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From Isolation to Inclusion: Does Digital Adoption Enhance Educational Access in Indonesia's 3T Areas?

Dari Isolasi Menuju Inklusi: Apakah Adopsi Digital Meningkatkan Akses Pendidikan di Wilayah 3T Indonesia?

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Abstract
This study aims to analyze how digital adoption, such as internet access and ownership of technological devices, contributes to the educational continuity of children in Disadvantaged, Frontier, and Outermost or *Tertinggal*, *Terdepan*, and *Terluar* (3T) regions. The research employs the Propensity Score Matching (PSM) method using SUSENAS 2022 data, which enables comparisons between households in 3T and non-3T regions with similar socio-economic characteristics to isolate the impact of digital adoption on educational access. The findings reveal that, after matching, there is no statistically significant difference in school participation between children in 3T and non-3T regions, as long as households have comparable access to technology and similar socio-economic conditions. When 3T households have internet connectivity, ownership of digital devices, and access to social protection on par with their non-3T counterparts, their children are just as likely to attend school. The implication is that policies focused solely on spatial targeting may overlook children in need outside 3T boundaries and overgeneralize those within them. As a result, educational interventions must shift toward multidimensional and needs-based strategies that prioritize digital inclusion, income security, and tailored social support.

Keywords
Educational Inequality; Digital Adoption; 3T Regions; Internet Access

Abstrak
Penelitian ini bertujuan untuk menganalisis bagaimana adopsi teknologi, seperti akses internet dan kepemilikan perangkat digital, berkontribusi terhadap keberlanjutan pendidikan anak-anak di wilayah Tertinggal, Terdepan, dan Terluar (3T) di Indonesia. Penelitian ini menggunakan metode Propensity Score Matching (PSM) dengan data SUSENAS 2022 yang memungkinkan perbandingan antara rumah tangga di wilayah 3T dan non-3T dengan karakteristik sosial ekonomi yang serupa, guna mengisolasi dampak adopsi teknologi terhadap akses pendidikan. Hasil penelitian menunjukkan bahwa setelah proses pencocokan, tidak terdapat perbedaan yang signifikan secara statistik dalam partisipasi sekolah antara anak-anak di wilayah 3T dan non-3T, selama rumah tangga memiliki akses teknologi dan kondisi sosial ekonomi yang sebanding. Ketika rumah tangga di wilayah 3T memiliki konektivitas internet, perangkat digital, dan akses terhadap program perlindungan sosial yang setara dengan rumah tangga di wilayah non-3T, kemungkinan anak-anak mereka untuk bersekolah sama besarnya. Temuan ini menunjukkan bahwa kebijakan yang hanya berfokus pada klasifikasi spasial berisiko mengabaikan anak-anak yang rentan di luar wilayah 3T dan sekaligus menyamaratakan kondisi mereka yang berada di dalamnya. Oleh karena itu, intervensi pendidikan perlu diarahkan pada pendekatan multidimensional dan berbasis kebutuhan yang mengutamakan inklusi digital, ketahanan ekonomi rumah tangga, serta dukungan sosial yang disesuaikan.

Kata Kunci
Ketimpangan Pendidikan; Adopsi Digital; Wilayah 3T; Akses Internet

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1. Introduction

Educational inequality remains a persistent challenge in developing countries, particularly in remote and underdeveloped regions where infrastructure, economic opportunities, and access to digital technology are limited. In Indonesia, the Disadvantaged, Frontier, and Outermost (*Tertinggal, Terdepan, dan Terluar*/3T) regions experience significant disparities in educational access due to geographical isolation, economic constraints, and inadequate digital infrastructure. The Indonesian government officially designates 62 regencies and cities as 3T regions, based on Presidential Regulation Number 63 of 2020 on the Determination of Underdeveloped Regions for 2020–2024, with criteria such as low economic development, poor infrastructure, and limited access to basic services, including education.

The Indonesian government's designation of 3T areas is aimed at ensuring equitable development and reducing regional disparities. Programs such as the Smart Indonesia Program or *Kartu Indonesia Pintar* (KIP), Village Fund (*Dana Desa*), and Universal Service Obligation (USO) for telecommunication infrastructure have been implemented to improve education, economic opportunities, and digital access in these regions (Faoziyah & Salim, 2020; Ghina et al., 2024; Indartuti, 2022; Ridwan & Afriadi, 2023). However, despite these efforts, 3T areas continue to face structural barriers, particularly in terms of educational access and digital adoption (Azmi et al., 2025; Falah & Hadna, 2022). Many schools lack basic technological infrastructure, and even where digital access is available, students and teachers often struggle with limited digital literacy and inadequate learning resources.

