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Mapping Inclusive Education Support Priorities in Indonesia: A Public Data-Driven Spatial Decision Analytics Framework

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Mapping inclusive education support priorities in Indonesia: A public data-driven spatial decision analytics framework

Abstract

Geographic disparities in specialized educational support can remain obscured when student-demand, school-resource, and digital-readiness statistics are reported separately. This study develops a transparent spatial decision analytics framework for identifying priority areas for inclusive education support planning in Indonesia. Public administrative and statistical datasets are harmonized for 38 provinces and 514 districts/cities. An Inclusive Education Support Priority Index (IESPI) combines recorded demand pressure, special-school service availability, school-capacity constraints, and regional digital-readiness gaps. Provincial rankings and choropleth maps are complemented by component profiles, alternative weighting scenarios, spatial autocorrelation diagnostics, and provenance-specific robustness checks. The baseline index varies substantially across provinces; alternative weighting schemes yield Spearman rank correlations of 0.905–0.940. A four-nearest-neighbor Global Moran's I of 0.298 ($p = 0.0045$, 9,999 permutations) indicates positive geographic association under the specified proximity definition, although the magnitude varies with neighborhood specification and influential provinces. The index is a screening indicator, not a direct measure of inclusive education quality, specialist service effectiveness, or individual assistive technology need. The framework illustrates how fragmented public data can support geographically differentiated planning while making measurement gaps, administrative boundary changes, and ranking uncertainty explicit.

Keywords: spatial inequality; public-service accessibility; inclusive education; composite indicator; regional prioritization; spatial autocorrelation

1 Introduction

Inclusive education is a public-policy problem as much as an educational or technological one. It requires governments to coordinate student identification, school placement,

teacher and support-staff capacity, accessibility, specialist services, assistive technology assessment, family engagement, and resource allocation across highly uneven territories. The United Nations Convention on the Rights of Persons with Disabilities frames inclusive education as a right, while the global assistive technology agenda emphasizes that products, services, and systems must be planned as part of wider support ecosystems rather than as isolated procurement activities (UNESCO 2020; United Nations 2006; World Health Organization and UNICEF 2022). Yet many education systems do not have integrated data infrastructures that connect recorded student demand, specialist support capacity, school resources, and digital readiness.

Indonesia is a useful case for examining this problem because it combines a large and geographically dispersed education system with increasing availability of public administrative data. Public sources report students with special educational needs and disabilities, special-school services, school-resource indicators, information and communication technology (ICT) readiness, and geospatial boundaries. These datasets are valuable, but they are usually published separately. As a result, planners may know where students are recorded, where special-school services exist, or which provinces have lower digital readiness, but still lack an integrated evidence workflow for determining where further validation and support planning should begin.

A central spatial-policy challenge is that recorded demand and provision do not necessarily coincide geographically. A province-level count alone does not reveal whether recorded demand, specialist services, and school resources are aligned across territories; a map alone does not establish a spatial relationship. Applied spatial analysis therefore requires both explicit geographic units and diagnostic tests of spatial association, while avoiding inference that provincial averages represent within-province access or individual outcomes (Fotheringham and Wong 1991; Guagliardo 2004; McLafferty 2003; Pham 2026). Transparent administrative-data integration remains necessary because inconsistencies in provenance, temporal coverage, and measurement can influence apparent territorial differences (Asensio et al. 2025; Hawn Nelson et al. 2024). The available Indonesian datasets do not measure actual assistive technology ownership, product-level need, individual functioning, or service-delivery quality. Accordingly, assistive technology is treated here as a downstream planning domain rather than as the quantity directly measured by the index.

This study develops an Inclusive Education Support Priority Index (IESPI) that combines four policy-relevant layers: demand pressure, special-service availability gap, school-capacity gap, and digital-readiness gap. The index is explicitly a proxy screening tool. It does not measure inclusive education quality, legal compliance, disability prevalence, or student-level need. Rather, it identifies provinces where public data suggest a mismatch between recorded demand and support conditions, and where field validation, school-level

audit, stakeholder consultation, and future assistive technology needs assessment should be prioritized.

The study makes four contributions. First, it demonstrates how fragmented public administrative, statistical, digital-readiness, and geospatial datasets can be transformed into a single decision-support workflow for policy prioritization. Second, it clarifies how special-school data can be used cautiously as a proxy for specialized support capacity without equating special schools with the full inclusive education system. Third, it characterizes territorial variation across 38 Indonesian provinces, using district/city counts as a supporting within-country demand-distribution layer and formally evaluating geographic association using a proximity-based Moran's I diagnostic. Fourth, it tests both weighting uncertainty and source-specific ICT imputation choices, distinguishing stable priority signals from rankings dependent on analytical assumptions.

The study is guided by the following research questions:

1. How are recorded students with special educational needs and disabilities distributed across Indonesian provinces and districts/cities?
2. Which provinces show the largest mismatch between recorded student demand and specialized educational support availability?
3. How do school capacity and digital readiness modify provincial support-priority patterns?
4. Do high IESPI values exhibit geographic association under alternative proximity-neighbor definitions, or is the observed variation primarily province-specific?
5. How stable are geographic priority patterns to alternative index weights and inherited ICT values for newly created provinces?

2 Geographic and institutional context

2.1 Inclusive education as a system-level readiness problem

Inclusive education is not achieved merely by placing students with disabilities in mainstream or formal educational settings. It requires coordinated changes in pedagogy, teacher preparation, school leadership, resource allocation, accessibility, and support services. Prior work emphasizes inclusion as a system-level transformation concerned with participation and equity (Ainscow 2020; Florian 2014; Haug 2017; Nilholm and G"oransson 2017). Teacher readiness, school capacity, institutional support, and classroom implementation remain central determinants of whether inclusive education can

function in practice (Avramidis and Norwich 2002; de Boer et al. 2011; Forlin and Chambers 2011; Sharma et al. 2012; Waitoller and Artiles 2013).

Evidence on inclusive education outcomes is also context-sensitive. Reviews and meta-analyses indicate that inclusive settings can benefit students with and without special educational needs, but such effects depend on classroom support, teacher preparation, peer context, learning adaptation, and school organization (Lindsay 2007; Ruijs and Peetsma 2009; Szumski et al. 2017). This implies that readiness mapping should not be limited to counting schools or students. It should also consider whether the system has sufficient capacity to support access, participation, and learning.

2.2 Indonesian inclusive education and special-school provision

In Indonesia, educational provision for students with disabilities and special educational needs includes both special-school provision and inclusive placement in regular schools. Special schools, known as *Sekolah Luar Biasa* (SLB), are specifically organized to support students with disabilities and special educational needs. The service tiers used in the administrative data include TKLB, SDLB, SMPLB, and SMLB, corresponding respectively to special-school provision at kindergarten, primary, lower-secondary, and upper-secondary levels (Kementerian Pendidikan Dasar dan Menengah 2025, 2026b).

