Empowering Southeast Asia's Young Adults

Digital Inclusion as a Pathway for Youth Not in Employment, Education, or Training

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Abstract

This study investigates the relationship between digital inclusion and youth who are not in education, employment, and/or training (NEET) across 11 Southeast Asian countries. The analysis employs panel regression using annual data from the mobile connectivity index (MCI) and youth NEET in aggregate and disaggregated by gender. The MCI's four pillars —infrastructure, affordability, consumer readiness, and content and services—were analyzed for the period 2014 to 2024. Empirical evidence suggests that affordability (the relative costs of mobile internet services, devices, and taxation), consumer readiness (basic skills and mobile ownership), and content and services (local relevance) are strongly associated with youth NEET in the region, and that the strength of the relationship and the influence of gender vary between them. Indicators for infrastructure did not exhibit statistical significance. These findings indicate that having digital connectivity access and application services is not, by itself, sufficient to achieve economic productivity gains. The results also highlight the importance of economic accessibility as a critical entry barrier to improving digital inclusion for underserved communities and for addressing youth NEET. Southeast Asian countries have yet to reap the benefits of their mobile connectivity development to address digital inclusion for productive use. Policy interventions should shift from generalized to focused programs tailored to local conditions, gender-specific needs, institutional coordination, effective information dissemination, and dedicated, necessary incentive structures in affected areas. The study provides policymakers and organizations with valuable insights for designing and implementing their respective targeted interventions. Furthermore, it could also serve as a basis for further research and for guiding policy implementations to support regional initiatives in achieving the Association of Southeast Asian Nations' Vision 2045 and the Digital Economic Framework Agreement in the context of social inclusion objectives.

Empowering Southeast Asia's Young Adults

Digital Inclusion as a Pathway for Youth Not in Employment, Education, or Training

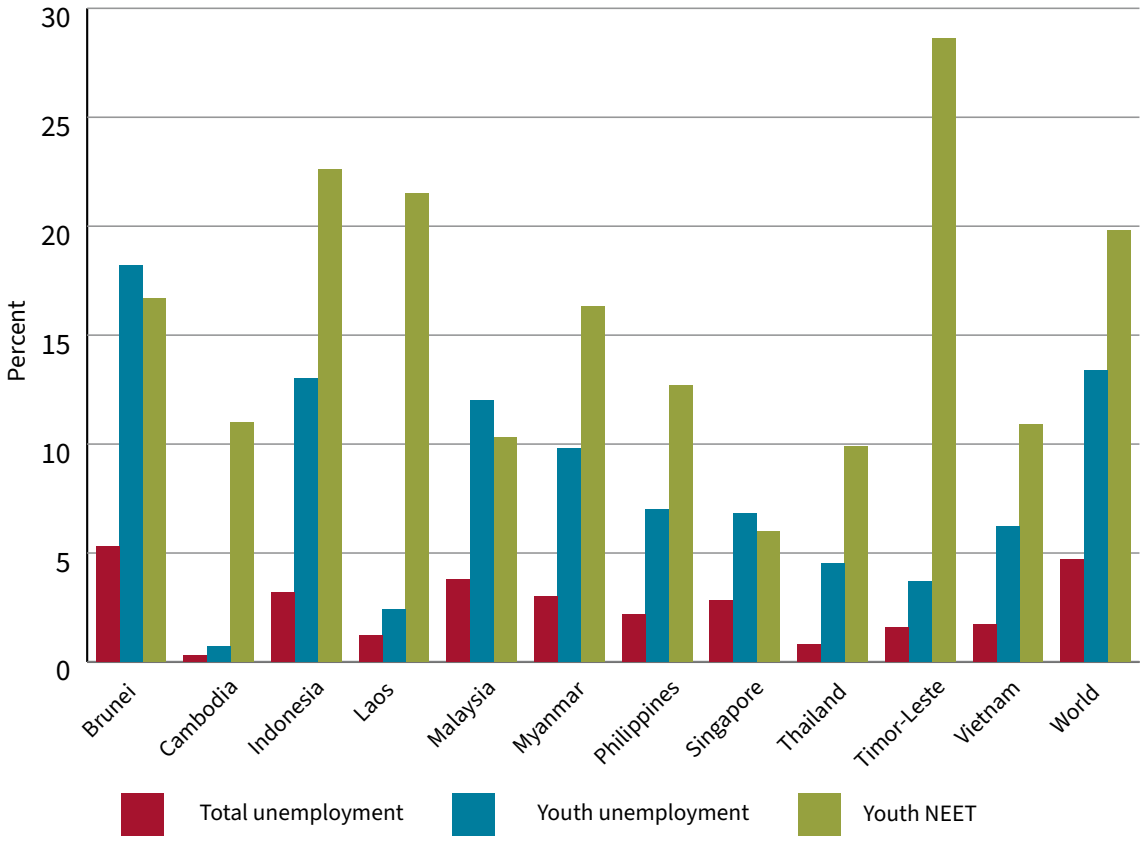
There are growing concerns about widening social inequality, fueled by the significant number of young people who are not engaged in employment, education, or training (NEET) relative to the overall youth population. As one of the key parameters of human capital and social inclusion, these numbers are consistently and alarmingly high—often two to three times the overall employment and youth unemployment rates (ILO 2025; O'Higgins 2025). The risks associated with youth NEET cannot be underestimated, as they have a long-term adverse impact on individual vulnerabilities and entire social systems (Gunnes et al. 2025). While progress in reducing the NEET rate among youth has been achieved through expanded economic growth and targeted interventions in upper-middle- and high-income countries, the recovery has not been consistent, particularly in low- and middle-income countries, due to varying educational quality, structural limitations, and social and cultural norms (ILO 2025).

Despite these social and economic challenges, indicators of digital access and usage have shown significant growth worldwide, driven by ongoing infrastructure investments and high adoption of mobile and digital services (GSMA 2026; ITU 2025). In low- and middle-income countries, mobile technologies have been the catalyst for communication and digital inclusion—a trend likely to continue in the near- to medium-term future (GSMA 2026; ITU 2025). Unsurprisingly, the youth segment represents the largest user base, accounting for 82 percent of internet penetration, 10 percentage points above the global average (ITU 2025). This phenomenon raises a critical issue—the extent to which digital development will influence future generations, particularly for those who are unemployed and economically inactive, with limited access to infrastructure resources and minimal workforce skills.

This paper focuses on the 11 Southeast Asian countries that are members of the Association of Southeast Asian Nations (ASEAN): Brunei, Cambodia, Indonesia, Laos, Malaysia, Myanmar, Thailand, the Philippines, Singapore, Timor-Leste, and Vietnam. These countries have diverse

demographic profiles, economic conditions, and digital adoption rates. Figure 1 shows the varying levels of unemployment and NEET rates in the region (World Bank 2026), suggesting that the greater use of mobile technologies has yet to play a larger role in providing opportunities for youth, particularly in rural areas.