The digital divide further exacerbates this issue, as many households in these areas struggle with poor digital infrastructure and low technological literacy, making it difficult for students to benefit from digital learning tools and online education opportunities. While technology is often seen as a transformative solution to expand educational access, the extent to which digital adoption effectively improves school participation in 3T regions remains uncertain. These challenges raise concerns about whether digital transformation can truly bridge educational gaps in 3T regions or if additional policy interventions are needed to enhance the effectiveness of digital adoption in supporting equitable education.

The Digital Divide Theory provides a crucial framework for understanding how technological disparities shape educational inequalities (Pierce & Cleary, 2024; van Dijk, 2017). The first-level digital divide refers to unequal access to digital infrastructure, while the second-level digital divide concerns differences in digital literacy and the ability to use technology effectively. Both levels significantly influence educational outcomes, particularly in rural and underprivileged communities.

In addition, Human Capital Theory posits that education is a form of investment in human resources that yields returns in the form of higher productivity, improved employment opportunities, and economic growth (Osiobe, 2019; Widarni & Bawono, 2021). In this framework, individuals acquire knowledge, skills, and competencies through schooling and training, which enhance their capacity to participate effectively in the labor market and society. When applied to the context of digital accessibility, this theory suggests that expanding access to technology and digital learning tools enables individuals (Haleem et al., 2022), especially in disadvantaged regions, to acquire valuable educational capital. In the case of Indonesia's 3T regions, where traditional barriers to schooling are compounded by infrastructural limitations, digital inclusion becomes a strategic pathway to equip young people with the competencies needed for future employment and civic engagement. Investments in digital education thus serve not only as a means to reduce current educational disparities but also as a catalyst for building a more skilled and competitive workforce in the long run (Das, 2024; Kalyani, 2024).

Inclusion in education is fundamental to ensuring that every citizen, regardless of their geographic location, socio-economic status, gender, or disability, has an equal opportunity to realize their potential (Medina-García et al., 2020). An inclusive education system promotes social cohesion, reduces inequality, and strengthens the foundations of democracy by empowering marginalized groups to participate fully in the development process (Shaeffer, 2019). For countries like Indonesia, where geographic diversity often translates into unequal access to basic services, educational inclusion is critical to bridging regional gaps and achieving national development goals. Moreover, inclusive education fosters a culture of tolerance and respect, enabling diverse populations to contribute meaningfully to collective progress (Singha & Singha, 2023). By ensuring that children in 3T regions are not left behind, Indonesia can unlock the human potential needed to drive sustainable and equitable growth across all its regions.

Despite extensive research on technology and education, few studies have specifically examined the impact of digital adoption on school participation in Indonesia's 3T regions. Previous studies have primarily explored the general role of digital infrastructure in improving educational outcomes, often focusing on urban or economically developed areas. Research by Rafique (2023) and Haleem et al. (2022) has demonstrated how internet access and digital learning tools can enhance school participation and student performance. However, these studies do not address the unique challenges faced by geographically remote and economically disadvantaged regions, where poor infrastructure, limited digital literacy, and socio-economic constraints hinder the effectiveness of digital interventions.

Similarly, research on Indonesia's digital education policies, such as the KIP and various online learning platforms, has shown positive effects on school enrollment and student retention. However, studies such as Djulius et al. (2022) primarily focus on financial assistance programs, overlooking the economic barriers that prevent poor families from fully benefiting from education. Since access to technology is often linked to household income, parental education, and regional infrastructure, previous research may not have adequately isolated the direct impact of digital access on school participation in disadvantaged areas.

This study seeks to fill this gap by employing Propensity Score Matching (PSM) to compare households in 3T and non-3T regions with similar socio-economic characteristics. By controlling for confounding variables, this approach provides a more rigorous estimation of how digital adoption influences school participation in 3T areas. Unlike prior research that focuses on broad national trends, this study specifically examines underprivileged regions where digital interventions have the greatest potential to create meaningful change. The findings of this research could offer valuable policy insights to guide targeted digital inclusion strategies, more specifically for 3T regions.

The objective of this study is to analyze whether digital adoption, particularly internet access and ownership of digital devices, contributes to improving educational access in Indonesia's 3T regions. By leveraging data from National Socioeconomic Survey (SUSENAS) 2022 and applying PSM techniques, this research aims to provide empirical evidence on the role of digitalization in education and inform policy recommendations to bridge the educational gap in disadvantaged communities.

2. Methods

2.1. Data

This study adopts a quantitative approach using nationally representative data from the SUSENAS 2022 conducted by Statistics Indonesia (BPS). The analysis draws on a matched sample of 256,199 households with school-aged children, providing a comprehensive view of educational participation across diverse socio-economic and geographic contexts in Indonesia.