This distinction is important for interpretation. SLB provision is not the whole inclusive education system. Inclusive education also includes regular or mainstream schools that serve students with special educational needs and disabilities. Therefore, a province with no recorded SLB service in the dataset should not be interpreted as having no disability-related educational support of any kind. In this study, SLB service availability is used as a proxy for specialized educational support capacity. The broader inclusive education ecosystem may include regular schools, designated inclusive schools, special schools, local education offices, teachers, families, community services, and cross-sectoral disability-support arrangements. The IESPI therefore identifies where recorded demand and support conditions appear misaligned; it does not measure the full quality or inclusiveness of provincial education systems.

2.3 Assistive technology as a downstream planning domain

Assistive technology is understood broadly as products, systems, and related services that maintain or improve functioning, participation, and learning for students with disabilities. This includes mobility products, vision-related products, hearing-related products, communication supports, cognitive and learning supports, accessible digital technologies, and associated services such as assessment, fitting, maintenance, user training, and follow-up

(Alper and Raharinirina 2006; de Witte et al. 2018; World Health Organization and UNICEF 2022). In education, assistive technology should not be treated as a standalone device-procurement issue. Its effectiveness depends on the fit between student needs, school capacity, teacher knowledge, family support, infrastructure, and service continuity (Bouck 2016; Fuhrer et al. 2003; Okolo and Diedrich 2014; Scherer et al. 2005).

The public datasets used in this study do not record assistive product ownership, product-level need, or individual-level functional assessment. For this reason, the IESPI should not be interpreted as a direct assistive technology needs index. Instead, it indicates where future assistive technology needs assessment may be more urgent. A future extension could map disability-type or functional-disability data to broad product domains, such as the WHO Priority Assistive Products List (World Health Organization 2016), but such mapping would remain a planning heuristic rather than an individual-level prescription.

2.4 Spatial prioritization using administrative data

Administrative data can support public-service planning when they are transformed into interpretable evidence, but they also create risks when used without attention to coverage, meaning, bias, institutional context, and the governance of data integration (Attard et al. 2015; boyd and Crawford 2012; Hawn Nelson et al. 2024; Janssen et al. 2012; Kitchin 2014). Data-policy research increasingly treats public and administrative data not as neutral inputs but as components of socio-technical systems in which provenance, interoperability, organizational capability, and interpretation shape what analytics can legitimately support (Asensio et al. 2025; van den Berg et al. 2025; Verhulst et al. 2019). Open government data are valuable for transparency and reuse, but their policy value depends on whether users can interpret the data-generating process, the population covered, and the limits of the indicators. In disability and inclusive education, these concerns are especially important because administrative categories are not equivalent to clinical assessment, functional need, or lived experience (Mitra 2006; World Health Organization and UNICEF 2022).

Spatial decision analytics can make fragmented data more actionable by connecting social demand, service capacity, and geographic location. Prior work on spatial access to services shows that service counts alone are insufficient; access depends on the distribution of need, service locations, distance, capacity, and aggregation choices (Apparicio et al. 2008; Delamater 2013; Fotheringham and Wong 1991; Guagliardo 2004; Higgs 2004; Luo and Wang 2003; McLafferty 2003; Neutens 2015; Pham 2026). Composite indicators can support communication and prioritization, but their construction requires transparency about normalization, weighting, and robustness (Becker et al. 2017; Greco et al. 2019; OECD and European Commission Joint Research Centre 2008; Paruolo et al. 2013;

Saisana et al. 2005; Saltelli 2007). This study builds on those principles by presenting the IESPI as a transparent proxy indicator, not as a definitive measurement of inclusion or disability support.

3 Data and study design

3.1 Study area and unit of analysis

The study covers 38 provinces in Indonesia and 514 districts/cities. The main composite index is constructed at provincial level because the key service-capacity, school-resource, ICT-readiness, and geospatial indicators are consistently available at that level. District/city records are used to describe local demand concentration within provinces but are not used directly in the provincial composite index. This choice prioritizes consistency and reproducibility over finer spatial resolution.

3.2 Data sources and temporal alignment

The study uses six categories of public data, summarized in Table 1. The education reference datasets are 2026 administrative snapshots; Special School Statistics refer to the 2024–2025 school year; the ICT Development Index represents 2024; and the Long Form Population Census provides 2020 disability context. The analytical index therefore constitutes a cross-source harmonized planning snapshot rather than a same-year panel. Long Form Population Census indicators are used only for national contextual interpretation and do not enter the IESPI calculation (Badan Pusat Statistik 2023, 2025; Kementerian Pendidikan Dasar dan Menengah 2025, 2026a, b).

3.3 Coverage, measurement boundaries, and interpretive limits

After harmonization, the analytical dataset contains 38 provincial observations, 514 district/city observations, 38 provincial geospatial features, 38 ICT-index observations, and 38 province-level records derived from the Special School Statistics publication. Non-domestic records such as *Luar Negeri* were excluded from the domestic spatial analysis. Province-name harmonization was conducted to align administrative datasets and the GeoJSON layer.

The student-demand layer is based on national education reference data on students recorded as having special educational needs or disabilities. The dataset is treated as an administrative record of recorded demand, not as a clinical prevalence estimate. The public data used in this study do not provide individual placement histories, detailed

Table 1: Administrative and statistical sources used for the 38-province analysis.

Source	Period	Content and analytical role	Coverage
Education reference: student records	2026 snapshot	Recorded disability/special-education students, valid enrollment and multiple-disability share; demand layer	Province; district/city
Education reference: SLB service tiers	2026 snapshot	TKLB, SDLB, SMPLB and SMLB service-unit counts; specialized-service gap	Province
Special School Statistics	2024/25	Schools, staff counts, classrooms, internet, learning computers and accreditation; capacity gap	Province
ICT Development Index	2024	Overall index, access and usage subindices used for digital gap; skill subindex descriptive	Province
Provincial boundary GeoJSON	38-province frame	Boundary geometry for maps and proximity diagnostics; not a substantive index input	Province
Long Form Population Census	2020	National disability and population context; *excluded from IESPI*	National

Note. SLB denotes *Sekolah Luar Biasa* (special schools). TKLB, SDLB, SMPLB and SMLB denote kindergarten, primary, lower-secondary and upper-secondary special-school tiers. Source periods differ and should not be interpreted as a single-year observation.

functional assessment, assistive product needs, or systematic data on support pathways in mainstream schools. Consequently, the study does not assume that all recorded students are enrolled in SLB, and it does not claim to fully capture all students with disabilities in mainstream schools. This boundary is important because the purpose of the index is to screen for potential priority areas, not to replace local assessment.

3.4 Data harmonization, missing values, and provenance

Province names were standardized before joins across education, ICT, school-statistics, and geospatial sources. Non-domestic records such as *Luar Negeri* were excluded. Continuous pressure indicators with long right tails were winsorized at the 5th and 95th percentiles before min–max normalization. For continuous indicators with missing values, the provincial median was imputed before normalization; binary absence flags were retained as observed 0/1 values. Indicators representing favorable readiness were reverse-normalized so that larger values consistently represent larger planning gaps.

The bundled replication materials enable complete numerical reproduction of the index and the analyses reported here from the harmonized, processed provincial dataset, including rank-sensitivity and proximity-based spatial tests. In contrast, *end-to-end re-extraction* from the original administrative ZIP/PDF files requires separately obtained

source documents, whose public portal locations and expected input filenames are documented in the replication README. This distinction is material because PDF table extraction and the interpretation of administrative nulls may not be stable across source revisions.