FIGURE 1 Unemployment and youth NEET, 2025



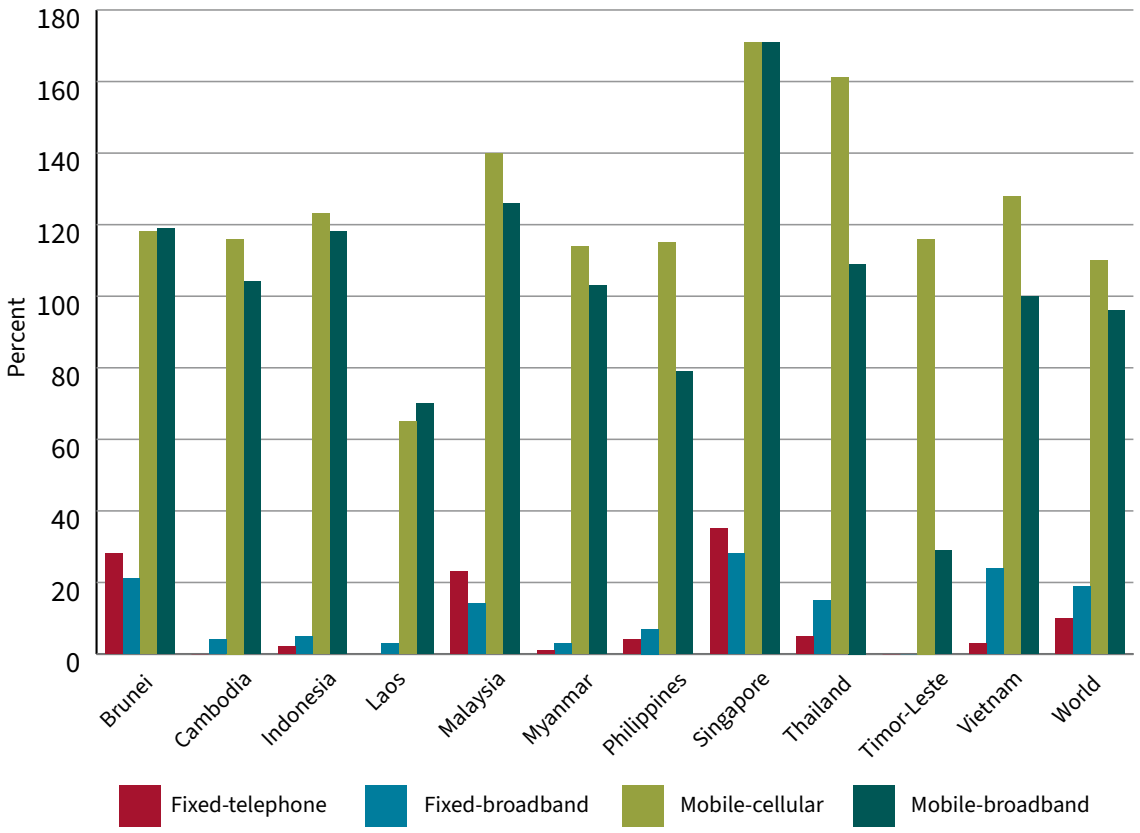
Note: Figures are based on ILO modeled estimates in line with the 13th International Conference of Labour Statisticians (ICLS) guidelines

Source: World Bank 2026.

As shown in figure 2, mobile connectivity in Southeast Asia has surged far beyond fixed-line penetration. The trend is expected to continue as governments and companies prepare for the next phase of digital transformation and widespread adoption of fifth-generation (5G) wireless technology (Okeleke and Joiner 2025). Despite significant growth in the mobile industry, there is a lack of empirical data measuring the direct link between mobile internet adoption and youth NEET in Southeast Asian countries. Considering this gap, the purpose of this paper is to contribute to the limited body of research by providing an understanding of how access to and usage of mobile internet connectivity can be expanded effectively among youth populations in

the region, particularly for those who are socially excluded. The study examines the influence of mobile internet connectivity on youth NEET rates, both aggregated and gender-specific, in Southeast Asia, in the context of economic development and policy support for digitalization and labor force expansion. The analysis employs panel regression using annual data from 11 Southeast Asian countries between 2014 and 2024.

FIGURE 2 Fixed and mobile penetration rates, 2024



Source: ITU n.d.

Understanding Youth NEET

Despite its limitations, the concept of youth NEET continues to evolve and remains a valuable reference for measuring the state of the youth labor market and deficiencies in education, social conditions, and economic structures. Comparing NEET across countries is a difficult task given the differences in labor structure, i.e., formal and informal employment, and socioeconomic conditions. ILO (2025) defines NEET as young people who are disconnected from the labor and education systems, but the parameters are not internationally standardized, i.e., the age range (15–24 years or 15–29 years) and the employment structure. With the modification of

ILO's classification of employment to include only individuals engaged in remunerated work, young people who are involved in unpaid activities and with no education or training involvements (both formal and informal) are classified as NEET (O'Higgins 2025). The adjustment can affect the number of NEETs reported in countries with high informal economies (e.g., domestic housework and farming), including those in Southeast Asia. Nevertheless, the NEET measure remains widely accepted as one of the key indicators of vulnerability in social and youth development (O'Higgins 2025).

The United Nations (UN n.d.) includes youth NEET as an indicator for Sustainable Development Goal 8.6—to strive for "full and productive employment and decent work for all" with the objective of significantly lowering the rate of youth NEET by 2020. Despite this explicit aspirational goal, many countries continue to face structural and latent issues (e.g., weak educational systems, lack of social support, economic volatility) that hinder meaningful reductions in youth NEET rates. The average global rate of youth NEET remains high (20 percent) in 2025 (ILO 2025); most of these underserved communities come from developing countries, including Southeast Asia (World Bank 2026). The lack of progress often leads to "scarring effects" (i.e., an increased risk of future unemployment, a reduction of lifetime wages attributable to joblessness in young adulthood, and mental health issues) that limit national economic development (Schmillen and Umkehrer 2017, 2). Addressing the core problem of vulnerable young adults is particularly important as the data from the Global Risks Perception Survey (August–September 2025) suggests that social inequality and the lack of economic opportunity pose major global risks to individual self-sustainability, national and regional economic development, and political stability in the near to long term (World Economic Forum 2026).

Considering the ongoing geopolitical tensions and economic pressure, youth NEET are at higher risk for poverty and social exclusion as they typically live in disadvantaged areas with limited income and resources. Prior studies indicate that past global crises (e.g., the Asian financial meltdown in the late 1990s, the global economic crisis in 2008 and 2009, and the global COVID-19 pandemic in the early 2020s) have exacerbated youth NEET conditions (Aina et al. 2025; Avagianou et al. 2022; Choudhry et al. 2012). Researchers highlight that young adults are generally worse off during economic crises and that they rebound (regain employment) much later than older adults. Their findings are relevant for young adults in Southeast Asia, as most work in cyclical industries, including services (e.g., retail, hospitality, and food services) and the agricultural sector; they frequently work part-time, which exposes them to greater economic volatility. Across the region, manufacturing accounts for a significant share of youth employment in only Cambodia and Vietnam, at roughly one-third of total employment (ASEAN

2025a). Excluding Singapore, Brunei, and Malaysia, the other eight Southeast Asian countries included in this study are engaged in agriculture, with Laos and Myanmar having the largest share, around half of their employment base (ASEAN 2025a).

Moreover, in times of crisis, many companies work to reduce costs and accelerate technological advancement, such as automation and emerging artificial intelligence (AI), to maintain financial viability and a competitive edge, driving a structural labor shift. Such streamlining and cost-cutting business strategies have been proven to disproportionately affect young adult workers, particularly in entry-level positions where employees are increasingly challenged by skill gaps and reskilling requirements (Junankar 2016; Ng et al. 2025). Martínez-Cañas et al. (2023) point out that, as a result, younger workers often turn to self-employment, driven by push motivations (i.e., the necessity to survive due to lack of opportunities or poverty) rather than pull factors (i.e., factors associated with innovation, market opportunity, and time flexibility). These push-and-pull motivations influence an individual's perception of entrepreneurial creativity, opportunity, and risk-taking, all of which require specific entrepreneurial skills, policies, and interventions. Notably, the push motivations are the dominant factors for entrepreneurship in developing markets (Hill et al. 2026).

