Final Index Construction, Entropy Weights, and Provincial Classification

The final data audit retained five variables with complete, definitionally comparable 2025 observations for all 38 provinces. The digital dimension used youth cellular-phone use, computer use, and internet use from the March 2025 Susenas framework, while the educational dimension used APS for ages 16–18 and senior-secondary APM. This fixed specification replaces the earlier conditional indicator architecture and ensures that every component entering DEVI is observed under the same current provincial structure.

Entropy weighting produced substantial differentiation within the digital dimension. Cellular-phone use received a within-DVI weight of 0.5210 and internet use 0.4443, whereas computer use received 0.0346. The result reflects the entropy method's response to cross-provincial information content rather than a normative judgment about educational importance. Within EVI, senior-secondary APM received a weight of 0.5716 and APS 16–18 received 0.4284.

After the two dimensions were assigned equal contributions to DEVI, the effective weights were 0.2605 for cellular-phone use, 0.0173 for computer use, 0.2222 for internet use, 0.2142 for APS 16–18, and 0.2858 for senior-secondary APM. The equal dimensional contribution preserves the conceptual distinction between digital and educational vulnerability while allowing data-driven differentiation among indicators inside each domain.

The completed DEVI ranged from 0.0004 to 0.9441. Highland Papua recorded the highest vulnerability (0.9441), followed by Central Papua (0.8868), South Papua (0.5738), Papua (0.3105), West Papua (0.2956), and Southwest Papua (0.2711). The lowest scores occurred in DI Yogyakarta (0.0004), Bali (0.0320), Riau Islands (0.0403), East Kalimantan (0.0780), and DKI Jakarta (0.0827). The magnitude of the upper tail confirms that the strongest territorial disadvantage is not a marginal deviation around the national center but a pronounced concentration in parts of eastern Indonesia.

The quintile classification generated fixed empirical cut-offs at 0.1263, 0.1698, 0.2032, and 0.2395. Eight provinces were classified as very high vulnerability and eight as very low, with the remaining provinces distributed across high, moderate, and low categories. West Kalimantan and North Sulawesi entered the very-high group despite comparatively modest DVI values because their EVI scores were substantially higher, illustrating that the integrated index does not collapse educational disadvantage into a proxy for connectivity.

The dimensional scores also expose meaningful differences beneath the combined ranking. Central Papua had the highest EVI (1.0000), while Highland Papua had the highest DVI (1.0000) and an EVI of 0.8882. West Kalimantan combined a low DVI of 0.0607 with a much higher EVI of 0.4732, whereas DI Yogyakarta combined near-zero digital vulnerability (0.0008) with the minimum EVI. These contrasts support the use of separate DVI and EVI components before integration.

Table 2 reports the final operational architecture and the weights actually used in the completed index. The effective DEVI weights sum to 1 and preserve an exact 0.5 contribution from each dimension.

The fixed architecture makes the empirical interpretation transparent: entropy weighting determines the relative influence of indicators only within each dimension, while the integration rule determines the relative influence of the two substantive domains. This separation is central to the conceptual purpose of DEVI because it prevents the number of indicators in a domain from determining its total contribution.

Table 2. Final Operational Architecture and Entropy Weights of DEVI

Code	Dimension	Indicator	Year	Direction	Within-dimension EWM weight	Effective DEVI weight
D1	Digital	Youth cellular-phone use	2025	Reversed	0.5210	0.2605
D2	Digital	Youth computer use	2025	Reversed	0.0346	0.0173
D3	Digital	Youth internet use	2025	Reversed	0.4443	0.2222
E1	Educational	School Participation Rate (APS), age 16-18	2025	Reversed	0.4284	0.2142
E2	Educational	Net Enrolment Rate (APM), senior- secondary	2025	Reversed	0.5716	0.2858

The digital entropy weights are strongly shaped by the exceptional deficits in mobile and internet use observed in several Papuan provinces. Computer use remains substantively important for interpreting the quality and diversity of digital access, but its normalized provincial distribution contains less entropy-based discriminatory information and therefore receives a smaller weight. This feature demonstrates why the entropy specification must be evaluated against an alternative weighting rule rather than interpreted as an intrinsic measure of policy importance.