The analysis focuses on households with children aged 7 to 18 years, which represent the school-age population in Indonesia. The primary aim is to investigate whether digital adoption, proxied by two indicators: (i) internet access in the household, and (ii) ownership of digital devices such as smartphones, laptops, or computers, with particular emphasis on the differences between households located in 3T (Disadvantaged, Frontier, and Outermost) regions and those in non-3T areas. The designation of 3T regions refers to the 62 districts and municipalities officially listed under Presidential Regulation Number 63 of 2020.

2.2. Variables

The analysis in this study employs a set of household-level covariates to estimate the propensity score for residing in a 3T region. These variables capture key dimensions that are theoretically and empirically linked to school participation, including access to digital infrastructure, socioeconomic status, and receipt of

Table 1. Research Variables

Variables	Definition	Classification
Dummy 3T Region (3T_region)	Dummy variable indicating whether the household resides in a 3T (Disadvantaged, Frontier, and Outermost) region	1 = 3T Region; 0 = Non-3T Region
Children School Participation (schooling)	Indicates whether a school-aged child (7-18 years old) in the household is currently attending school	1 = Attending; 0 = Not Attending
Cellular/ Mobile Phone Ownersihp (cellular)	Indicates whether the household owns a mobile/cellular phone	1 = Yes; 0 = No
Internet Usage (internet)	Indicates whether the household uses the internet	1 = Yes; 0 = No
Internet Subsidy (internet_sub)	Indicates whether the household receives internet-related subsidies (e.g., free data or educational quota)	1 = Yes; 0 = No
Kartu Indonesia Pintar (kip)	Indicates whether the household receives the Kartu Indonesia Pintar for school-aged children	1 = Yes; 0 = No
Program Indonesia Pintar (pip)	Indicates whether the household receives education-related cash transfer via PIP	1 = Yes; 0 = No
Program Keluarga Harapan (pkh)	Indicates whether the household is a beneficiary of the conditional cash transfer program PKH	1 = Yes; 0 = No
Bantuan Pangan Non Tunai (bpnt)	Indicates whether the household receives food assistance through the BPNT program	1 = Yes; 0 = No
Household Size (hh_size)	Total number of individuals living in the household	Continuous (integer count)
Household Expenditure per Capita (hh_percapita)	Monthly household expenditure divided by household size	Continuous (numeric, in currency)
House Ownership (house)	Indicates whether the household owns the house it resides in	1 = Own; 0 = Rent/ Other

Source: *SUSENAS (2022), modified.*

social protection. Indicators such as internet access, cellular phone ownership, and receipt of internet subsidies are used to represent the degree of digital adoption within households. These factors are central to understanding how technological connectivity can influence educational engagement, especially in regions with limited physical access to schools.

In addition to digital access, the model incorporates multiple indicators of household vulnerability and state support. Variables such as household per capita expenditure, total household size, and ownership of physical assets reflect the economic standing of the household, which influences a family's capacity to support children's schooling. Moreover, participation in major government assistance programs, namely the Smart Indonesia Card/Kartu Indonesia Pintar (KIP), Smart Indonesia Program/Program Indonesia Pintar (PIP), the Family Hope Program/Program Keluarga Harapan (PKH), and the Non-Cash Food Assistance/ Bantuan Pangan Non Tunai (BPNT) are included to assess the extent to which state support intersects with geographic and digital disadvantage.

The selection of variables in this study is grounded in both theoretical considerations and empirical evidence regarding determinants of educational access in geographically marginalized contexts. Digital infrastructure indicators, such as internet access, cellular phone ownership, and receipt of internet subsidies, were included not only because of their direct relevance to digital learning but also as proxies for household connectivity and inclusion in national ICT development efforts. The rationale aligns with the Digital Divide Theory, which posits that unequal access to information and communication technologies exacerbates existing social and spatial inequalities, as previously studied in Vassilakopoulou & Hustad (2023) and Aissaoui (2022).

Empirical studies, such as those by Synowiec (2021) and Golden et al. (2023) have demonstrated that digital exclusion is strongly associated with rurality and infrastructural deficits, thereby limiting access to digital public services, including education. Similarly, Avanesian et al. (2021) emphasized how variations in digital access during COVID-19 disrupted educational continuity in underprivileged areas, reinforcing learning gaps across regions.

Socioeconomic variables, like per capita expenditure and asset ownership, were selected to capture household wealth dimensions, which are known to influence the affordability of school-related costs (Penne et al., 2021). Social protection indicators, including receipt of government subsidies or PKH participation, serve to represent institutional support mechanisms that may mitigate financial constraints. These variables together allow for a multidimensional estimation of propensity to reside in a 3T region, offering a robust control for selection bias in assessing educational outcomes. The combined use of these indicators ensures that the model accounts not only for structural barriers but also for policy-relevant levers of inclusion. A summary of the variables used in the propensity score estimation is presented in Table 1.