The majority of entrepreneurs in Southeast Asia work in the informal employment sector, which is likely to remain unchanged in the near to medium term. In all Southeast Asian countries except Singapore, Malaysia, and Brunei, informal employment accounts for 60–80 percent of total employment (ASEAN 2025a). Although micro, small, and medium enterprises are considered the backbone of the domestic market, strengthening this segment is hampered by a serious lack of real-time data on Southeast Asia's informal employment sector. The high level of informal employment in the region often exposes workers to greater risks (e.g., low wages, information asymmetry, and restricted access to financing and digital services), as well as limited legal and social protections (Ghorpade et al. 2024).

Rahmani et al. (2024) have emphasized that the marginalization of youth is detrimental to individual development and to society as a whole. Their findings revealed significant correlations between youth NEET and demographic profile, family background, educational attainment, socioeconomic characteristics, and health and well-being. These vulnerable youth could remain excluded from formal learning and the labor market once they enter the NEET segment, especially in the absence of early detection and intervention programs, i.e., adolescence, family, and school-to-job transition programs (Veldman et al. 2024). In fact, mental health disorders and behavioral issues, i.e., depression and anxiety among youth in general and youth NEET in

particular, have surged rapidly across the South and Southeast Asia regions, all of which have a direct financial and psychological toll on individuals, families, and society (Mudunna et al. 2025a, 2025b). These researchers note limited funding, community awareness, data availability, and the consistency of monitoring as contributing factors to youth NEET, particularly in rural areas, where it is difficult to assess and support direct interventions for these youth. As a result, youth NEET has become a critical factor for individuals and an urgent societal challenge that must be addressed in national and regional agendas across Southeast Asia.

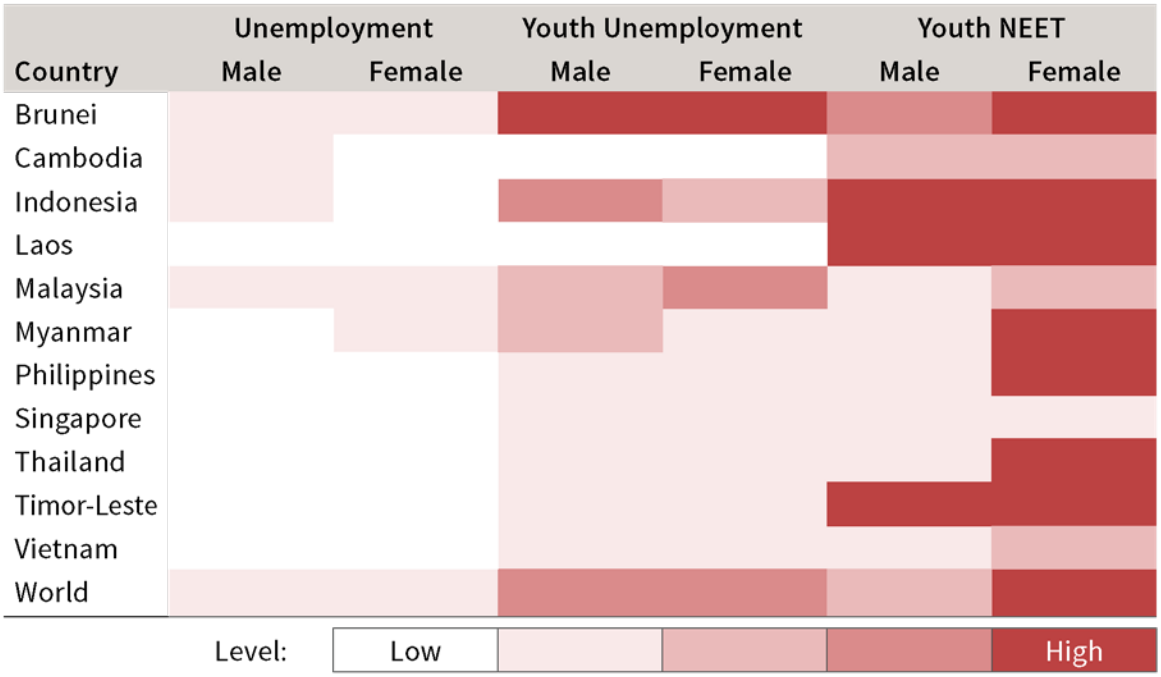
Youth NEET and Gender

What is more concerning and requires urgent attention is the high NEET persistence and the significant difference between the share of youth NEET and the share of youth unemployment in some countries in the region (Timor-Leste, Indonesia, Laos, Myanmar, Brunei, Thailand, and the Philippines), as highlighted in figure 3 (World Bank 2026). In line with global trends, it shows NEET rates among youth are even higher for young women, as gender inequalities in labor force participation persist in most countries in the region (World Economic Forum 2025). This gender disparity affects younger workers and the overall working-age population (ages 15 to 64), given that half of the total Southeast Asian population is female (ASEAN 2025a). Consequently, these gaps pose potential risks and opportunity losses for the region's productivity. The region cannot achieve its full economic potential if a significant portion of the population (women) is left behind.

In their studies with private companies in India, Jalota and Xu (2025) highlight that localized recruitment, favorable workplace policies (e.g., remote work), and community engagement to support job development have proven to incentivize women to enter the workforce. These proactive measures and a supportive ecosystem help transform the labor market into a more inclusive environment for women. While mobile connectivity and digital adoption are critical in driving these initiatives, closing the digital divide—the disparities between those who have and do not have access to and the ability to use information and communications technologies—becomes more complex and requires a nuanced approach when taking gender and other demographic factors into consideration (ITU 2025). Efforts to narrow the digital divide have not shown significant progress, as measured by mobile phone ownership by gender in rural communities or in low- to middle-income countries, including those women who live in Southeast Asia (Jeffrie et al. 2025). Women exhibit lower mobile internet usage even when matched with men with similar socio-demographic profiles (i.e., age, marital status, education);

this trend is especially true in Cambodia, Myanmar, and Timor-Leste, where gender inequality is more pronounced (GSMA 2025).

FIGURE 3 Heat map visualization of the percentage of unemployment and youth NEET by gender, 2025



Note: Adapted by the author based on ILO Modeled estimates in line with the 13th ICLS guidelines. The color transitions represent white and very light pink hues which indicate a low percentage level of below 10 percent, scaling up to the darkest color of above 15 percent.

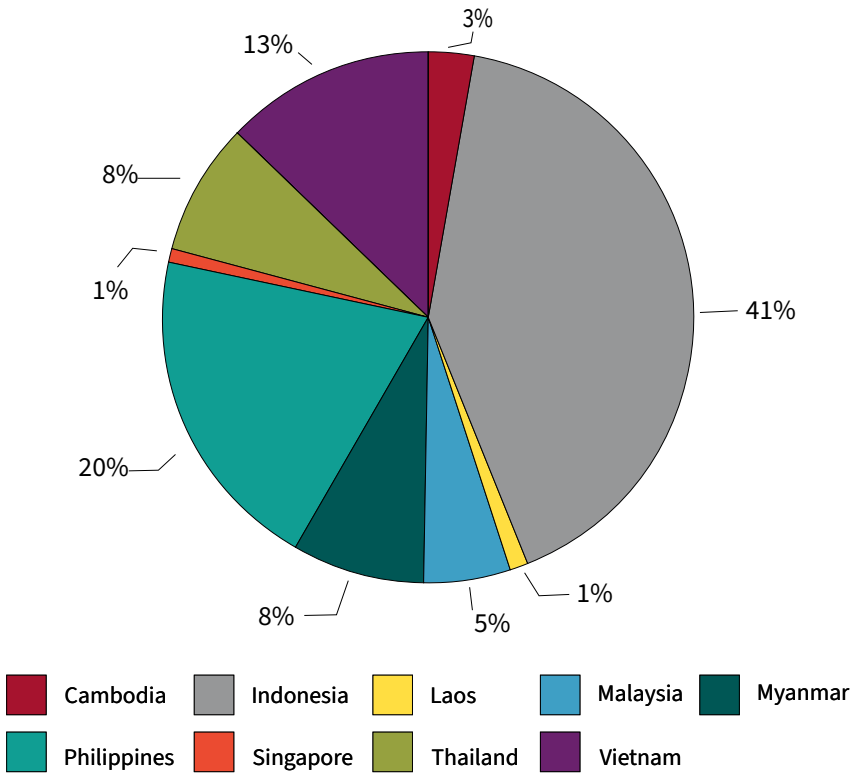
Source: World Bank 2026.