The educational weights are more balanced. Senior-secondary APM contributes 57.16% of EVI and APS 16–18 contributes 42.84%, reflecting complementary variation in age-appropriate enrolment and continued educational participation. The highest EVI scores occur in Central Papua (1.0000), Highland Papua (0.8882), and South Papua (0.6702), while DI Yogyakarta (0.0000) and Bali (0.0523) occupy the lowest end of the educational-vulnerability distribution.

The completed dimensional scores therefore show both cumulative and asymmetric vulnerability. The Papuan provinces dominate the upper tail because substantial digital and educational disadvantages often coincide, but the positions of West Kalimantan, North Sulawesi, and several Kalimantan and Sulawesi provinces demonstrate that educational participation can remain comparatively weak even where basic digital access is less constrained.

Interprovincial Educational Participation Vulnerability

The first substantive evidence of educational vulnerability emerges from the School Participation Rate (APS) among the population aged 16–18 years. In 2025, the official national APS for this age group stood at 77.86%, indicating that slightly more than one-fifth of the corresponding age population was no longer participating in formal education. More importantly, the provincial distribution reveals substantially greater heterogeneity than the national aggregate suggests. Across the 38 provinces, APS ranged from 44.61% to 93.03%, producing a 48.42-percentage-point difference between the lowest- and highest-performing provinces. This magnitude of dispersion supports the proposition that educational participation in Indonesia cannot adequately be interpreted through national averages alone, particularly in a geographically extensive and socioeconomically differentiated education system (Wirandana & Khoirunurrofik, 2024).

A simple, equally weighted calculation across the 38 provincial observations yields a mean APS of 76.75%, a median of 77.35%, and a standard deviation of 8.95 percentage points. The resulting coefficient of variation is approximately 11.66%, demonstrating a non-trivial degree of interprovincial dispersion in upper-secondary-age participation. The unweighted provincial mean is slightly lower than the official national estimate of 77.86% because the two statistics answer different questions: the former assigns identical analytical importance to every province, whereas the official national estimate reflects the national survey population structure. This distinction is particularly important for the DEVI framework because the purpose of the index is not to reproduce the national demographic average but to identify territorial units experiencing comparatively high vulnerability.

The upper end of the distribution is dominated by a relatively small group of provinces. DI Yogyakarta recorded the highest APS among 16–18-year-olds at 93.03%, followed by Bali at 90.68%, Kepulauan Riau at 88.24%, DKI Jakarta at 88.22%, and West Sumatra at 85.04%. East Kalimantan also

recorded a comparatively strong value of 84.15%, while North Kalimantan reached 81.93%. These figures demonstrate that high educational participation is not confined exclusively to Java, although several of the strongest-performing jurisdictions possess relatively favorable combinations of educational infrastructure, urban accessibility, institutional density, or longstanding educational participation. The pattern is consistent with spatial-inequality research showing that educational opportunities frequently concentrate in territories with comparatively strong institutional and socioeconomic resources (Jiang et al., 2022; Zahl-Thanem & Rye, 2024).

A markedly different pattern appears at the lower end of the distribution. Central Papua recorded an APS of only 44.61%, followed by Highland Papua at 50.79% and South Papua at 66.97%; Central Kalimantan and West Kalimantan recorded 70.76% and 70.95%, respectively. North Sulawesi stood at 71.45%, Gorontalo at 72.00%, and West Sulawesi at 73.22%. Particularly striking is the separation of Central Papua and Highland Papua from the central portion of the provincial distribution, suggesting that educational vulnerability in these territories is not simply a modest deviation from the national pattern but represents a substantially different participation environment. Similar geographically concentrated disadvantage has been documented in spatial education studies elsewhere, in which peripheral location, accessibility constraints, and uneven resource distribution generate persistent territorial gaps (Delprato et al., 2024; Sajjad et al., 2022).