2.3. Propensity Score Estimation Using Probit Regression

To estimate the causal effect of digital adoption on educational access in Indonesia's 3T regions, this study first models the probability of a household residing in a 3T region using probit regression. The treatment assignment is defined by a binary variable, where indicates that household resides in 3T region, and otherwise. The propensity score, represents the conditional probability that a household belongs to the treatment group given a set of observed covariates . The probit model used to estimate the propensity score is specified as follows:

$$P(T_i = 1|X_i) = \left(\frac{e^{\beta_0} + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki}}{1 + e^{\beta_0} + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki}}\right)$$

In this formulation, includes a vector of covariates such as parental education, household per capita expenditure, the occupation, age, and gender of the household head, household size, urban-rural classification, access to electricity, and ownership of digital devices like smartphones or computers. The resulting propensity scores are then used to match households from 3T regions with observationally similar households from non-3T regions, based on nearest-neighbor matching within a caliper range. The goal of this matching procedure is to ensure that treatment and control households are statistically comparable with respect to observed characteristics, thereby minimizing bias due to selection on observables.

2.4. Propensity Score Estimation Using Logistic Regression Estimating the Average Treatment Effect on the Treated (ATT)

After obtaining matched pairs of treated and control households based on similar propensity scores, the next step is to estimate the Average Treatment Effect on the Treated (ATT), which quantifies the effect of residing in a 3T region on educational outcomes under different levels of digital adoption. Let denote the potential outcome (school participation) for household if treated, and the potential outcome if untreated. The ATT is then defined as the expected difference in outcomes for treated units relative to their matched controls:

$$ATT = E[Y_i(1) - Y_i(0)|T_i = 1]$$

Because only one of these outcomes is observed for each household in practice, the counterfactual for treated households is inferred from the outcomes of matched control households. This relies on the conditional independence assumption (CIA), which states that potential outcomes are independent of treatment assignment, conditional on the covariates used in the matching process. It also assumes the existence of common support, meaning that for each treated household, there is at least one non-treated household with a comparable propensity score.

The ATT is calculated using the matched sample, typically through a difference in means of the outcome variable between treated and control households. In this study, the outcome variable is a binary indicator of whether a school-aged child (7–18 years old) is enrolled in school. A positive and statistically significant ATT would suggest that, after accounting for socio-economic similarities, residing in a 3T region with digital adoption is associated with increased likelihood of school participation.

3. Results and Discussion

3.1. Probit Estimation of Propensity Score

The probit regression results presented in Table 2 serve as the foundational step for estimating the propensity scores used in matching households located in Indonesia's 3T regions with comparable non-3T households. These scores are critical for isolating the causal impact of geographical remoteness on schooling participation. The model includes 256,199 observations and achieves a robust likelihood ratio chi-square value of 8,221.88 ($p < 0.0001$), indicating that the set of covariates significantly predicts the probability of a household being located in a 3T area.

Table 2. Probit Regression Estimation of Propensity Scores for 3T Region Classification

Variable	Coef	Std. Error	z	Prob.
cellular	-0.1110	0.0092	-12.01	0.000*
internet	-0.2784	0.0094	-29.59	0.000*
Internet_sub	-0.2233	0.0112	-19.90	0.000*
kip	0.1583	0.0121	13.06	0.000*
pip	-0.1345	0.0105	-12.72	0.000*
pkh	0.4080	0.0087	46.51	0.000*
bpnt	-0.0730	0.0094	-7.69	0.000*
hh_size	0.0572	0.0098	5.79	0.000*
hh_percapita	-0.1285	0.0107	-12.00	0.000*
house	0.2717	0.0108	25.13	0.000*
Constant	0.3544	0.1475	2.40	0.016
Number of observations	256,199			
LR chi2	8221.88			
Prob > chi2	0.0000			

Source: *Author's Data Analysis (2025)*
Note: *significant in

The variables of primary interest in this analysis are those related to digital access and socioeconomic support, as they represent core channels through which exclusion and inclusion operate in the education system. Notably, internet access has the most negative and significant association with being in a 3T region (Coef = -0.278; z = -29.59; $p < 0.001$), followed by internet subsidies (Coef = -0.223; z = -19.90) and cellular access (Coef = -0.111; z = -12.01). These values suggest that households in 3T regions are structurally disadvantaged in accessing digital infrastructure. This aligns strongly with the Digital Divide Theory (van Dijk, 2017), which posits that access to technology is not evenly distributed but rather influenced by systemic factors such as geography, institutional reach, and infrastructural investment.