A specific provenance issue arises for the 2024 ICT Development Index. The published appendix uses pre-split Papua groupings and does not separately report all newly formed Papua provinces. To maintain the 38-province analytical frame, the 2024 values for Papua were inherited by Papua Selatan, Papua Tengah, and Papua Pegunungan, while Papua Barat values were inherited by Papua Barat Daya. These records were explicitly flagged in the analytical dataset. Because this assumption can affect spatial rankings, a dedicated robustness analysis replaces inherited digital-readiness values with the median value among directly observed provinces and, separately, recomputes rankings without the digital-readiness layer.

4 Spatial decision analytics and index construction

4.1 Analytical overview

The framework links public data acquisition, extraction and harmonization with feature engineering, index construction, spatial visualization, spatial autocorrelation diagnostics, and uncertainty assessment. Figure 1 shows the workflow. The four analytical layers are designed to represent distinct policy questions: where recorded student demand is concentrated, where specialized support availability appears limited, where recorded school capacity is strained, and where digital readiness may constrain technology-enabled support.

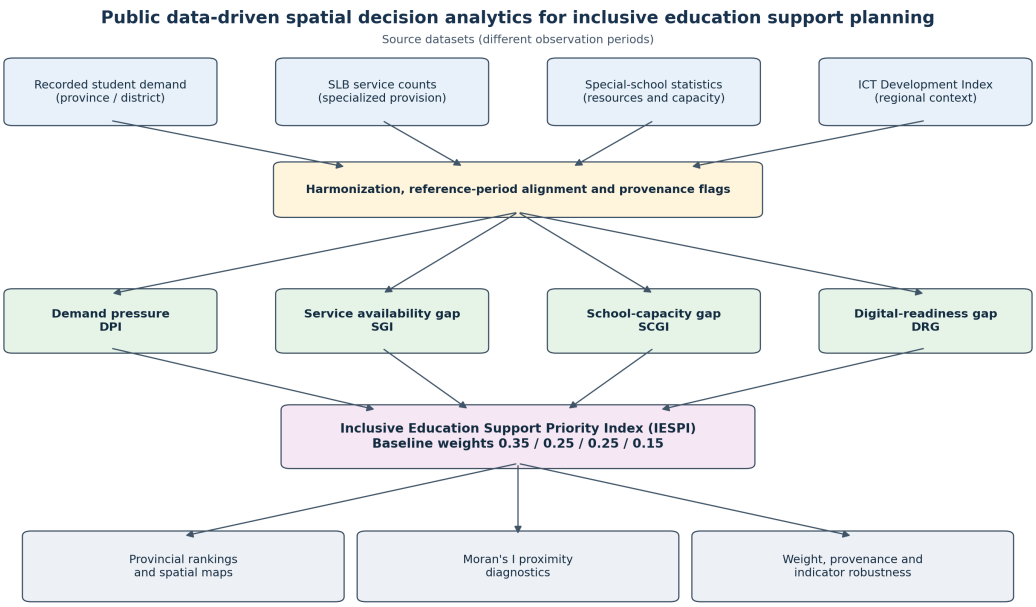


Figure 1: Public data-driven spatial decision analytics framework for inclusive education support planning.

4.2 Indicator construction and normalization

All analytical components were transformed so that larger values represent greater support priority. For a continuous variable x, let $W_{0.05,0.95}(x)$ denote winsorization at the 5th and 95th percentiles. The direct min–max transformation is

$$N^{+}(x_i) = \frac{W_{0.05,0.95}(x_i) - \min W_{0.05,0.95}(x)}{\max W_{0.05,0.95}(x) - \min W_{0.05,0.95}(x)}, \tag{1}$$

and the reverse transformation for favorable readiness indicators is $N^{-}(x_i) = 1 - N^{+}(x_i)$. Where winsorization was not required for bounded readiness percentages and ICT indicators, the same min–max transformation was applied without percentile clipping. Missing continuous values were median-imputed before normalization. The four IESPI layer weights are demand pressure = 0.35, special-service availability gap = 0.25, school-capacity gap = 0.25, and digital-readiness gap = 0.15. The weights are explicit planning assumptions rather than statistically estimated parameters: demand receives the largest weight because the index is intended first to identify the scale and intensity of recorded need; service and school capacity receive equal secondary weights; and digital readiness is treated as an enabling contextual constraint rather than a direct service outcome. Alternative weighting structures are evaluated in sensitivity analysis.

4.3 Demand pressure layer

Let BK_i denote the number of valid students recorded with special educational needs or disabilities in province i, VS_i the number of valid students, and MD_i the number of recorded students with multiple disabilities. The relative demand rate and multiple-disability share are

$$BKRate_i = \frac{BK_i}{VS_i} \times 1000, \tag{2}$$

$$MDShare_i = \frac{MD_i}{BK_i} \times 100. \tag{3}$$

The implemented pipeline gives equal within-layer weight to normalized absolute demand, relative demand rate, and multiple-disability share:

$$DPI_i = \frac{N^+(BK_i) + N^+(BKRate_i) + N^+(MDShare_i)}{3}. \tag{4}$$

All three demand components are winsorized at the 5th and 95th percentiles before normalization.

4.4 Special-service availability gap layer

Let $SLBServ_i$ denote recorded SLB service units. Two demand-to-service quantities are constructed:

$$BPS_i = \frac{BK_i}{SLBServ_i}, \tag{5}$$

$$SPK_i = \frac{SLBServ_i}{BK_i} \times 1000. \tag{6}$$

Let A_i^S be an absence flag equal to 1 when no SLB service unit is recorded and 0 otherwise. The implemented special-service gap is

$$SGI_i = \frac{N^+(BPS_i) + A_i^S + N^-(SPK_i)}{3}. \tag{7}$$

For provinces with positive recorded demand and nonzero service counts, the two service-pressure ratios are algebraic reciprocals. Including both therefore emphasizes a single demand-to-service relationship; it is not independent evidence of two different capacity dimensions. The removal of one reciprocal term is examined in an additional specification

check. The continuous service-pressure components are winsorized at the 5th and 95th percentiles. When $SLBServ_i = 0$ and recorded demand is positive, the implemented pipeline replaces the undefined BPS_i ratio with a finite penalty equal to 1.25 times the largest observed finite student-per-service ratio before winsorization and normalization. The structural absence itself is retained explicitly through $A_i^S = 1$, while $SPK_i = 0$ produces the maximum inverse service-density gap. Thus zero recorded service is represented through three transparent signals without forcing the entire layer to an arbitrary value of 1. This layer remains a proxy for recorded specialized support availability and does not represent the complete inclusive education service ecosystem.