Table 3. Selected Provincial Extremes in School Participation among the Population Aged 16–18 Years, 2025

Position	Province	APS 16–18 (%)	Difference from national APS (percentage points)
1	DI Yogyakarta	93.03	+15.17
2	Bali	90.68	+12.82
3	Kepulauan Riau	88.24	+10.38
4	DKI Jakarta	88.22	+10.36
5	West Sumatra	85.04	+7.18
—	Indonesia	77.86	0.00
34	Central Kalimantan	70.76	−7.10
35	West Kalimantan	70.95	−6.91
36	South Papua	66.97	−10.89
37	Highland Papua	50.79	−27.07
38	Central Papua	44.61	−33.25

Source: Authors' calculations based on Statistics Indonesia, National Socioeconomic Survey (Susenas), March 2025. Provincial APS values are reported by BPS; differences from the national rate are calculated by the authors.

The contrast displayed in Table 3 has substantial implications for the construction of Educational Vulnerability Index. If participation were represented exclusively by the national figure, the extreme disadvantage observed in Central Papua and Highland Papua would effectively disappear from the analytical narrative. Central Papua's APS was 33.25 percentage points below the national estimate, while Highland Papua was 27.07 points below it. Conversely, DI Yogyakarta exceeded the national rate by 15.17 points. The resulting asymmetry illustrates why the present study treats provinces as substantive territorial units rather than as interchangeable observations nested within a national education system.

The decline becomes even clearer when participation is examined through the Net Enrolment Rate (APM), which applies a stricter criterion by identifying whether students of the corresponding age are enrolled at the educational level appropriate to that age. Nationally, the APM for senior secondary education (SMA/SMK or equivalent) was only 67.44% in 2025, substantially below participation at earlier educational levels. The same data reveal an urban APM of 69.84% compared with 63.83% in rural areas, amounting to an urban–rural difference of 6.01 percentage points. This spatially structured disparity reinforces the argument that educational vulnerability is partly territorial and that geographic accessibility remains relevant even after substantial expansion of the Indonesian education system.

Socioeconomic differentiation is even more pronounced. The senior-secondary APM among individuals in the highest expenditure quintile reached 70.63%, whereas the corresponding rate among the lowest expenditure quintile was 59.54%, producing a gap of 11.09 percentage points. Female participation at the appropriate secondary level was 68.66%, compared with 66.24% among males, while the overall rate remained 67.44%. These figures indicate that provincial education outcomes represent the territorial aggregation of multiple forms of inequality rather than geography alone. This interpretation accords with the broader literature demonstrating that socioeconomic resources condition access to educational and digital opportunities and may generate cumulative rather than isolated disadvantages (Mascheroni et al., 2022; Ren et al., 2022).

Provincial APM values provide further evidence that high general participation does not necessarily translate perfectly into age-appropriate progression. DI Yogyakarta recorded an APM for senior-secondary education of 78.42%, while Kepulauan Riau reached 76.54%, Bali 76.06%, East Kalimantan 73.96%, and North Kalimantan 73.13%. Aceh, North Sumatra, West Sumatra, East Java, and West Nusa Tenggara recorded values around or above 70%, whereas several other provinces remained substantially lower. The divergence between APS and APM therefore captures a conceptually important distinction: young people may remain attached to the education system but not necessarily progress through educational levels according to the conventional age structure. Including both variables in the EVI consequently contributes information that would be lost if participation were measured using only a single enrolment statistic.

The extreme values also caution against interpreting educational vulnerability purely through a Java-versus-non-Java dichotomy. Bali and Kepulauan Riau perform strongly, while East Kalimantan and North Kalimantan exhibit relatively favorable upper-secondary participation outcomes. Conversely, several provinces outside the easternmost Indonesian regions also record participation below the national benchmark, including West Kalimantan, Central Kalimantan, North Sulawesi, and West Sulawesi. Such variation suggests that geographical disadvantage is multidimensional and cannot be reduced to physical distance from the national capital. Educational infrastructure, settlement patterns, household resources, fiscal capacity, labor-market incentives, and institutional effectiveness can jointly influence whether adolescents remain in school (Wirandana & Khoirunurrofik, 2024).