In the context of education, this divide has real implications: students in digitally disconnected regions have reduced exposure to online learning platforms, fewer opportunities for distance learning, and diminished access to digital resources that could support school participation. This is supported by empirical findings from Onoja & Ajala (2022), who emphasized that disparities in ICT access reinforce existing social inequalities, particularly in low-income, rural, or minority communities. Similarly, a study by Caldarulo et al., (2023) in the US found that broadband expansion in rural areas significantly increased students' academic achievement, highlighting the transformative role of digital infrastructure in education.

Access to digital technology is increasingly recognized as a determinant of educational access and quality, especially after the COVID-19 pandemic, which accelerated the global shift toward remote learning. In remote Indonesian regions, the absence of connectivity effectively means the absence of education during periods of school closure and beyond. The negative association of digital variables with 3T residence confirms that without intervention, children in these regions face substantial structural barriers to sustained schooling participation. This is consistent with UNICEF Indonesia (2021), which reported that school-age children in Eastern Indonesia faced longer learning disruptions due to the digital gap. Moreover, Srinivasan et al. (2021) documented how inadequate internet access during the pandemic widened the education gap across socioeconomic and geographical lines, a pattern that resonates with the disparities captured in this model.

This finding underscores the urgent need for targeted digital inclusion policies in Indonesia, particularly in 3T areas. Concrete policy actions may include expanding the national broadband infrastructure to underserved areas through public-private partnerships, subsidizing internet access and digital devices for students from low-income households, and integrating offline-compatible learning resources to accommodate limited connectivity. Furthermore, strengthening teacher capacity in digital pedagogy is critical to ensuring that the adoption of technology translates into meaningful learning outcomes. The government could also leverage community-based digital learning centers to bridge access gaps in the short term, especially in remote villages where home-based internet remains infeasible.

The model also explores the role of social protection programs in shaping 3T region residency. Households that receive the KIP are more likely to be in 3T areas (Coef = 0.158; z = 13.06), as are those receiving PKH (Coef = 0.401; z = 46.51). These findings reflect the intended targeting of these programs to Indonesia's most socioeconomically vulnerable regions and underscore their potential to mitigate structural disadvantages through conditional cash transfers and educational support. Studies by Purba (2019) and Rizky (2024) support this interpretation, showing that Indonesia's social assistance programs can improve household welfare as well as educational outcomes when well-targeted. On the other hand, the PIP and BPNT have negative associations with 3T residence (Coef = -0.135 and -0.073, respectively), which could indicate that their coverage is more national in scope and less targeted to remote populations. These contrasting findings illustrate how not all social interventions are equally responsive to geographic disadvantage. A reevaluation of the spatial targeting strategy of some assistance programs may be warranted, particularly those with objectives tied to reducing dropout rates and improving schooling continuity. This supports the findings of Rosmana et al. (2022) who noted that while Indonesian education programs have improved in coverage, regional targeting remains inconsistent, especially in outer island provinces.

Beyond digital and social assistance factors, household-level characteristics further contextualize the structural realities of 3T life. Per capita household expenditure is negatively associated with 3T region classification (Coef = -0.129; z = -12.00), signaling the ongoing economic marginalization of these areas. Households in 3T regions generally have fewer monetary resources, which may indirectly limit children's ability to remain in school due to costs associated with transportation, school supplies, uniforms, or even opportunity costs related to child labor. This is in line with findings from Tieken & Montgomery (2021) which have consistently highlighted poverty as a significant barrier to education in rural and remote communities. In contrast, ownership of household assets shows a positive and significant relationship with 3T residence (Coef = 0.272; z = 25.13), which, although seemingly counterintuitive, may be explained by the presence of in-kind assets (e.g., land, livestock) that are common in agrarian or semi-subsistence households but do not necessarily translate into cash liquidity or educational access.

These findings highlight the importance of tailoring the existing poverty alleviation and education support programs, such as Program Keluarga Harapan and Kartu Indonesia Pintar, to better address the specific needs of households in 3T regions. While PKH provides conditional cash transfers linked to school attendance, its nominal value may be insufficient to cover indirect education cost such as transportation, especially in geographically isolated areas. Policymakers could consider enhancing the PKH education benefit specifically for 3T beneficiaries or integrating transportation and nutritional support within the program.

Similarly, the KIP program, though designed to provide educational assistance, often face challenges in distribution and utilization in remote areas due to administrative bottlenecks and lack of awareness. Streamlining KIP disbursement through digital platforms, aligned with ongoing efforts to expand digital infrastructure in remote areas, while simultaneously strengthening offline outreach, would significantly improve the program effectiveness and equity.