As a result, addressing social and cultural barriers to improve the gender gap in mobile internet adoption will have a more profound effect in low- to middle-income regions, including those in Southeast Asian countries, given that the regional labor market is expected to transform over the next 10 years (see figures 4 and 5). While the youth and working-age adult populations in Southeast Asia remain substantial, the growth of the youth population is in decline due to lower fertility rates attributable to urbanization, economic factors, higher educational attainment, and greater workforce participation by women (ASEAN 2025a). Nevertheless, this segment remains sizable within the global population and represents a critical resource to leverage as a demographic bonus in some Southeast Asian countries.

Southeast Asian governments have acknowledged that digitalization no longer serves primarily as a means of basic communication but has become a key enabler for improving productivity,

fostering innovation, and addressing economic disparities and social exclusion faced by vulnerable communities. These challenges require targeted interventions, particularly in rural areas where more than half of Southeast Asian populations reside (ASEAN 2025a). Even though network coverage in rural areas has expanded significantly over the last decade, disparities persist between rural and urban populations in how people access and use mobile internet effectively (Jeffrie et al. 2025). All of these aspects require targeted policies and incentive measures (e.g., spectrum, financing structures, and advanced technology specifications) to stimulate adoption and more investment in network access, performance, and quality (Kyathari et al. 2026; Mawn et al. 2017).

FIGURE 4 Adult working population, age 15–64



Note: N = 531 million. Based on estimates for 2025. Brunei and Timor-Leste are not shown because their share of total population is less than 1 percent.

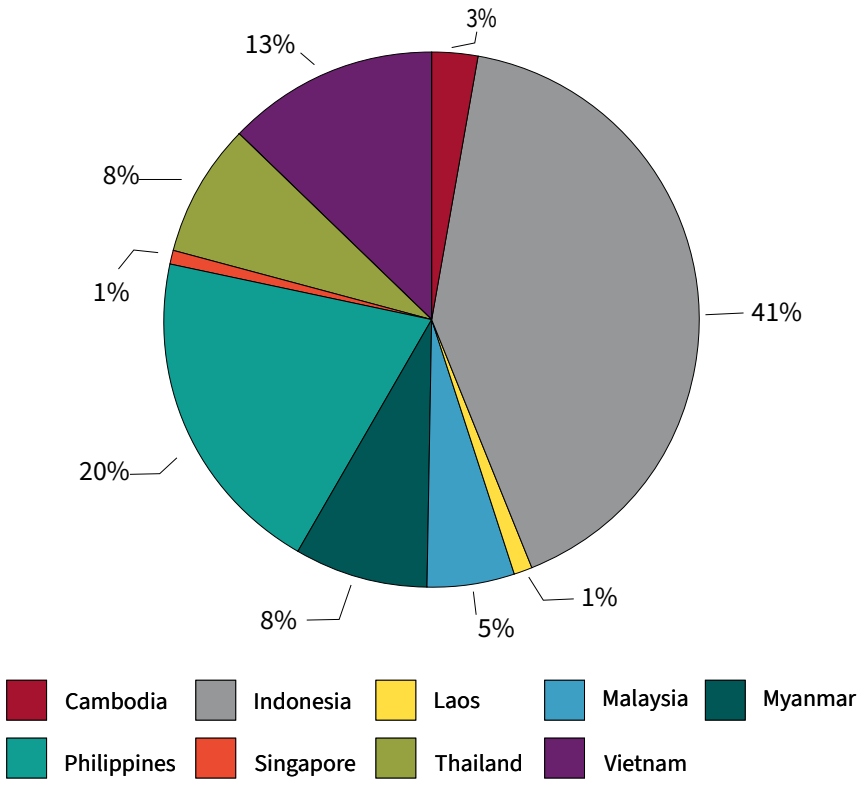
Source: United Nations 2024.

The Importance of Youth and Connectivity for ASEAN

ASEAN's (2025b) strategic blueprint, the *ASEAN Community Vision 2045,* is a 20-year roadmap for the region, built on the previous agreement, which ended in 2025. In the new framework, youth and connectivity are identified as key critical drivers for regional development; the plan

commits to engage in major initiatives to strengthen regional cooperation through four main pillars: (1) political-security community, (2) economic community, (3) socio-cultural community, and (4) connectivity strategic plans. Integrating connectivity into one of the main pillars underscores its strategic importance for advancing and strengthening the underlying synergies within the Southeast Asian region and, more broadly, the global community. Social inclusion and protection are important components of the framework, aligned with the new vision's theme and subtitle: "resilient, innovative, dynamic, and people-centered ASEAN" (ASEAN 2025b, 15). Furthermore, ASEAN's Digital Economic Framework Agreement (DEFA) constitutes another important conduit for the region to align its regulatory framework and strengthen coordination across all member countries to leverage the untapped digital economy and integrated ecosystem (Boston Consulting Group 2024; ASEAN Economic Council 2025). Among other things, both frameworks focus on reducing regional disparities, enhancing talent mobility, boosting productivity, strengthening resilience, and advancing social inclusion across all member countries of the region (ASEAN 2025b; ASEAN Economic Community Council 2025).

FIGURE 5 Youth population, age 15–24



Note: N = 111 million. Based on estimates for 2025. Brunei and Timor-Leste are not shown because their share of total population is less than 1 percent.

Source: UN 2024.

The components of the ASEAN *Community Vision 2045* and the DEFA are comprehensive yet will require tremendous effort, strategic alignment, and coordination, particularly since each country in the region operates at a different stage of demographic transition, infrastructure, data governance, technological readiness, and economic development. These initiatives are expected to bring new hope for social inclusiveness that can improve youth NEET in the region. However, the success of these initiatives hinges on targeting evidence-based approaches for underserved areas, including aligning regulatory efforts and policies, improving data quality, and extending knowledge sharing and capacity development—not only between central governments but also among local authorities, social institutions, communities, and enhanced public-private partnerships.

Research Methodology

The study used a balanced panel data design framework to evaluate the relationship between the GSMA mobile connectivity index (MCI) and youth NEET rates across 11 Southeast Asian countries: Brunei, Cambodia, Indonesia, Laos, Malaysia, Myanmar, Thailand, the Philippines, Singapore, Timor-Leste, and Vietnam. Combining time-series and cross-sectional data, panel regression was used to analyze these variables over an 11-year period (2014–24) in R version 4.5.0 (R Core Team 2025).

Dependent variables comprised youth NEET rates for populations aged 15 to 24 in Southeast Asia. They were used in aggregate and segregated based on gender (total NEET, male NEET, and female NEET). The calculation of youth NEET rates is based on the percentage of youth who were neither employed nor in education or training within the total youth population, using the 13th ICLS framework to ensure a continuous time series. This segment includes youth who are unemployed (but still seeking a job) and not in education, as well as those who are inactive in both the labor force and the education system.