4.5 School-capacity gap layer

The school-capacity layer uses six components from the Special School Statistics 2024–2025 dataset. Let SPT_i denote SLB students per recorded headmaster/teacher, CPC_i classes per classroom, A_i^C a flag equal to 1 when no SLB school is recorded, INT_i the percentage of recorded SLB schools with internet access, $COMP_i$ the percentage with computers available for learning, and ACC_i the share with accreditation A or B. The implemented index is

$$SCGI_i = \frac{1}{6}\big[N^+(SPT_i) + N^+(CPC_i) + A_i^C + N^-(INT_i) + N^-(COMP_i) + N^-(ACC_i)\big]. \tag{8}$$

Student-to-teacher and class-to-classroom pressure are winsorized at the 5th and 95th percentiles. Readiness percentages are reverse-normalized without percentile clipping. Missing continuous values are median-imputed before normalization. The school-absence flag therefore records structural absence directly, while the remaining components retain comparable information for provinces with available data. Students per SLB school and other descriptive ratios are retained in the processed dataset for interpretation but are not components of the implemented SCGI. The layer measures structural capacity in the recorded SLB system; it does not indicate whether teachers have specific training in inclusive education or assistive technology service delivery.

4.6 Digital-readiness gap layer

The digital-readiness layer uses three 2024 ICT Development Index indicators: the overall ICT index (ICT_i), access and infrastructure subindex ($ACCESS_i$), and usage subindex (USE_i). The skill subindex is retained descriptively but is not included in the imple-

mented digital-readiness gap. The layer is

$$DRG_i = \frac{N^-(ICT_i) + N^-(ACCESS_i) + N^-(USE_i)}{3}. \tag{9}$$

The overall ICT Development Index incorporates dimensions that overlap with its access and usage subindices. Equal within-layer averaging may thus implicitly emphasize related information rather than three independent digital constructs. Additional specifications use access and usage alone or the overall index alone. These variables are contextual measures of regional digital readiness rather than direct measures of inclusive education quality. Missing continuous values are median-imputed before normalization. The provenance treatment for newly formed Papua provinces is described above and tested explicitly in robustness analysis.

4.7 Inclusive Education Support Priority Index

The final Inclusive Education Support Priority Index (IESPI) combines the four layers:

$$IESPI_i = 100 \times (0.35DPI_i + 0.25SGI_i + 0.25SCGI_i + 0.15DRG_i), \tag{10}$$

where DPI_i is demand pressure, SGI_i is the special-service availability gap, $SCGI_i$ is the school-capacity gap, and DRG_i is the digital-readiness gap. Multiplication by 100 converts the composite score into a 0–100 scale. Provinces are ranked by $IESPI_i$. Priority classes are assigned into four rank-based planning groups: the top 10 provinces are classified as Very High, ranks 11–19 as High, ranks 20–28 as Medium, and ranks 29–38 as Low. Rank-based grouping supports comparative policy prioritization under a fixed national planning context; it does not define absolute service adequacy thresholds.

4.8 Robustness to indicator redundancy and administrative-zero uncertainty

Two potentially dependent index components require explicit checks. First, the demand-per-service and service-per-demand ratios are reciprocal when denominators are positive. A reduced service specification averages normalized demand-per-service pressure with the recorded-service absence flag, omitting inverse service density. Second, because the overall ICT index overlaps conceptually with the access and usage subindices, alternative digital layers are constructed using either the two subindices alone or the overall ICT index alone. In each test, the baseline four-layer policy weights are held constant and the relevant layer alone is substituted.

An additional conservative scenario treats provinces with zero recorded SLB services or zero recorded SLB schools as *administratively unverified*, rather than assuming actual absence. For those observations only, the entire affected service or capacity layer is replaced by the median layer value among provinces with positive recorded counts; other observations and layers remain unchanged. This is an uncertainty stress test, not a revised measurement of actual services. A combined specification applies the reduced service layer, the digital two-subindex specification, and the conservative school-zero treatment. Spearman rank correlation, mean absolute rank shift, maximum rank shift, and top-ten membership overlap are used to compare results with the unchanged baseline.

4.9 Exploratory spatial autocorrelation diagnostics

A choropleth shows geographic variation, but by itself cannot establish whether nearby provinces have systematically similar IESPI values. Therefore, exploratory Global Moran's I is calculated from the baseline province scores (Moran 1950). Indonesia's archipelagic geography produces disconnected land-contiguity neighborhoods, so this study uses a *proximity*, rather than shared-boundary, definition of a neighborhood. The representative point of the largest land polygon of each province is extracted from the standardized GeoJSON; great-circle distances between these points determine each province's k closest neighbors. For the primary specification, $k = 4$ and the k-nearest-neighbor spatial weights are row-standardized. This choice gives each province four neighbors, including on islands, but does not imply direct overland accessibility or an administrative linkage.

For centered scores $z_i = IESPI_i - \overline{IESPI}$ and spatial weights w_{ij}, the statistic is

$$I = \frac{n}{S_0} \frac{\sum_i \sum_j w_{ij} z_i z_j}{\sum_i z_i^2}, \qquad S_0 = \sum_i \sum_j w_{ij}. \tag{11}$$

A two-sided permutation test with 9,999 random rearrangements, fixed random seed 20261024, compares the observed deviation from the randomization expectation $-1/(n-1)$ to the permutation distribution. Sensitivity is checked for $k = 3, 5, 6, 8$, and by repeating the four-neighbor test after excluding selected high-ranked provinces or the four newly formed Papua provinces. The test examines descriptive geographic association only; it does not estimate spatial spillovers, travel-time access, causal relationships, or within-province inequality.

4.10 Sensitivity analysis

Sensitivity analysis varies component weights and evaluates rank stability. The baseline scenario uses demand, service, capacity, and digital-readiness weights of 0.35, 0.25, 0.25, and 0.15, respectively. Alternative scenarios include equal weighting, demand-heavy weighting, service-heavy weighting, capacity-heavy weighting, and digital-readiness-heavy weighting. Stability is summarized using Spearman rank correlation with the baseline, mean absolute rank shift, maximum rank shift, top-10 overlap, and province-level rank range across scenarios. Table 2 reports the scenario weights. The separate ICT-provenance robustness analysis described above is not a weighting scenario; it tests a source-specific assumption affecting newly formed Papua provinces.

Table 2: Weighting scenarios used in the sensitivity analysis.

Scenario	Demand	Service	Capacity	Digital
Baseline	0.35	0.25	0.25	0.15
Equal weight	0.25	0.25	0.25	0.25
Demand-heavy	0.50	0.20	0.20	0.10
Service-heavy	0.25	0.40	0.25	0.10
Capacity-heavy	0.25	0.20	0.40	0.15
Digital-heavy	0.30	0.20	0.20	0.30

5 Results

5.1 National overview

The processed dataset covers 38 provinces and 514 districts/cities. Full province-level components, district/city demand summaries, and provenance and sensitivity tables are provided in Online Resource 1 (*ESM_1.pdf*). Nationally, the integrated dataset records 245,311 valid students with special educational needs or disabilities, 7,188 special-school services, and 2,366 special schools. The average provincial ICT Development Index is 5.89. The baseline IESPI indicates substantial spatial variation in support priority, with the highest-priority provinces driven by different combinations of demand pressure, service scarcity, school-capacity constraints, and digital-readiness gaps.

Table 3: National summary of the processed analytical dataset.

Indicator	Value
Number of provinces	38
Number of districts/cities	514
Valid students with special educational needs or disabilities	245,311
Total special-school services	7,188
Total special schools	2,366
Average ICT Development Index 2024	5.89
Provinces with zero recorded SLB service	1

Table 4: Distribution of IESPI scores and priority classes.