The Papua-region results nevertheless warrant particular analytical attention because the magnitude of their disadvantage differs qualitatively from ordinary provincial variation. Central Papua and Highland Papua occupy the two lowest positions in APS 16–18, while South Papua also remains substantially below the national figure. These outcomes are consistent with a spatial-vulnerability framework in which disadvantages can become geographically concentrated rather than randomly distributed across administrative units. Comparable studies have shown that educational inequalities exhibit spatial clustering and can be reinforced by neighboring territorial conditions and resource structures (Delprato et al., 2024; Sajjad et al., 2022). The integrated spatial analysis tests this pattern formally through Global Moran's I and Local Moran's I rather than inferring spatial concentration solely from the apparent geographical grouping of low participation values.

Educational participation also has important implications for the digital dimension of the study. Unequal connectivity may contribute to educational disadvantage, but the relationship should not be assumed to be deterministic. Studies have found that broadband availability and internet access can improve educational opportunities and performance, while also showing that benefits depend on socioeconomic resources, modes of use, institutional capacity, and the quality of digital engagement (Caldarulo et al., 2023; Cambini et al., 2024; Korkmaz et al., 2022). Consequently, a province with comparatively high internet penetration may still display weak APS or APM, while a province with more limited digital infrastructure may exhibit relatively resilient educational participation. Identifying precisely these mismatches constitutes one of the principal advantages of maintaining separate DVI and EVI measures before constructing the integrated DEVI.

The 2025 participation results are incorporated directly into the completed EVI. Central Papua records the maximum EVI of 1.0000, followed by Highland Papua at 0.8882 and South Papua at 0.6702. West Kalimantan also records a comparatively high EVI of 0.4732 despite a much lower DVI of 0.0607, demonstrating that weak educational participation is not confined

to provinces with extreme digital exclusion. Conversely, DI Yogyakarta and Bali combine strong participation with low educational vulnerability. These results confirm that APS and APM capture related but non-identical aspects of upper-secondary participation and that their weighted combination produces a differentiated educational-vulnerability profile.

Digital Vulnerability and the Interprovincial Digital Divide

The digital dimension reveals an even sharper territorial differentiation once connectivity is examined beyond national averages. Statistics Indonesia reported that 77.63% of the population aged five years and above had used the internet during the preceding three months in 2025, confirming that internet connectivity had become widespread but was far from universal. The same official statistical framework treats internet use as actual engagement with online facilities—including information retrieval, communication, social media, and related activities—rather than merely the physical availability of a network connection. This distinction is analytically important because digital inclusion depends on realized access and use rather than infrastructure availability alone, a position consistent with contemporary digital-divide research emphasizing differences in access, usage, competence, and the capacity to derive benefits from digital technologies (Kaarakainen & Saikkonen, 2023; Mirazchiyski, 2025; Ragnedda et al., 2022).

For an education-oriented assessment of this divide, the 2025 *Indonesian Youth Statistics* provides particularly informative supplementary evidence because it reports cellular-phone use, computer use, and internet use for young people in all 38 provinces under a common Susenas framework. Nationally, 97.41% of Indonesian youth used cellular phones, 96.69% used the internet, but only 25.27% used computers. The contrast is substantial: mobile and internet access have approached saturation among young Indonesians, whereas access to computer-based digital environments remains comparatively restricted. This pattern supports the argument that the first-level digital divide is increasingly accompanied by more differentiated inequalities in the type and quality of technology available for educational purposes (Corkin et al., 2022; Pedaste et al., 2023; Wang et al., 2024).