Independent variables included MCI's dimensions derived from four primary critical enablers: infrastructure, affordability, consumer readiness, and content and services (GSMA 2025). These variables were chosen for this panel data because mobile subscriptions and internet penetration are high in the region, and therefore the MCI's index scores are valuable and practical references for measuring digital adoption and for cross-country comparisons. MCI is a weighted input index (0–100 score) that evaluates and tracks mobile connectivity adoption in 173 countries, covering 99 percent of the total global population, to understand the digital inclusion landscape (GSMA 2025). MCI tracks 32 indicators across 11 dimensions, grouped into four main pillars.

Table 1 presents the independent variables incorporated into the models, along with their descriptions. The control variable was included mainly in robustness checks analysis; GDP per capita was based on a constant 2015 US$ and in natural logarithm form. Annual data for all dependent, independent, and control variables were obtained from secondary sources via the GSMA (2025) and the World Development Indicators database (World Bank 2025). Using GSMA's (2025) classifications, 12 panel models were formed and divided by the four different MCI subcomponents (see table 2).

TABLE 1 Independent variables

MCI enabler	Description	Dimensions (independent variables)
Infrastructure	The availability and quality of mobile networks	• Network coverage • Network performance • Spectrum
Affordability	The affordability of handsets and mobile internet services	• Mobile data affordability • Handset affordability • Taxation
Consumer readiness	The level of awareness and demand for mobile internet services	• Mobile ownership • Basic skills • Gender equality
Content and services	The availability of relevant and engaging mobile content and services	• Local relevance • Online security

Source: GSMA 2025.

Descriptive Statistics and Typology

Descriptive statistics were computed for the 11 countries across 11 years for youth NEET, based on the total population (total NEET) and segregated by gender (NEET male, NEET female), along with the MCI indicators, as presented in table 3. These indicators highlight the significant divergence of mobile connectivity and income levels. The outcomes also reflect that these countries are in different stages of digital transformation. Among the dependent variables, the female NEET (M = 19.54; SD = 7.02) was higher than the male NEET (M = 13.88; SD = 5.64), resulting in upward pressure on total NEET scores (M = 16.65; SD = 5.97). For independent variables, network coverage (M = 84.45; SD = 15.82), taxation (M = 93.05; SD = 15.00), and mobile ownership (M = 76.29; SD = 19.81) had high mean scores, while network performance (M = 45.73; SD = 23.97) had the lowest mean scores. The GDP per capita (M = 11,382) showed a significant range of income levels (Min = 1,099; Max = 68,219) in these countries.

TABLE 2 Mobile connectivity index subcomponents

Enabler	Subcomponents
Infrastructure	Access to critical infrastructure that connects people online; the independent variables that were used included network coverage (2G,3G,4G,5G population coverage), network performance (speed and latencies), and spectrum indicators
Affordability	Pathways for adoption and use of mobile internet. In this case, availability of services and devices was examined using each country's affordability with pricing and national income per capita as reference points. The selected indicators for the independent variables are mobile data affordability, handset affordability, and taxation (handset and mobile data)
Consumer readiness	Knowledge and skills as prerequisites to optimize the usage and benefit of mobile internet connectivity; the independent variables that were used included basic skills (literacy rates and school life expectancy), gender equality (mobile ownership and internet use), and mobile ownership
Content and services	Online security along with localized content and services (E-government, social media penetration, local apps, and digital support) accessible to the local population as its key measures

Source: GSMA 2025.

TABLE 3 Descriptive statistics

Variable	Name	*M*	*SD*	*Med*	Min	Max
Dependent Variables						
Total NEET	total_neet	16.65	5.97	15.20	6.62	31.17
Male NEET	male_neet	13.88	5.64	11.39	7.12	29.82
Female NEET	female_neet	19.54	7.02	19.63	5.57	32.55
Independent Variables						
Infrastructure						
Network coverage	infra_nc	84.45	15.82	89.00	34.60	100.00
Network performance	infra_np	45.73	23.97	45.36	1.70	98.05
Spectrum	infra_spec	46.78	19.32	39.90	22.48	91.71
Affordability						
Mobile data	afford_mda	59.52	20.36	62.60	12.13	97.75
Handset	afford_ha	49.94	22.85	47.08	3.84	100.00
Taxation	afford_tax	93.05	15.00	100.00	48.85	100.00
Consumer readiness						
Basic skills	read_bs	65.80	13.74	67.36	21.79	90.16
Gender equality	read_ge	70.94	12.36	73.28	38.80	100.00
Mobile ownership	read_mo	76.29	19.81	80.96	31.69	100.00

Variable	Name	*M*	*SD*	*Med*	Min	Max
Content and services						
Local relevance	cons_lr	55.97	15.66	57.20	22.09	87.77
Online security	cons_os	54.87	32.33	56.10	0.00	100.00
Control variable						
GDP per capita	gdppc	11,382	17,857	3,410	1,099	68,219

Note: N = 121; *M* = mean; *SD* = standard deviation; *Med* = median; Min = minimum; Max = maximum.

To track countries' digitalization progress in the MCI, the GSMA has conceptualized five stages, each associated with its penetration rate and enabling environment, from the latest to the earliest stage of adoption—leader, advanced, transitioner, emerging, and discoverer (Baxter 2024; GSMA 2025). Table 4 shows that all Southeast Asian countries have raised their clusters to higher categories, reflecting improvements across all MCI subdimensions. Malaysia, Myanmar, and the Philippines demonstrated the strongest progress, advancing by two tiers from their initial classification in 2014. Furthermore, all countries exhibited positive performance during the 11-year study period (2014–24), with Indonesia, Myanmar, and Laos recording the highest growth rates, largely driven by infrastructure development (GSMA 2025).

TABLE 4 Country clusters and MCI performance in Southeast Asia

Country	Cluster		Index scores		Performance growth (%)
	2014	2024	2014	2024	
Singapore	Leader	Leader	81.38	93.39	14.76
Malaysia	Transitioner	Leader	60.31	80.31	33.16
Vietnam	Transitioner	Advanced	50.51	79.45	57.30
Thailand	Transitioner	Advanced	59.36	78.57	32.36
Indonesia	Emerging	Advanced	43.99	76.32	73.49
Brunei	Transitioner	Advanced	55.61	74.59	34.13
Philippines	Emerging	Advanced	48.62	71.54	47.14
Cambodia	Emerging	Transitioner	40.58	61.72	52.09
Laos	Emerging	Transitioner	35.00	57.65	64.71
Myanmar	Discoverer	Transitioner	31.03	52.66	69.71
Timor-Leste	Discoverer	Emerging	29.99	47.89	59.87

Note: Performance growth is from 2014 to 2024. Leaders: ≥ 80; Advanced: ≥ 65, <80; Transitioners: ≥ 50, <65; Emerging: ≥ 35, <50; Discoverers <35.

Source: Baxter 2024; GSMA 2025.

Table 5 summarizes the countries' digital development and income levels relative to their youth NEET position. Using this typology, Singapore and Malaysia showed positive performance

relative to their income segment and youth NEET levels, supported by their focus on upskilling initiatives. Thailand, Vietnam, and the Philippines have room to further improve youth NEET rates, given their advanced mobile adoption. The other five countries, Brunei, Indonesia, Laos, Myanmar, and Timor-Leste, are associated with high youth NEET rates at varying levels, but their digital adoption rates are comparable to or even better than those of their peers. This relative comparison reveals that while digital inclusion and disconnected youth are complex and multifaceted issues, the upper-middle- and high-income countries in Southeast Asia, such as Brunei and Indonesia, have yet to reap the benefits of their digital and economic progress for social inclusion. Cambodia, Laos, Myanmar, and Timor-Leste are still at the early stage of their digitalization, and therefore, the focus of expansion would be building digital infrastructure access, knowledge and awareness, higher usage, and economic opportunities for the underserved communities.