Indicator	Value
Minimum IESPI	24.04
Mean IESPI	35.44
Median IESPI	33.30
Maximum IESPI	76.67
Standard deviation	10.83
Very High priority provinces	10
High priority provinces	9
Medium priority provinces	9
Low priority provinces	10

The IESPI distribution shows a clear separation between the highest-priority provinces and the national distribution. The maximum value of 76.67 is substantially higher than the mean value of 35.44 and the median value of 33.30, indicating that a small number of provinces represent pronounced priority cases. The rank-based grouping provides a balanced planning segmentation across 38 provinces while preserving the ability to distinguish very high-priority outliers.

5.2 Geographic patterns of support priority

Table 5 shows the top ten provinces by IESPI. Papua Pegunungan ranks first, followed by Papua Tengah, Jawa Tengah, Nusa Tenggara Timur, Jawa Timur, and Jawa Barat. The ranking reflects different policy problems. Some provinces are prioritized because of low service availability and low digital readiness, while others are prioritized because of very large absolute recorded demand.

Table 5: Top ten provinces by Inclusive Education Support Priority Index.

Rank	Province	IESPI
1	Papua Pegunungan	76.67
2	Papua Tengah	71.48
3	Jawa Tengah	46.00
4	Nusa Tenggara Timur	45.87
5	Jawa Timur	40.55
6	Jawa Barat	40.23
7	DI Yogyakarta	40.14
8	Kepulauan Bangka Belitung	39.51
9	DKI Jakarta	38.80
10	Papua Barat	38.73

The highest-ranked province, Papua Pegunungan, should be interpreted carefully. The result is an administrative-data signal: valid students with special educational needs or disabilities are recorded, while no SLB service unit or SLB school is recorded in the corresponding service and school-capacity datasets. The implemented service layer represents this through an explicit service-absence flag and zero service density, while the school-capacity layer includes a school-absence flag alongside median-imputed continuous readiness components. This does not prove that no support exists in practice. Newly established administrative structures, incomplete synchronization, cross-boundary service use, non-SLB support arrangements, and reporting delays remain plausible explanations. Papua Tengah also combines high recorded demand-to-service pressure with constrained school capacity and a digital-readiness value inherited from the pre-split Papua grouping. In contrast, Jawa Barat, Jawa Tengah, and Jawa Timur rank highly mainly because of large absolute recorded demand, even though their recorded service bases are larger than those in many other provinces.

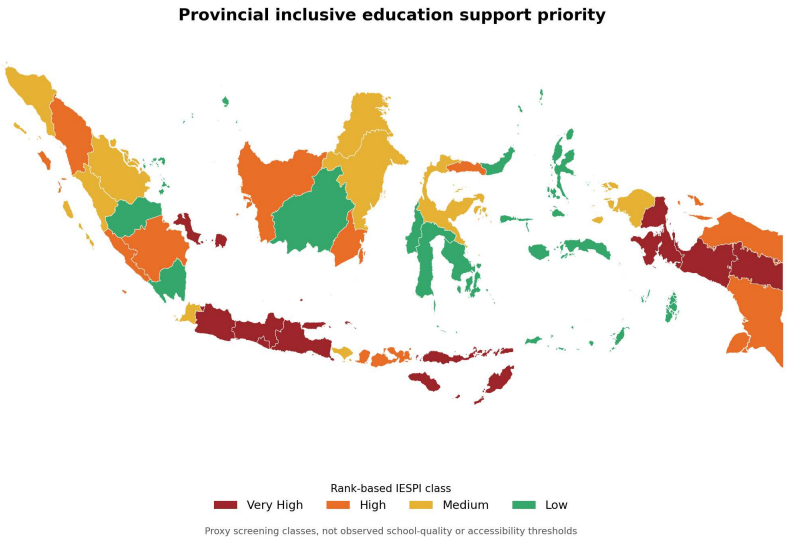


Figure 2: Provincial choropleth map of the Inclusive Education Support Priority Index (IESPI). Colors indicate rank-based priority class: Very High, High, Medium, and Low.

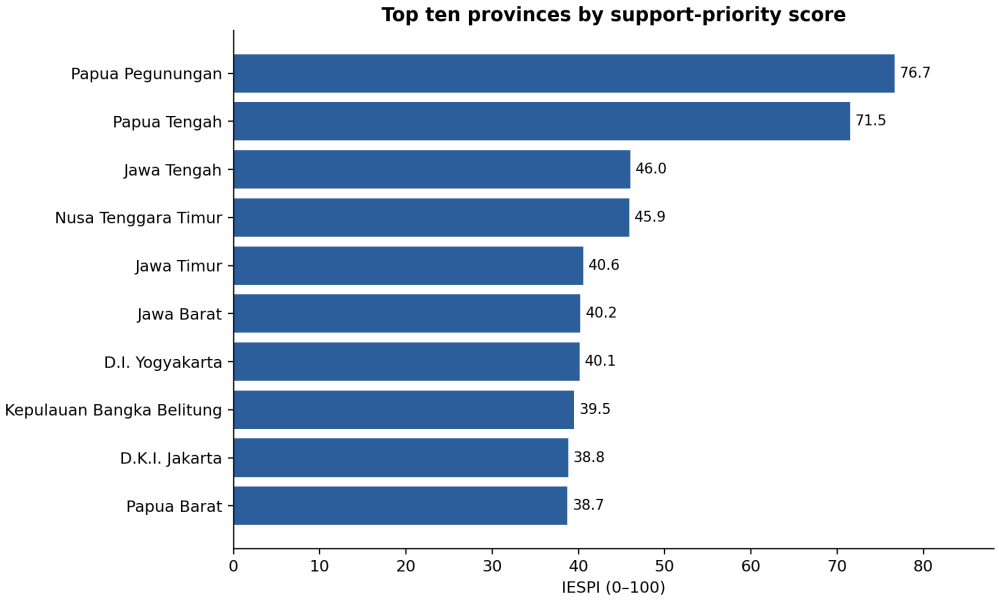


Figure 3: Top ten provinces by Inclusive Education Support Priority Index (IESPI).

5.3 Spatial association and neighborhood sensitivity

The mapped priority scores display statistically detectable positive geographic association under the specified four-nearest-neighbor proximity criterion. Global Moran's I is 0.298, with a two-sided permutation p-value of 0.0045. The association is sensitive to spatial scale as represented by the neighborhood size: I falls from 0.395 with three neighbors to 0.102 with eight neighbors (Table 6). This pattern indicates that similarity is stronger under smaller proximity neighborhoods. It should not be interpreted as evidence that

provincial service systems causally affect one another.

Table 6: Exploratory Global Moran's I under proximity-based neighbor definitions. Two-sided permutation tests use 9,999 randomizations and seed 20261024.

Sample	k	Moran's I	p-value
All 38 provinces	3	0.395	0.0021
All 38 provinces (baseline)	4	0.298	0.0045
All 38 provinces	5	0.229	0.0073
All 38 provinces	6	0.171	0.0127
All 38 provinces	8	0.102	0.0370
Excluding Papua Pegunungan (37)	4	0.142	0.0526
Excluding four newly formed Papua provinces (34)	4	0.183	0.0429

One influential observation matters to the diagnostic: omitting Papua Pegunungan alone produces $I = 0.142$ ($p = 0.0526$), whereas omitting all four newly formed Papua provinces gives $I = 0.183$ ($p = 0.0429$). Thus evidence for spatial association is sensitive to both neighborhood construction and influential regional composition. Figure 4 presents the exploratory spatial-lag scatterplot. Its quadrants depict relationships to a descriptive proximity neighborhood and should not be interpreted as significant local clusters.