Household size (Coef = 0.057; z = 5.79) also shows a small but significant positive relationship with 3T classification. Larger families may be more common in rural or traditional communities, and this dynamic could have dual implications. On the one hand, more siblings may dilute resources available per child, affecting educational outcomes (Cooper & Stewart, 2021). On the other hand, extended family structures may offer informal support systems that can enable some children to stay in school while others work, although this requires deeper exploration through qualitative data. In rural Bangladesh, for example, Islam & Hoque (2022) observed how household structure played a critical role in supporting school continuity among children in vulnerable families, suggesting similar dynamics could exist in Indonesia's peripheries.

The results of the probit model reflect deep spatial disparities that intersect with digital access, poverty, and program targeting. The stark digital divide remains a major challenge, one that directly undermines children's ability to participate in school, particularly in areas that are structurally disconnected. The high statistical significance of digital access variables supports existing literature on technology-driven educational inequality (Chari, 2024), while the role of assistance programs underscores the importance of well-designed public policy. The next step, estimating the ATT, will reveal whether the compounded disadvantage of 3T households translates into significant gaps in schooling participation once these background characteristics are accounted for.

3.2. Propensity Score Matching using ATT

The ATT output derived from the PSM method provides critical insight into whether children living in Indonesia's 3T regions are significantly more or less likely to attend school compared to matched counterparts in non-3T regions. This analysis was conducted using nearest-neighbor matching with a caliper of 0.05, and the matching was performed based on key covariates such as household digital access, income level, and participation in social protection programs.

Table 3 presents that, before matching, the difference in school participation rates between the treated (3T) group and control (non-3T) group was very small, 92.41% vs. 92.25%, with an insignificant difference of just +0.16 percentage points ($t = 0.92$). After applying the PSM procedure, the matched ATT estimate indicates that 92.41% of treated households had children attending school compared to 91.22% of their matched control group. This results in a slightly larger difference of +1.20 percentage points. However, the standard error is relatively high (0.0275), and the t-statistic is only 0.43, indicating that the difference remains statistically insignificant at conventional levels ($p > 0.05$).

This finding is noteworthy because it challenges the commonly held assumption that residence in a 3T region automatically equates to lower educational access. The result implies that once digital access, economic capacity, and social program participation are accounted for, the location-specific disadvantage associated with being in a 3T region appears to dissipate. In other words, the educational gap is not driven solely by geography, but more precisely by unequal access to enabling factors, many of which are prevalent in, but not exclusive to, 3T areas.

This aligns with previous studies, such as Nita et al. (2021) who argue that poverty, rather than remoteness per se, is a more powerful predictor of school dropout and low educational attainment. In the Indonesian context, this is also supported by empirical insights from Asian Development Bank (2022), which showed that children from poor households in urban slums and peri-urban communities can be just as vulnerable to school exclusion as those in remote rural areas. Therefore, policies based solely on spatial classification (i.e., labeling regions as 3T) may miss vulnerable children who reside outside of officially designated areas.

Children in 3T regions may still be able to attend school if their households are adequately supported through subsidies, connectivity, and social services. Conversely, households in non-3T areas may fail to send their children to school if they lack those essential enablers. Thus, the intersectionality of digital exclusion, economic deprivation, and weak institutional support should be at the core of educational policy design.

The findings of this study reflect broader global patterns in which interplay of digital exclusion, economic hardship or poverty, and weak institutional support significantly undermines school attendance among marginalized students. For example, in rural Nigeria, Olanrewaju et al. (2021) documented that inadequate internet infrastructure and high connectivity costs severely disrupted e-learning, leading to widespread disengagement from remote schooling in under-resourced communities. Similarly, Hendricks et al. (2023) found among rural university students in

Table 3. Average Treatment Effect on the Treated (ATT) of 3T Region Residence on School Participation

Var.	Sample	Treated	Controls	Difference	S.E.	t-stat
schooling	unmatched	0.924106344	0.922541752	0.001564592	0.001692399	0.92
	ATT	0.924106344	0.912155151	0.011951193	0.027479337	0.43

Source: *Author's Data Analysis (2025).*

South Africa that the shift to online learning during COVID-19 was undermined by intersecting challenges, including unreliable connectivity, limited digital literacy, and financial strain, that together created "paragons of inequality" in access. Across all these contexts, in Indonesia's 3T regions, Nigeria, and South Africa, the convergence of digital exclusion and socioeconomic deprivation, compounded by weak institutional scaffolding, creates a multi-layered barrier to educational participation.