TABLE 5 Digital adoption and youth NEET typology

Country	Income segment	Mobile internet adoption	NEET category
Singapore	High	Leader	Low
Malaysia	Upper middle	Leader	Low
Vietnam	Lower middle	Advanced	Medium
Thailand	Upper middle	Advanced	Medium
Indonesia	Upper middle	Advanced	High
Brunei	High	Advanced	High
Philippines	Lower middle	Advanced	Medium
Cambodia	Lower middle	Transitioning	Medium
Laos	Lower middle	Transitioning	High
Myanmar	Lower middle	Transitioning	High
Timor-Leste	Lower middle	Emerging	High

Note: Country income segments are based on World Bank classification. Mobile internet adoption is clustered by GSMA. Youth NEET 2025 numbers are based on ILO estimates. The NEET categories were adapted by the author based on the NEET averages of global and developed countries, including Organisation for Economic Co-operation and Development (OECD) countries, with low < 10.5, medium ≥10.5 ≤ 15.0, and high >15.0.

Source: Baxter 2024; GSMA 2025; Metreau et al. 2025; OECD 2025; World Bank 2025.

Correlation Analysis

A Pearson correlation matrix (see appendix A) shows that local relevance, mobile data affordability, network performance, and online security have strong correlations with the three

dependent variables (total NEET, male NEET, and female NEET). For total NEET, the strongest associations are local relevance (−0.66) and mobile data affordability (−0.63). Male NEET demonstrates a strong relationship with local relevance (−0.49), mobile data affordability (0.48) followed by online security (0.48), and online security (0.48). Like total NEET, the two strongest determinants for female NEET are local relevance (0.73) and mobile data affordability (0.68).

Overall, local relevance emerges as the strongest driver, particularly for female NEET. On the other hand, all indicators under the infrastructure subcomponent (network coverage, network performance, and spectrum) exhibit the lowest correlations for factors for total NEET, male NEET, and female NEET. Among the independent variables, there were strong positive correlations between several indicators, including local relevance and online security (0.80), network performance and basic skills (0.78), local relevance and mobile data affordability (0.78), and local relevance and handset affordability (0.78). In addition, GDP per capita shows a high correlation with several independent variables, including mobile data affordability (0.74), handset affordability (0.85), local relevance (0.79), and gender equality. Nevertheless, the variance inflation factor (VIF) of these variables remained below 5, indicating that multicollinearity was within acceptable limits.

Panel Regressions

Following Greene's (2018) framework, panel regression models were constructed for 11 countries (see table 6) where $i = 1, \ldots, n$ and $t = 1, \ldots, t$, with n being the number of countries ($N = 11$) and t being the number of time periods during the study duration of 2014–24 ($t = 11$). Furthermore, α was the intercept and βs were the regression coefficients. The u_i captured the country-specific effect, while the error term ε_{it} represented the random disturbance of unobserved factors across countries and over time.

Furthermore, several diagnostic tests were performed to evaluate the validity of the models (see appendix B). VIF analysis was employed to examine multicollinearity among the independent variables, confirming that none was present. The Hausman statistic was used to evaluate whether the random effects model was preferred over the fixed effects model using a threshold of $p > 0.05$ (Hausman 1978). To address heteroskedasticity and autocorrelation, the analysis relied on robust standard errors through clustered standard errors (Breusch-Pagan test, $p < 0.05$). The normality of the errors was also evaluated through quantile-quantile plots, which revealed that it was not achieved for all panel regression models due to deviations in the tails. Consequently, robust or clustered standard errors for the models were used to ensure valid inference. The Pesaran (2021) cross-sectional dependence was tested to check if panel data

residuals were correlated across entities (countries) and if $p > 0.05$. If cross-sectional dependence was detected, standard errors were adjusted using the Driscoll-Kraay (1998) methods.

TABLE 6 Formulas for empirical modeling

Category	Model Formula
Infrastructure	
Model 1	$total\_neet_{it} = \beta 0 + \beta 1\ infra\_nc_{it} + \beta 2\ infra\_np_{it} + \beta 3\ infra\_spec_{it} + u_i + \varepsilon_{it}$
Model 2	$male\_neet_{it} = \beta 0 + \beta 1\ infra\_nc_{it} + \beta 2\ infra\_np_{it} + \beta 3\ infra\_spec_{it} + u_i + \varepsilon_{it}$
Model 3	$female\_neet_{it} = \beta 0 + \beta 1\ infra\_nc_{it} + \beta 2\ infra\_np_{it} + \beta 3\ infra\_spec_{it} + u_i + \varepsilon_{it}$
Affordability	
Model 4	$total\_neet_{it} = \beta 0 + \beta 4\ afford\_mda_{it} + \beta 5\ afford\_ha_{it} + \beta 6\ afford\_tax_{it} + u_i + \varepsilon_{it}$
Model 5	$male\_neet_{it} = \beta 0 + \beta 4\ afford\_mda_{it} + \beta 5\ afford\_ha_{it} + \beta 6\ afford\_tax_{it} + u_i + \varepsilon_{it}$
Model 6	$female\_neet_{it} = \beta 0 + \beta 4\ afford\_mda_{it} + \beta 5\ afford\_ha_{it} + \beta 6\ afford\_tax_{it} + u_i + \varepsilon_{it}$
Consumer readiness	
Model 7	$total\_neet_{it} = \beta 0 + \beta 7\ read\_bs_{it} + \beta 8\ read\_ge_{it} + \beta 9\ read\_mo_{it} + u_i + \varepsilon_{it}$
Model 8	$male\_neet_{it} = \beta 0 + \beta 7\ read\_bs_{it} + \beta 8\ read\_ge_{it} + \beta 9\ read\_mo_{it} + u_i + \varepsilon_{it}$
Model 9	$female\_neet_{it} = \beta 0 + \beta 7\ read\_bs_{it} + \beta 8\ read\_ge_{it} + \beta 9\ read\_mo_{it} + u_i + \varepsilon_{it}$
Content and services	
Model 10	$total\_neet_{it} = \beta 0 + \beta 10\ cons\_lr_{it} + \beta 11\ cons\_os_{it} + u_i + \varepsilon_{it}$
Model 11	$male\_neet_{it} = \beta 0 + \beta 10\ cons\_lr_{it} + \beta 11\ cons\_os_{it} + u_i + \varepsilon_{it}$
Model 12	$female\_neet_{it} = \beta 0 + \beta 10\ cons\_lr_{it} + \beta 11\ cons\_os_{it} + u_i + \varepsilon_{it}$

Results and Discussion

Tables 7–10 present the results of the analysis for the 12 panel regression models. Parameter estimates are presented, and standard errors for all models are shown in parentheses. F statistics represent the overall significance for fixed-effects (FE) and Wald χ^2 (Wald Chi-square) for random-effects (RE) models. The FE model excludes constants because they are absorbed by the country-fixed effects. Diagnostic tests (Breusch-Pagan and Pesaran CD) confirmed heteroskedasticity and spatial correlation, justifying the use of robust estimators.

Table 7 shows the results of the infrastructure sub-component model. The three-panel regressions demonstrated that none of the independent variables (infra_nc, infra_np, infra_spec) were statistically significant. The values of *R*-squared for total NEET (total_neet; $R^2 = 0.10$; $\chi^2 = 13.12$) and male NEET (male_neet; $R^2 = 0.08$; $\chi^2 = 9.58$) were relatively low. Only female NEET

(female_neet) showed a moderate explanatory power with R^2 (0.24) and significance ($\chi^2 = 36.00$) relative to the other dependent variables. These findings imply that while infrastructure is a meaningful dimension for female NEET, the lack of significance for the individual indicators in this subcomponent suggests that female NEET is associated with the three infrastructure sub-components as a whole; however, none of the three variables had a unique, independent contribution that stood out clearly after controlling for the other two.