The provincial distribution demonstrates why very high national youth connectivity should not be interpreted as the disappearance of the digital divide. An unweighted calculation across the 38 provinces produces a mean youth internet-use rate of 91.24%, substantially below the population-weighted national estimate of 96.69%. The provincial median is 97.43%, while the standard deviation reaches approximately 16.98 percentage points and the coefficient of variation is 18.61%. This unusually large difference between the median and unweighted mean is primarily generated by extremely low observations in several newly established Papuan provinces, illustrating how population-weighted national statistics can obscure severe digital exclusion in smaller territorial units. The same analytical problem underlies the need for a province-based vulnerability index: territorial disadvantage must remain visible even when it affects provinces representing a relatively small share of the national population.

At the upper end of the distribution, DI Yogyakarta recorded youth internet use of 99.48%, followed by Bali at 99.09%, Riau Islands at 98.92%, DKI Jakarta at 98.77%, and Central Java at 98.59%. Cellular-phone use was similarly extensive, reaching 99.40% in Riau Islands, 99.29% in DI Yogyakarta, 99.27% in Bali, and 99.02% in East Kalimantan. Yet these near-saturation rates should not be interpreted as proof of equivalent digital capabilities. Research increasingly shows that the educational value of connectivity depends on the device used, the intensity and purpose of technology use, digital competence, household resources, and institutional conditions rather than on binary connectivity alone (Cambini et al., 2024; Kastorff et al., 2025; Ren et al., 2022).

The most pronounced digital vulnerability occurs in the Papua region. Youth internet use stood at only 17.62% in Highland Papua, 37.10% in Central Papua, and 59.86% in South Papua, compared with the national rate of 96.69%. Papua recorded 81.95% and Southwest Papua 85.99%, while West Papua reached 86.46%. Cellular-phone use displayed the same hierarchical pattern, falling to only 27.27% in Highland Papua, 43.46% in Central Papua, and 66.36% in South Papua. These observations indicate that the digital divide is not merely a matter of moderate interprovincial variation but includes territories whose levels of connectivity remain structurally separated from the national mainstream.

Table 4. Selected Indicators of Youth Digital Access across Indonesian Provinces, 2025

Province	Cellular-phone use (%)	Computer use (%)	Internet use (%)	Digital profile
DI Yogyakarta	99.29	44.86	99.48	Very high, diversified access
DKI Jakarta	98.90	42.76	98.77	Very high, diversified access
Bali	99.27	34.00	99.09	Very high connectivity
Riau Islands	99.40	32.39	98.92	Very high connectivity
East Kalimantan	99.02	32.63	98.51	High connectivity and computer use
Indonesia	97.41	25.27	96.69	National population-weighted estimate
West Papua	88.34	12.52	86.46	Below national digital access
Southwest Papua	87.85	17.09	85.99	Below national connectivity
Papua	84.27	20.52	81.95	Substantial connectivity deficit
South Papua	66.36	15.38	59.86	High digital vulnerability
Central Papua	43.46	6.25	37.10	Very high digital vulnerability
Highland Papua	27.27	1.66	17.62	Extreme digital vulnerability

Source: Statistics Indonesia, National Socioeconomic Survey (Susenas), March 2025. The national figure is the official population-weighted estimate; provincial observations are not weighted equally in the national estimate.

The computer-use indicator is especially revealing because its provincial dispersion is considerably greater than might be inferred from mobile connectivity. Across the 38 provinces, the unweighted mean computer-use rate among youth is approximately 22.47%, with a standard deviation of 8.22 percentage points and a coefficient of variation of 36.61%. DI Yogyakarta records the highest rate at 44.86%, followed by DKI Jakarta at 42.76%, Bali at 34.00%, East Kalimantan at 32.63%, and Riau Islands at 32.39%. At the opposite end, computer use falls to 1.66% in Highland Papua and 6.25% in Central Papua, while West Papua records 12.52% and North Maluku 13.76%.