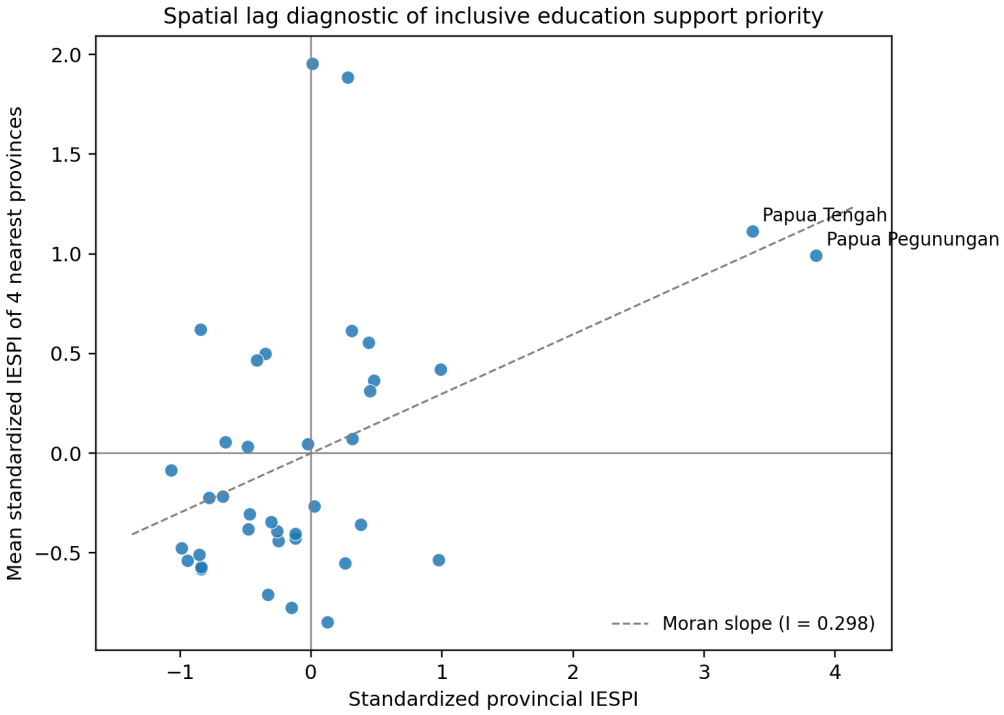


Figure 4: Four-nearest-neighbor Moran scatterplot of the provincial IESPI. The slope summarizes Global Moran's I; location labels identify illustrative high-scoring cases rather than statistically significant local clusters.

5.4 Component contributions and rank stability

The component profile in Figure 5 shows that priority scores are produced by different combinations of pressure and gap indicators. Papua Pegunungan and Papua Tengah combine strong service and digital-readiness gaps, while high-population provinces in Java are more strongly influenced by demand pressure. This distinction is important for policy interpretation because a single national ranking can hide different intervention logics.

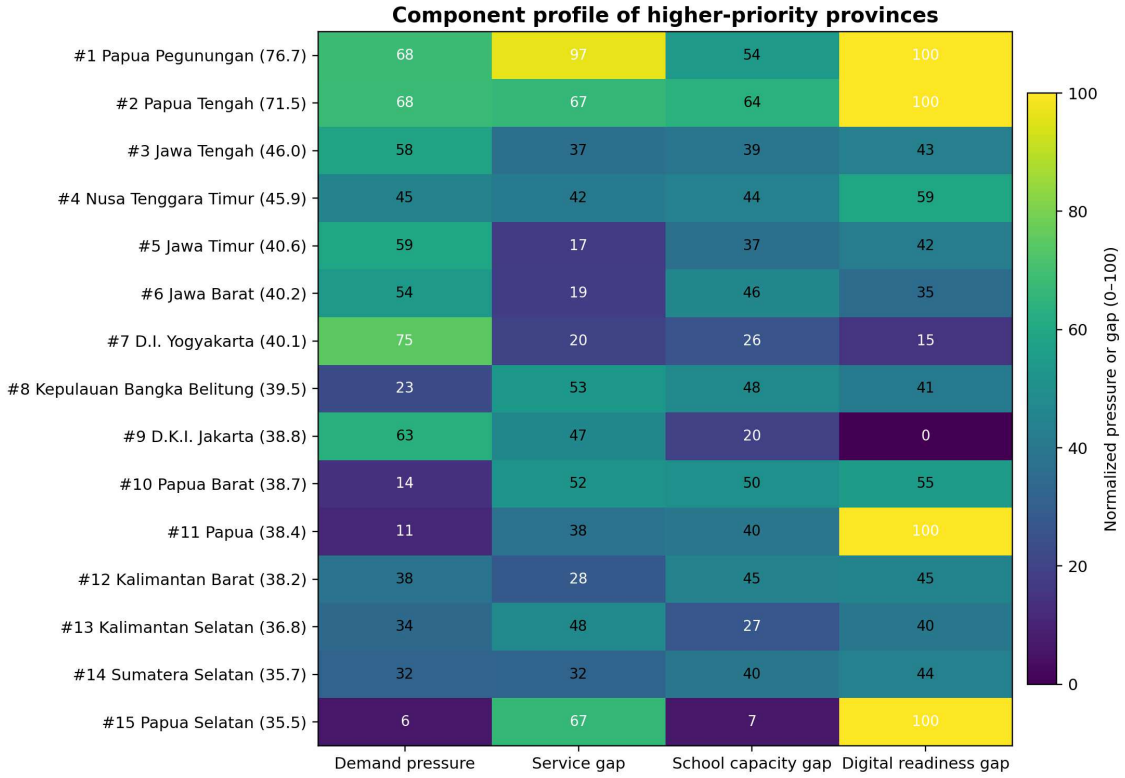


Figure 5: Component-level profile of high-priority provinces. Cell values are normalized pressure or gap scores on a 0–100 scale. Values in parentheses on the y-axis show the baseline IESPI score.

Sensitivity analysis shows which priorities are stable under alternative weighting assumptions (Figure 6). Across the five alternative scenarios, Spearman rank correlations with the baseline range from 0.905 to 0.940 (Table 7). Mean absolute rank shifts range from 2.79 to 3.42 positions. The top 10 retain seven or eight provinces depending on the scenario, while 12 of 38 provinces have a rank range of at least 10 positions across all six weighting schemes. Thus, the highest-priority cases show meaningful robustness, but a substantial middle portion of the ranking remains weight-sensitive. Papua Pegunungan and Papua Tengah remain ranks 1 and 2 under every tested weighting scenario; DI Yogyakarta and DKI Jakarta show considerably larger variation.

Table 7: Rank-stability statistics for alternative weighting scenarios.