TABLE 7 Findings for infrastructure sub-component

Variable	total_neet	male_neet	female_neet
infra_nc	0.044	0.042	0.048
	(0.039)	(0.046)	(0.037)
infra_np	−0.035	0.000	−0.074
	(0.029)	(0.021)	(0.039)
infra_spec	−0.040	-0.050	-0.030
	(0.038)	(0.044)	(0.036)
Constant	16.375	12.655	20.223
	(2.812)	(2.764)	(3.111)
Model	RE	RE	RE
Type	Clustered	Clustered	Clustered
R^2	0.101	0.076	0.235
Wald χ^2	13.123	9.581	36.004
Observations	121	121	121

Table 8 shows findings for affordability, the second sub-component panel model in this study. Mobile data affordability (afford_mda) exhibited a statistically negative relationship with total NEET and female NEET. Although the coefficient was also negative for male NEET, the significance effect was weaker for the male models. There was a statistically positive relationship between handset affordability (afford_ha) and total NEET. The result was also positive, but not statistically significant for the male and female NEET. Taxation (afford_tax) had positive and significant associations with the measure of total NEET and female NEET, but not male NEET. Taxation on mobile devices and data varies across Southeast Asia and can be high in many countries, often passed on to consumers (Pedros and Sivakuraman 2019). Providing tax incentives and harmonizing regulatory costs across regions could be part of targeted interventions for underserved communities.

TABLE 8 Findings for the affordability subcomponent

Variable	total_neet	male_neet	female_neet
afford_mda	−0.079***	−0.057*	−0.112***
	(0.019)	(0.025)	(0.031)
afford_ha	0.039**	0.050	0.019
	(0.012)	(0.038)	(0.015)
afford_tax	0.106***	−0.001	0.178***
	(0.023)	(0.063)	(0.033)
Constant	—	14.903	—
	—	(7.020)	—
Model	FE	RE	FE
	Driscoll	Clustered	Driscoll
R^2	0.206	0.120	0.296
F-Statistic/Wald χ^2	9.248	15.973	15.029
Observations	121	121	121

Note: *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$

The results align with those of Jeffrie et al. (2025), who identify the affordability subcomponent as one of the key barriers to mobile internet adoption, particularly in low- and middle-income countries. The explanatory power of male NEET ($R^2 = 0.12$) was significantly lower relative to the other dependent variables. In contrast, female NEET had the highest goodness-of-fit ($R^2 = 0.30$; $\chi^2 = 15.03$), reflecting a higher correlation with the affordability subcomponent.

The key observations from these findings suggest that reducing mobile data pricing and taxation are strongly associated with improvements in female NEET status. Notably, mobile data subscription costs in many Southeast Asian countries are among the highest in the world, and therefore still far from ITU's 2030 goal of having affordable broadband subscription costs of "less than 2% of gross national income per capita" and "less than 2% of average income of the bottom 40% of the population" (ITU 2022).

In the consumer readiness subcomponent in table 9, the coefficient of basic skills (read_bs) was negative for female NEET and marginally significant (p<0.10). However, the relationship did not reach statistical significance for the total and male NEET. These results underscore the importance of digital literacy in increasing mobile internet adoption among young women, supporting their entry into the labor force, and helping curb the gender gap in youth NEET. In contrast, there was a robust positive association between mobile ownership (read_mo) and the total and male NEET, but the relationship was not statistically significant for female NEET.

TABLE 9 Findings for the consumer readiness subcomponent

Variable	total_neet	male_neet	female_neet
read_bs	-0.047	0.010	-0.110*
	(0.026)	(0.019)	(0.043)
read_ge	-0.003	0.011	-0.024
	(0.016)	(0.014)	(0.035)
read_mo	0.061***	0.078***	0.037
	(0.008)	(0.010)	(0.031)
Constant	—	—	25.631
	—	—	(4.349)
Model	FE	FE	RE
Type	Driscoll	Driscoll	Clustered
R^2	0.115	0.145	0.204
F-Statistics/Wald χ^2	4.619	6.044	30.059
Observations	121	121	121

Note: *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$

The significant positive association between mobile ownership and higher total NEET and male NEET is indeed paradoxical, given that having a mobile phone is considered the first entry point to digital inclusion. However, the results revealed that having a mobile phone is not directly related to improvement in overall youth NEET, particularly male NEET. Most young people use mobile phones for basic communication, social media, and entertainment, exposing them to greater social and well-being risks (ITU 2025). Other indicators in the consumer readiness subcomponent showed no statistically significant relationship between gender equality (read_ge) and total, male, or female NEET. Only the coefficients in the female NEET panel regressions demonstrated moderate R^2 values ($R^2 = 0.20$), while the others were relatively low. Both *F*-statistics and χ^2 statistics were statistically significant across the models.

The findings for the sub-component of content and services (see table 10) revealed that an increase in local relevance (cons_lr) was associated with higher levels of male NEET, but not in total and female NEET. Despite rising safety concerns that inhibit digital adoption (Jeffrie et al. 2025), online security (cons_os) did not show a statistically significant relationship with total, male, and female NEET. All indicators had low explanatory powers (R^2: 0.008-0.127). Both *F*-statistics for males and Wald χ^2 for females exhibited coefficient results that were jointly significant across all specifications, indicating that the two content and services sub-components as a whole explained a meaningful amount of variance in the dependent variables.

However, neither variable made a unique, independent contribution that stood out clearly after controlling for the other.

TABLE 10 Findings for content and services sub-component

Variable	total_neet	male_neet	female_neet
cons_lr	0.025	0.101***	−0.113
	(0.021)	(0.023)	(0.080)
cons_os	−0.015	−0.002	−0.021
	(0.017)	(0.015)	(0.039)
Constant	—	—	26.986
	—	—	(3.468)
Model	FE	FE	RE
Type	Driscoll	Driscoll	Clustered
R^2	0.008	0.057	0.127
F-Statistics/Wald χ^2	0.435	3.275	17.183
Observations	121	121	121

Note: *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$

The positive and significant coefficient between local relevance (e.g., the availability of localized mobile content and services) and male NEET likely resulted from structural limitations and the fact that digital connectivity in the region is mostly used for non-productive activities, e.g., entertainment and consumption. The other indicator, online security, was not closely linked to youth NEET improvement, indicating a minimal association between local relevance and cybersecurity awareness for this segment. As stipulated in its digital governance regulation (Indonesia 2025), Indonesia's recent move to ban social media nationwide (e.g., TikTok, Instagram, YouTube) for children under 16 and effective in March 2026, except for educational platforms, would be a big step for the country to address youth issues associated with reducing risk exposure for safety, social relationships, mental health, and well-being concerns. Malaysia is also following these actions under the Malaysian Online Safety Act 2025 to be implemented in 2026 (Malaysia 2025). This evolving regulatory framework could have implications on the trajectory relationship of content and services to youth NEET in the medium-to-long term.

Robustness Checks

Three robustness checks were done with different scenarios to review the validity of the models (see appendix C). These alternative model specifications included (a) a one-way fixed effects model with GDP as a control variable; (b) changing the model form for all panels under RE to

an FE model, and (c) two-way effects, for both country and time, to take into account common global economic cycles based on FE for all models.

The first robustness check model (see appendix C, tables C1 to C4) demonstrates that the coefficients of the independent variables show similar signs as in the baseline model across all specifications when GDP is used as the control variable. With the exception of mobile ownership, the levels of statistical significance are weaker for mobile data, taxation, and basic skills indicators relative to the baseline model (i.e., without control variables), reflecting stark differences in economic development and the need for a deeper understanding of policies relevant to youth across the 11 countries in the region.