This device-based disparity is theoretically more consequential than it may initially appear. Smartphones can provide communication, multimedia content, search functions, and access to learning applications, but they do not necessarily provide an equivalent environment for complex academic production, spreadsheet analysis, coding, extended writing, statistical software, or other computer-intensive educational activities. Consequently, two provinces with similarly high internet-use rates may still differ substantially in their capacity to support advanced forms of digital learning. Research on the digital divide increasingly recognizes this distinction between connectivity and the ability to transform digital resources into educational advantage, particularly where socioeconomic differences determine device quality and patterns of use (Mascheroni et al., 2022; Ren et al., 2022; van de Werfhorst et al., 2022).

The urban–rural divide provides an additional dimension of this inequality. Among Indonesian youth in 2025, cellular-phone use reached 98.49% in urban areas compared with 95.65% in rural areas, while internet use stood at 98.13% and 94.35%, respectively. The largest disparity appeared in computer use: 31.57% of urban youth used computers compared with only 15.08% of rural youth, generating a 16.49-percentage-point gap and an urban rate more than twice the rural level. This pattern indicates that the geographic digital divide persists most strongly in access to more resource-intensive digital devices rather than in basic mobile connectivity. Such evidence is consistent with research demonstrating that rurality interacts with socioeconomic resources, institutional opportunities, and digital infrastructure to shape educational technology outcomes (Hannan & Eynon, 2025; Lin et al., 2023).

Integrated DEVI, Spatial Dependence, Regression, and Robustness

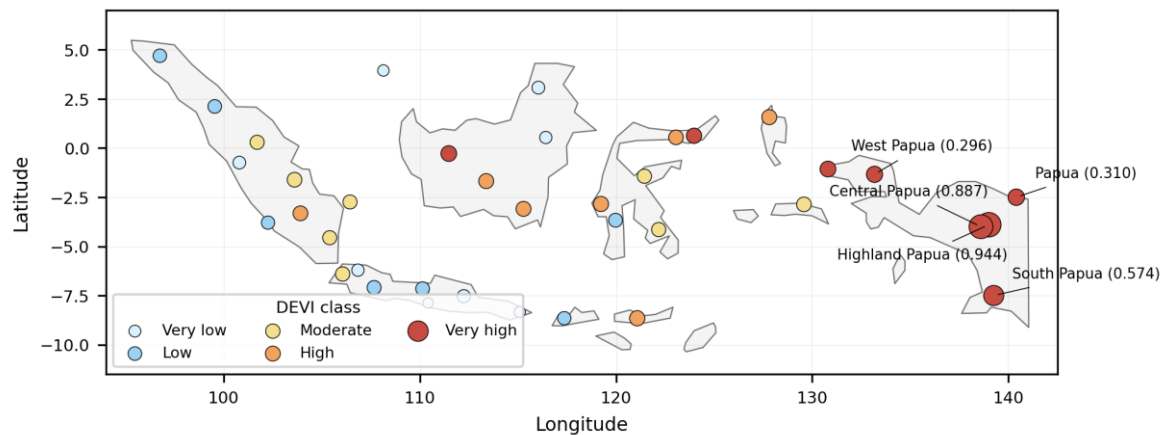
DVI and EVI were strongly and positively associated across the 38 provinces. Pearson's correlation was 0.848 ($p < 0.001$), while Spearman's rank correlation was 0.671 ($p < 0.001$), indicating that provinces with greater digital vulnerability generally also exhibit greater educational vulnerability even though the dimensional rankings are not identical. The completed DEVI ranking, reported in Table 5, places Highland Papua, Central Papua, and South Papua in the first three positions, whereas DI Yogyakarta, Bali, and Riau Islands occupy the lowest-vulnerability positions.

The baseline OLS model estimated $EVI = 0.2428 + 0.7981(DVI)$, with $R^2 = 0.719$. The DVI coefficient remained statistically significant with HC3 robust standard errors ($SE = 0.2086$, $p < 0.001$). Residual normality was not rejected by the Shapiro–Wilk test ($W = 0.9748$, $p = 0.537$), and the Breusch–Pagan test did not indicate heteroskedasticity ($LM = 0.1698$, $p = 0.680$). Externally studentized residuals identified DI Yogyakarta (-2.57), Bali (-2.04), and Highland Papua (-2.28) as notable observations with lower EVI than predicted from their DVI at the $|r| > 1.96$ diagnostic threshold. Highland Papua was influential (Cook's $D = 2.660$), but excluding it increased the DVI coefficient to 0.9848 (HC3 $SE = 0.0576$, $p < 0.001$; $R^2 = 0.682$), confirming that the positive province-level association was not dependent on that single observation.