The ATT estimation provides no statistically significant evidence that residence in a 3T area, by itself, negatively affects children's likelihood of school participation once socioeconomic and infrastructural characteristics are matched, suggesting that geographic remoteness does not inherently reduce educational access when other enabling conditions, such as internet connectivity, economic support, and asset ownership, are similar. This result invites a critical reevaluation of assumptions embedded in regional education policy, particularly those that equate remoteness with vulnerability in a linear way. While 3T areas are often underserved, this analysis emphasizes that disparities in access are shaped less by spatial labels and more by multidimensional household conditions that transcend administrative boundaries.

This insight carries important implications for policy formulation. Rather than relying solely on geographic targeting, policies should integrate more granular household-level data, such as access to internet, digital devices, or parental literacy, to identify children at risk of educational exclusion. If inclusion in education is to be meaningfully addressed, interventions must move beyond the traditional place-based framework and toward a more person-centered, needs-based approach. Children in non-3T areas may still suffer from exclusion if their households face digital deprivation or economic hardship, while some children in 3T areas may thrive educationally if supported adequately by public and private infrastructure. Therefore, educational inclusion must be driven not by geography alone, but by targeted investments in digital access, social protection, and community-level services that enable sustained school participation.

3.3. Balance Test

The balance test results presented in Table 4 assess the effectiveness of the propensity score matching procedure in equating the distribution of covariates between treated (3T region households) and control (non-3T region households) groups. This is a critical step in validating the robustness of the causal inference derived from Propensity Score Matching (PSM). A well-balanced matching ensures that any observed differences in outcomes can be attributed more confidently to the treatment (3T residence) rather than confounding variables.

The means of covariates between treated and control groups are closely aligned after matching, as presented in Table 4. For instance, the difference in average household internet access is negligible (Treated = 0.51404; Control = 0.51412), with a %bias of −0.0 and an insignificant t-test ($p = 0.986$), indicating excellent covariate balance. Similarly, other key variables such as cellular, kip, pip, pkh, and bpnt show %bias values close to zero and non-significant t-tests ($p > 0.1$), suggesting that the matching procedure effectively reduced observable systematic differences between the groups.

Two covariates household size (hh_size) and household expenditure per capita (hh_percapita) show slightly larger deviations. The %bias for hh_size is −1.6 with a t-test p-value of 0.074, while hh_percapita has a higher %bias of 3.0 and a statistically significant t-value ($p = 0.001$) and still within acceptable thresholds.

Table 4. Covariate Balance Test after Propensity Score Matching

Variables	Mean		%bias	t-test		V(T) / V(C)
	Treated	Control		t	Prob	
cellular	0.41332	0.41611	-0.6	-0.67	0.503	
internet	0.51404	0.51412	-0.0	-0.02	0.986	
Internet_sub	0.08423	0.08767	-1.1	-1.45	0.147	
kip	0.13955	0.13923	0.1	0.11	0.912	
pip	0.17225	0.17344	-0.3	-0.37	0.712	
pkh	0.39811	0.39979	-0.4	-0.41	0.685	
bpnt	0.26078	0.26468	-0.9	-1.05	0.295	
hh_size	1.1117	1.1172	-1.6	-1.78	0.074	0.96*
hh_percapita	13.467	13.457	3.0	3.37	0.001	1.08*
house	0.91162	0.90904	0.8	1.07	0.286	

Note: *if variance ratio outside [0.98; 1.02]

Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
0.000	18.06	0.054	0.9	0.7	3.6	1.05	100

Source: *Author's Data Analysis (2025).*

Nonetheless, the variance ratios (V(T)/V(C)) for both are still close to the ideal range (0.96 and 1.08, respectively), and the overall diagnostics further support the validity of the matching.

The bottom part of the table reports post-matching balance metrics, where Mean Bias is 0.9% and Median Bias is 0.7%, both well below the 5% threshold typically cited in PSM literature (Rosenbaum & Rubin in Maruyama et al., 2023). Meanwhile, the LR chi^2 statistic is 18.06 with a p-value of 0.054, indicating that there is no statistically significant joint difference in covariates between groups post-matching. Lastly, the R statistic is 1.05 and B (maximum bias) is 3.6%, which are comfortably within the recommended thresholds of [0.5, 2] and <25%, respectively.

Taken together, these results indicate that the PSM procedure successfully produced a matched sample with high covariate balance, thereby reducing bias from observed confounders. This strengthens the credibility of the ATT estimates and supports the interpretation that any differences in schooling participation between 3T and non-3T regions are less likely due to imbalance in these key variables. As such, this balance check reinforces the reliability of the causal inference drawn from the matched analysis.