Scenario	Spearman ρ	Mean abs. shift	Max. shift	Top-10 overlap
Demand-heavy	0.923	3.26	13	8
Service-heavy	0.940	2.79	9	7
Capacity-heavy	0.912	3.42	14	8
Digital-heavy	0.916	3.11	15	8
Equal-weight	0.905	3.42	14	7

5.5 Robustness to inherited ICT values for newly formed Papua provinces

The ICT source provenance has a material but uneven effect. Four provinces inherit 2024 ICT values because the source appendix uses pre-split Papua groupings. Two robustness checks were therefore conducted. First, inherited digital-readiness gaps were replaced by the median digital-readiness gap among provinces with directly reported ICT values. Second, the digital-readiness layer was removed and the remaining baseline weights were renormalized proportionally. As shown in Table 8, Papua Pegunungan and Papua Tengah remain ranks 1 and 2 under both checks, indicating that their priority is not solely a consequence of inherited ICT values. Papua Selatan, however, moves from rank 15 to rank 31 under both checks, while Papua Barat Daya moves from rank 24 to ranks 27 and 26. These results reinforce the need to treat lower-ranked results for newly formed Papua provinces as source-sensitive rather than definitive.

Table 8: Robustness of ranks for provinces with inherited 2024 ICT values.

Province	Baseline rank	Median ICT substitution	No digital layer
Papua Pegunungan	1	1	1
Papua Tengah	2	2	2
Papua Selatan	15	31	31
Papua Barat Daya	24	27	26

5.6 Additional indicator and administrative-zero stress tests

Table 9 compares the unchanged baseline with specifications that address reciprocal service ratios, overlapping ICT measures, and uncertain administrative zeros. Eliminating one of the reciprocal service terms yields a Spearman correlation of 0.974 with the baseline and preserves all ten top-priority provinces, although the maximum individual rank shift reaches eight positions. Using ICT access and usage alone or the overall ICT index

alone yields correlations of 0.998 and 0.997, respectively; the latter replaces one province in the top ten. These checks indicate that the core priority pattern is relatively insensitive to the digital aggregation choice, but some positions depend on how service pressure is encoded.

Treating zero SLB counts as unverified, with the relevant layer replaced by the nonzero-province median, exchanges ranks 1 and 2 between Papua Pegunungan and Papua Tengah while retaining the same top-ten provinces. This scenario does not resolve whether a service truly exists on the ground; it only exposes the consequences of interpreting an administrative zero differently. The combined specification yields a Spearman correlation of 0.973, a maximum rank shift of nine positions, and complete top-ten overlap. Full province-level results and the executable alternative calculations are supplied as supplementary CSV files.

Table 9: Index-specification stress tests relative to the baseline IESPI; the baseline scores and weights are unchanged.

Alternative specification	Spearman ρ	Mean shift	Max. shift	Top-10 overlap
One service ratio + absence flag	0.974	1.58	8	10
ICT access and usage only	0.998	0.26	2	10
Overall ICT index only	0.997	0.42	3	9
Administrative zeros unverified	1.000	0.05	1	10
Combined conservative	0.973	1.63	9	10

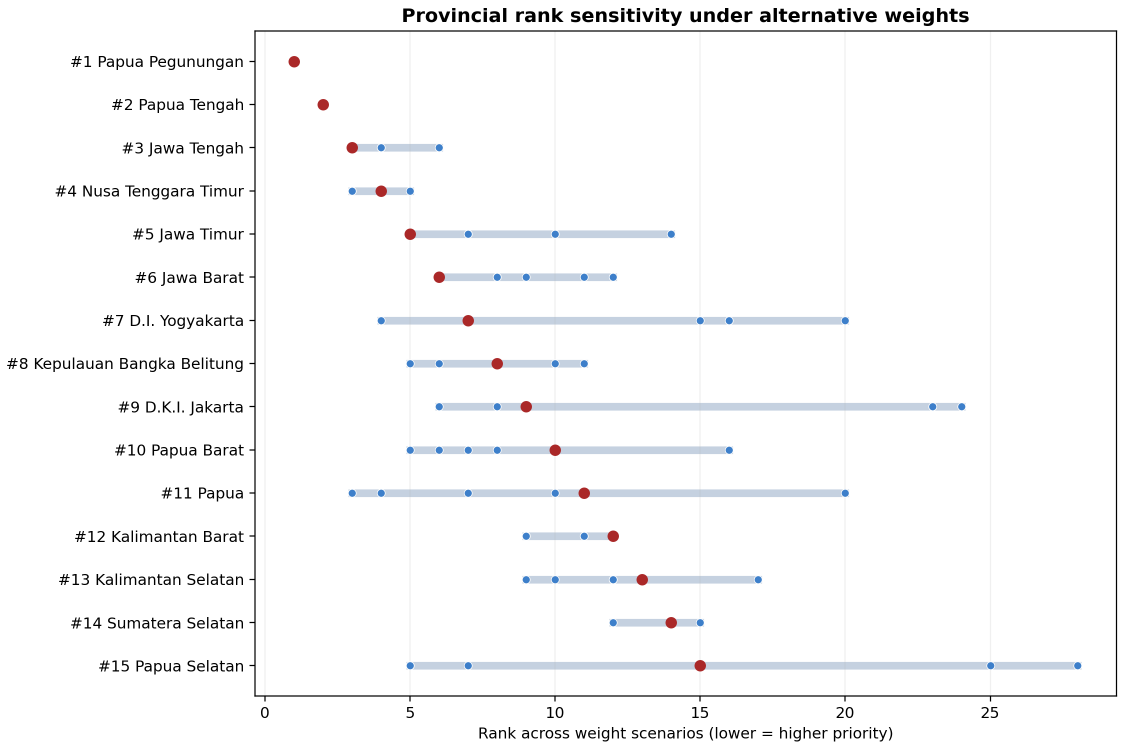


Figure 6: Rank stability of high-priority provinces under alternative weighting scenarios. Lower rank indicates higher priority.

6 Discussion

6.1 Spatial prioritization from fragmented public data

The main contribution of this study is not the claim that public data can fully measure inclusive education quality or assistive technology need. It is the demonstration that fragmented public datasets can be converted into a transparent, interpretable, and reproducible situation-analysis tool. This is directly aligned with data-policy interaction: data do not make policy decisions on their own, but they can structure where policy attention, validation, and resource planning should start. The IESPI supports this function by combining recorded demand, specialized support availability, school capacity, and digital-readiness context into a single spatial decision analytics workflow.

For policymakers, the value of the framework lies in its ability to separate different types of priority. High demand pressure suggests scale and coverage concerns. High special-service gaps suggest the need to verify whether specialized support pathways are available. High school-capacity gaps point toward staffing, classroom, resource, and institutional-readiness constraints within the recorded SLB system. High digital-readiness gaps indicate that technology-enabled interventions may require staged implementation,

offline-compatible tools, and infrastructure support. These interpretations are more useful than a single rank alone.

The additional specification checks refine what the rankings can support. The alternative service metric leaves all ten highest-priority provinces in that group but changes the order of some provinces outside it; this implies that top-ten membership is more stable than the exact national ordering. Digital-index simplification has a smaller effect, whereas administrative-zero uncertainty changes which of the two Papua provinces leads the ranking. Therefore, the IESPI is best used to triage follow-up assessment, with planning decisions informed by the component profile and data-quality flags rather than a precise ordinal position alone.