DEVI also exhibited significant spatial dependence. Global Moran's I was 0.5451 compared with a null expectation of -0.0270 , and the 9,999-permutation test yielded $p = 0.0001$. Local Moran analysis identified statistically significant High–High concentrations in West Papua ($p = 0.0365$), Papua ($p = 0.0001$), South Papua ($p = 0.0001$), Central Papua ($p = 0.0001$), and Highland Papua ($p = 0.0001$). Southwest Papua also had a positive High–High configuration, but its local statistic was not significant at $\alpha = 0.05$. No additional local configuration reached the 5% threshold. The pattern indicates that the highest integrated vulnerability is geographically concentrated rather than randomly distributed.

The equal-weight sensitivity analysis produced nearly the same territorial ordering. Spearman rank concordance between the entropy-weight and equal-weight DEVI rankings was 0.989 ($p < 0.001$), and the largest absolute rank change was four positions. Thirty-six of 38 provinces retained the same quintile vulnerability class; only Jambi and South Kalimantan moved by one adjacent class. The upper and lower extremes were unchanged, showing that the principal territorial conclusions are robust to the alternative weighting rule even though entropy weighting changes the relative influence of individual indicators.

Figure 2. Spatial Distribution of Provincial Digital–Education Vulnerability Index (DEVI), 2025



Source: Authors' calculations from 2025 BPS provincial data. Points show the representative provincial locations used for the $k=4$ spatial-weights matrix; symbol class indicates DEVI quintile classification.

Table 5. Complete Provincial DVI, EVI, DEVI Ranking and Vulnerability Class, 2025

Province	DVI	EVI	DEVI	Rank	Class
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Highland Papua	1.0000	0.8882	0.9441	1	Very High
Central Papua	0.7736	1.0000	0.8868	2	Very High
South Papua	0.4774	0.6702	0.5738	3	Very High
Papua	0.2240	0.3970	0.3105	4	Very High
West Papua	0.1765	0.4146	0.2956	5	Very High
Southwest Papua	0.1789	0.3633	0.2711	6	Very High
West Kalimantan	0.0607	0.4732	0.2670	7	Very High
North Sulawesi	0.0610	0.4199	0.2405	8	Very High
East Nusa Tenggara	0.1235	0.3523	0.2379	9	High
West Sulawesi	0.0517	0.4092	0.2305	10	High
North Maluku	0.1117	0.3335	0.2226	11	High
Central Kalimantan	0.0427	0.3987	0.2207	12	High
South Kalimantan	0.0290	0.4070	0.2180	13	High
South Sumatra	0.0433	0.3750	0.2092	14	High
Gorontalo	0.0390	0.3701	0.2046	15	High
Jambi	0.0356	0.3700	0.2028	16	Moderate
Maluku	0.1044	0.3012	0.2028	17	Moderate
Banten	0.0276	0.3451	0.1864	18	Moderate
Central Sulawesi	0.0745	0.2863	0.1804	19	Moderate
Southeast Sulawesi	0.0324	0.3207	0.1765	20	Moderate
Riau	0.0352	0.3143	0.1747	21	Moderate
Bangka Belitung Islands	0.0255	0.3170	0.1712	22	Moderate
Lampung	0.0364	0.3059	0.1711	23	Moderate
West Java	0.0281	0.3004	0.1643	24	Low
South Sulawesi	0.0314	0.2889	0.1601	25	Low
Central Java	0.0270	0.2748	0.1509	26	Low
North Sumatra	0.0485	0.2443	0.1464	27	Low
Aceh	0.0645	0.2145	0.1395	28	Low
Bengkulu	0.0329	0.2325	0.1327	29	Low
West Nusa Tenggara	0.0363	0.2289	0.1326	30	Low
East Java	0.0335	0.2106	0.1221	31	Very Low
North Kalimantan	0.0393	0.1688	0.1041	32	Very Low
West Sumatra	0.0342	0.1621	0.0982	33	Very Low
DKI Jakarta	0.0091	0.1563	0.0827	34	Very Low
East Kalimantan	0.0178	0.1381	0.0780	35	Very Low
Riau Islands	0.0130	0.0675	0.0403	36	Very Low
Bali	0.0118	0.0523	0.0320	37	Very Low
DI Yogyakarta	0.0008	0.0000	0.0004	38	Very Low