Confirming Table 3, Figure 1 displays the standardized percentage bias across covariates used in the PSM model, assessing the quality of covariate balance between treated (3T) and control (non-3T) groups after matching. The vertical axis lists the covariates, while the horizontal axis represents the standardized bias percentage. A value close to zero indicates good balance, whereas larger deviations suggest imbalance. From the graph, it is evident that the vast majority of covariates exhibit low standardized bias, mostly clustering between -2% and +2%, suggesting that the matching process was successful in minimizing systematic differences between groups.

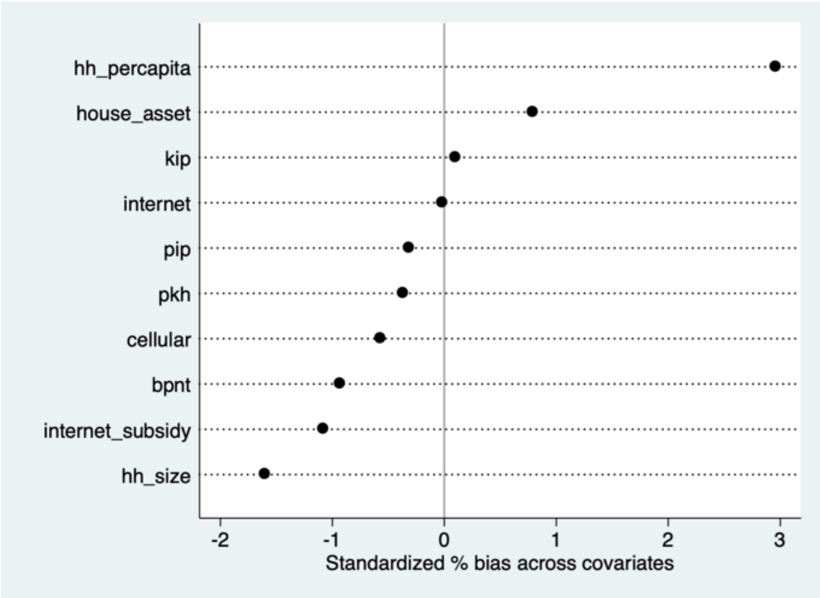

Figure 1. Standardized Percentage Bias across Covariates after Matching (Source: Author's Data Analysis, 2025).

Among the listed variables, hh_percapita shows the highest bias post-matching, slightly above 3%, followed by house_asset. Despite this, both remain within the widely accepted threshold of ±10%, which indicates adequate balance (Rosenbaum & Rubin in Maruyama et al., 2023). Variables such as internet, pip, pkh, bpnt, and internet_subsidy are tightly centered around zero, implying minimal bias and effective alignment of treatment and control units on those characteristics. Overall, the figure provides visual confirmation that the PSM method has substantially improved covariate comparability, supporting the validity of subsequent treatment effect estimations.

4. Conclusion

The results of this study reveal a crucial nuance in the relationship between spatial disadvantage and educational access. Once household-level variables, such as digital connectivity, access to government assistance, and indicators of economic capacity, are accounted for, the geographic status of being located in a remote or underdeveloped area no longer appears to significantly affect children's school participation. This suggests that the educational inequality often attributed to remoteness may, in fact, be more accurately explained by deeper, cross-cutting socio-economic inequalities. Consequently, policies that rely heavily on geographic targeting without considering the underlying multidimensional deprivation risk oversimplifying the problem and misallocating resources. What emerges is a clearer understanding that spatial disadvantage becomes a proxy for broader structural exclusion, which can also be found in urban peripheries or neglected rural zones outside of officially designated regions.

This finding necessitates a shift in how educational development policies are framed and implemented. If inclusion is the goal, then interventions must move beyond static administrative boundaries and instead embrace an integrated, equity-driven approach rooted in the lived realities of households. Digital infrastructure, economic empowerment, and targeted social protection should be prioritized as strategic levers to support sustained educational participation. Moreover, future research should delve deeper into within-region heterogeneity, recognizing that the 3T classification masks significant variation in access and opportunity. Longitudinal studies and mixed-method approaches would also enrich the understanding of how digital adoption interacts with cultural, institutional, and behavioral dynamics to influence educational outcomes. Such directions can ultimately lead to more adaptive and responsive education policies, capable of reaching those most in need, regardless of where they reside.

Future research should incorporate longitudinal household-level data to capture the dynamic effects of digital adoption, income fluctuations, and policy interventions on school participation over time. In-depth geospatial data on infrastructure quality, such as distance to school or transportation network, would further clarify the spatial constraints faced by 3T households. Additionally, qualitative studies exploring household decision-making and children's educational aspirations in remote regions could complement quantitative findings and inform more context-sensitive policy design.

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