6.2 Territorial association does not imply uniform accessibility

The Moran diagnostic provides information that a ranking alone cannot: provinces with similar IESPI values tend to be geographically proximate under the chosen nearest-neighbor definition, but the association weakens when more distant neighbors are admitted. Such patterns support coordinating diagnostic investigations across adjacent or nearby administrative territories, rather than treating every province as an independent service-planning problem. Nevertheless, physical proximity does not equal functional accessibility in an archipelago: transport, sea crossings, inter-island costs, and service-referral boundaries are not measured here. A genuine accessibility analysis would require geocoded schools and support facilities, travel networks, operational capacity and catchment definitions (Guagliardo 2004; Higgs 2004; McLafferty 2003). The influential-province analysis further shows why the map must be read together with uncertainty and provenance diagnostics. Spatial autocorrelation is not a substitute for field assessment or a causal explanation for regional disparities.

6.3 Special-school data and inclusive education readiness

A major interpretive risk is to confuse special-school provision with inclusive education itself. This study treats SLB data as a proxy for specialized educational support capacity rather than as a direct measure of inclusive education. This is still policy-relevant because specialized services, teachers, assessment pathways, and support resources often matter for students with disabilities even when the long-term policy goal is participation in mainstream schools. However, SLB data do not capture the full ecosystem of inclusive education. They do not measure the capacity of mainstream schools to adapt curricula, provide classroom accommodations, engage parents, coordinate support, or implement individualized learning plans.

Using special-school indicators within inclusive-education planning requires treating special schools as one component of a broader support system rather than as the inclusive system itself. The IESPI is not a special-school expansion index. It is a signal of where recorded demand, specialist service availability, school resources, and digital readiness appear misaligned. In some contexts, the policy response may be to strengthen mainstream-school inclusion. In others, it may involve resource centers, mobile assessment teams, teacher development, cross-district support, or better coordination between special and regular schools.

6.4 Assistive technology implications and product-domain limitations

The IESPI identifies where further support planning should be prioritized, but it does not identify which assistive products are needed. This limitation is substantively important. Service delivery and resource allocation require knowledge of whether students need mobility, vision, hearing, communication, cognition, self-care, or learning-related products. The public datasets used here do not include product-level assistive technology needs, individualized functional assessment, or data on actual assistive technology ownership and use.

Consequently, the index should be used as an entry point for assessment, not as a procurement formula. A future version of the framework could link provincial priority mapping with disability-type disaggregation and product-domain frameworks such as the WHO Priority Assistive Products List. Even then, product-domain mapping should remain indicative because assistive product selection requires person-centered assessment and follow-up. The practical implication is that provinces with high IESPI scores should be prioritized for school-level audits, mainstream and special-school pathway assessment, consultation with students and families, and assistive technology needs assessment.

6.5 Geographic specificity and the modifiable areal unit problem

The index is evaluated at the provincial scale because education and digital-readiness indicators are not consistently available below this level. Following the modifiable areal unit problem literature (Fotheringham and Wong 1991), provincial summaries should not be assumed to describe service reach or student conditions uniformly within each province. Province names are retained because the study uses aggregated public administrative data and aims to support geographically actionable policy planning. The unit of analysis is a public administrative region, not an individual, school, or household. No individual-level

student data, personally identifiable information, or school-identifiable student records are reported. Geographic identification is analytically necessary because the decision-support purpose is to locate where validation and support planning should be prioritized.

6.6 Transferability beyond Indonesia

The framework is transferable to other public-service planning contexts where administrative data are fragmented but policy decisions require integrated evidence. The substantive variables would need adaptation, but the general workflow can be reused: identify recorded demand, identify specialized support capacity, construct capacity and readiness indicators, normalize pressure and gap measures, test weight sensitivity, and present spatial outputs with explicit interpretive boundaries. This structure is relevant not only for inclusive education, but also for disability services, rehabilitation access, public health outreach, and other policy domains where service allocation depends on uneven territorial demand and limited local data.

6.7 Limitations and future work

This study has several limitations. First, the IESPI does not measure actual inclusive education quality, assistive technology ownership, assistive product need, service effectiveness, or student outcomes. Second, the provincial index may mask substantial variation within provinces (an ecological and areal-aggregation limitation), and the proximity neighborhoods used in the Moran diagnostic do not represent road, ferry, travel-time, or service-referral networks. Third, SLB service and school-capacity data are proxies for specialized support capacity and do not capture the full mainstream-school inclusion ecosystem. Fourth, school-capacity indicators do not measure whether teachers are trained in inclusive education or assistive technology service delivery. Fifth, the index depends on explicit weighting choices; the sensitivity analysis shows high overall rank correlation but non-trivial movement for some provinces. Sixth, the integrated sources refer to different periods, so the IESPI is a harmonized planning snapshot rather than a same-year measurement system. Seventh, the 2024 ICT source uses pre-split Papua groupings for four newly formed provinces; dedicated robustness checks show that the two highest-ranked provinces are stable but some lower-ranked Papua results are sensitive to this assumption. Eighth, service pressure includes reciprocal transformations of the same two counts and digital readiness combines an overall index with overlapping subindices; the specification stress tests address the ranking consequences but do not establish independent construct validity. Ninth, zero records can represent either genuine absence or incomplete registration; the counterfactual missing-zero test changes the ordering of the top two provinces and should not be interpreted as a verified replacement

for field data. Tenth, the included replication materials permit reanalysis from processed tables, while full raw-source re-extraction requires obtaining the original administrative files and independently checking their metadata. Finally, administrative data may contain reporting delays, incomplete synchronization, or category differences across source systems.

Future work should extend the model in four directions. First, the framework should be validated using school-level audits and stakeholder consultation involving students with disabilities, families, teachers, school leaders, and local policymakers. Second, mainstream-school inclusive education data should be integrated when available. Third, disability-type and functional-assessment data should be connected to broad assistive product-domain planning, while preserving person-centered assessment. Fourth, the replication package should be expanded into an annual monitoring workflow so that changes in student demand, service availability, capacity, and digital readiness can be tracked over time.

7 Conclusion

This study developed a public data-driven spatial decision analytics framework for inclusive education support planning in Indonesia. Using student-demand records, SLB service-reference data, school statistics, and ICT-readiness indicators, the study constructed an Inclusive Education Support Priority Index for 38 provinces. Geospatial boundaries supported visualization and exploratory proximity diagnostics, while population-census material supplied background context only and did not enter the score. The results show substantial geographic heterogeneity and a positive but neighborhood-sensitive proximity association in provincial IESPI scores. Some provinces are prioritized because of combined service, capacity, and digital-readiness gaps, while large-population provinces remain important because of high absolute recorded demand.

The contribution is deliberately bounded by the measurement limits of the public data. The IESPI is a planning and screening tool, not a measure of inclusive education quality, student-level need, disability prevalence, or actual assistive technology availability. Its practical value lies in identifying where further investigation should begin: data validation, school-level audit, mainstream and special-school support-pathway assessment, stakeholder engagement, and assistive technology needs assessment. Used in this way, fragmented public data can support more transparent and geographically targeted policy planning without overstating what administrative indicators can prove.

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