Source: Authors' calculations based on Statistics Indonesia, Susenas March 2025. Higher index scores denote greater vulnerability.

Table 6. Statistical, Spatial, and Sensitivity Results

Analysis	Result
Pearson correlation, DVI–EVI	$r = 0.8482$; $p < 0.001$
Spearman correlation, DVI–EVI	$\rho = 0.6709$; $p < 0.001$
OLS: EVI on DVI	$b = 0.7981$; HC3 SE = 0.2086; $p < 0.001$; $R^2 = 0.719$
Residual diagnostics	Shapiro–Wilk $W = 0.9748$ ($p = 0.537$); Breusch–Pagan LM = 0.1698 ($p = 0.680$)
Influence sensitivity	Max Cook's D = 2.660 (Highland Papua); leave-one-out $b = 0.9848$, HC3 SE = 0.0576, $p < 0.001$
Global spatial autocorrelation	Moran's I = 0.5451; $E[I] = -0.0270$; permutation $p = 0.0001$
Significant LISA High–High provinces	West Papua; Papua; South Papua; Central Papua; Highland Papua
Weighting sensitivity	Entropy vs equal-weight rank $\rho = 0.9895$; $p < 0.001$; maximum rank shift = 4
Class stability	36 of 38 provinces unchanged; Jambi and South Kalimantan moved one adjacent class

Source: Authors' calculations. Spatial p-values use 9,999 permutations and the row-standardized $k=4$ nearest-neighbor matrix.

CONCLUSION

The completed DEVI demonstrates that digital and educational vulnerability across Indonesian provinces is jointly structured but strongly uneven. Highland Papua, Central Papua, and South Papua record the highest integrated vulnerability, while DI Yogyakarta, Bali, and Riau Islands occupy the lowest end of the distribution. Digital and educational vulnerability are positively associated, yet the dimensional profiles are not interchangeable: West Kalimantan and North Sulawesi reach the very-high DEVI class primarily because educational vulnerability remains elevated despite relatively modest digital vulnerability, while several stronger provinces combine low values in both dimensions. Spatial analysis confirms that the upper tail is geographically concentrated, with significant High–High LISA patterns in West Papua, Papua, South Papua, Central Papua, and Highland Papua. The regression results further show a strong province-level association between DVI and EVI without supporting an individual-level or causal interpretation.

The index therefore supports differentiated territorial policy rather than a uniform connectivity strategy. Provinces in the significant Papuan High–High cluster require simultaneous attention to basic digital access, usable devices, and upper-secondary participation, whereas provinces with comparatively low DVI but elevated EVI require stronger emphasis on enrolment persistence and age-appropriate participation rather than connectivity expansion alone. The near-identical entropy-weight and equal-weight rankings indicate that these broad priorities are not artifacts of a single weighting rule. The study remains bounded by its cross-sectional ecological design and by the deliberately restricted five-indicator core required for fully comparable 2025 coverage; DEVI should consequently be interpreted as a reproducible provincial vulnerability instrument rather than a causal measure of educational performance. Within those limits, the completed weighting, ranking, spatial, regression, and sensitivity results provide a coherent empirical basis for identifying where digital and educational disadvantages coincide and where they diverge.

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