The second robustness checks (see appendix C, tables C5 to C8) reveal that coefficients and significance remained consistent with the baseline specification at varying levels. Interestingly, the significance of network coverage and network performance emerged, showing a strong relationship with female NEET and, to a lesser degree, with total and male NEET. Within the infrastructure subcomponent, spectrum had a weak relationship with male NEET and no association with total or female NEET. The affordability subcomponent (mobile data affordability and handset affordability) exhibited a strong and significant association with male NEET at the 1% level ($p < 0.01$).

The third and final robustness checks (see appendix C, tables C9 to C12) in the two-way fixed effect model suggest directional consistency with the main results, with reduced statistical power when considering country and time effects.

Conclusion

In the context of rapid technological change and lingering social inequality, this research aimed to investigate the relationship between mobile internet adoption and both aggregate and gender-specific NEET rates among youth in 11 Southeast Asian countries. The study applied a panel regression examining indicators across the MCI's four subdimensions (infrastructure, affordability, consumer readiness, and content and services) over an 11-year period from 2014 to 2024. Among the four noted subdimensions, the empirical evidence suggests that affordability is a key factor, with a strong correlation with the region's youth NEET rate.

The results reveal that affordable devices and mobile data costs are strongly associated with total and female NEET, but less strongly with male NEET. In addition, handset prices also had a statistically significant effect on affordability as they related to total NEET. This pattern,

however, did not hold when data were disaggregated by gender. These findings highlight the price sensitivity of the youth NEET population relative to digital inclusiveness, as well as the degree of digital adoption among male and female NEETs.

In addition, with respect to the consumer readiness subdimension, the findings showed a modest, statistically significant negative relationship between basic skills for female NEETs, but no statistical significance for total or male NEETs; in other words, in areas where women have better basic skills, there tends to be an association with lower female NEET rates. Surprisingly, mobile ownership—not basic skills or gender equality—was positively related to total and male NEET. This suggests that owning a mobile phone does not help reduce youth NEET. Similar results also occurred in the content and services segment (local relevance), which was strongly associated with higher male NEET, but not relevant to total or female NEET. None of the other indicators in other subcomponents have any meaningful associations with youth NEET; this contention is supported by the data, which showed that infrastructure (network coverage, network performance, and network spectrum) and content and services subdimensions (online security) had no significant relationships with aggregate or gender-specific youth NEET.

Given the complexities and divergent measures across Southeast Asian countries, the issue of youth NEET appears to be a structural constraint that limits the region's potential for digital transformation and economic growth. With the threat of technological advancements to entry-level jobs continuing to haunt many professions, this trend could worsen the NEET conditions among youth unless policies actively seek to counteract the negative effects while still leveraging the prospect of technology-enabled productivity improvements. These policy deficiencies stem from a lack of real-time data collection and analysis, a limited understanding of the challenges, insufficient coordination among relevant stakeholders, and a misalignment between needs and policies regarding youth NEET. Since digital connectivity is embedded in the region's strategic development framework, the findings highlight the importance of affordable mobile internet services and devices as part of policy implementation to address the digital gap, given their strong correlation with youth NEET status.

Generalized policy interventions should become more targeted, accounting for local conditions and gender-specific needs at the national and regional levels, to ensure that digital inclusion is well-targeted and achievable for underserved communities. Such interventions also include promoting institutional coordination, productive content and services, capacity building for underserved communities that are aligned with market demand, and incentive structures—including harmonizing underlying tax structures, spectrum allocation and pricing, dedicated

funding to cultivate youth, and capital expenditures in affected areas—so that they translate into more robust youth NEET improvements. All of these initiatives would be highly beneficial if supported by effective data collection, information dissemination, as well as monitoring and evaluation systems.

This study was subject to certain limitations (only 11 years of data and 11 Southeast Asian countries). Further research with a longer time frame, expanded country coverage beyond the region, and control variables would enhance the robustness and validity of the findings. In addition, future qualitative studies should explore the lived experiences of marginalized youth when using digital tools related to education and employment. Understanding key stakeholders, i.e., organizations and the government, as well as the challenges and opportunities local communities face when implementing intervention programs, would be useful to enhance the effectiveness of their initiatives and future collaboration. While this study was small and exploratory, it provides policymakers and organizations with valuable insights for designing and implementing targeted interventions. It can also be used as part of the guiding policy considerations for the ASEAN Community Vision 2045 and DEFA commitments to achieve social inclusiveness.

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Appendix A: Pearson Correlation Matrix

Variable	total_ neet	male_ neet	female_ neet	infra_ nc	infra_ np	infra_ spec	afford_ mda	afford_ ha	afford_ tax	read_ bs	read_ ge	read_ mo	cons_ lr	cons_ os	loggd ppc
total_neet	1.00														
male_neet	0.94	1.00													
female_neet	0.95	0.79	1.00												
infra_nc	-0.32	-0.22	-0.37	1.00											
infra_np	-0.49	-0.34	-0.58	0.70	1.00										
infra_spec	-0.34	-0.37	-0.28	0.47	0.32	1.00									
afford_mda	-0.63	-0.48	-0.68	0.42	0.58	0.16	1.00								
afford_ha	-0.44	-0.25	-0.56	0.49	0.61	0.20	0.71	1.00							
afford_tax	-0.29	-0.36	-0.20	0.18	0.09	0.14	0.20	0.19	1.00						
read_bs	-0.41	-0.3	-0.46	0.66	0.78	0.25	0.61	0.61	0.26	1.00					
read_ge	-0.30	-0.23	-0.33	0.39	0.40	0.31	0.62	0.66	0.39	0.53	1.00				
read_mo	-0.31	-0.21	-0.36	0.47	0.40	0.57	0.34	0.45	(0.06)	0.33	0.54	1.00			
cons_lr	-0.66	-0.49	-0.73	0.67	0.69	0.42	0.78	0.78	0.27	0.71	0.66	0.59	1.00		
cons_os	-0.51	-0.48	-0.48	0.59	0.64	0.54	0.60	0.56	0.32	0.70	0.65	0.59	0.80	1.00	
loggdppc	-0.44	-0.26	-0.55	0.45	0.52	0.26	0.74	0.85	0.22	0.59	0.77	0.49	0.79	0.62	1.00

Appendix B: Diagnostic Tests

TABLE B1 Hausman test

Hausman (p-value)	total_neet	male_neet	female_neet
Infrastructure	0.67	0.38	0.66
Model	RE	RE	RE
Affordability	0.01	0.10	0.01
Model	FE	RE	FE
Consumer readiness	0.00	0.00	0.79
Model	FE	FE	RE
Content and services	0.00	0.00	0.07
Model	FE	FE	RE

Note: FE = fixed effects model; RE = random effects model; $p < 0.05$ indicates FE is preferred; $p \geq 0.05$ shows RE is preferred.

TABLE B2 Multicollinearity

	VIF
Infrastructure	
infra_nc	2.27
infra_np	1.97
infra_spec	1.28
Affordability	
afford_mda	2.07
afford_ha	2.05
afford_tax	1.05
Customer readiness	
read_bs	1.39
read_ge	1.75
read_mo	1.42
Content and services	
cons_lr	2.76
cons_os	2.76

Note: VIF = variance inflation factor; VIF < 5 indicates no multicollinearity.

TABLE B3 Heteroskedasticity

Breusch–Pagan (BP p-value)	total_neet	male_neet	female_neet
Infrastructure	0.00	0.00	0.05
Affordability	0.67	0.02	0.21
Consumer readiness	0.01	0.02	0.02
Content and services	0.00	0.00	0.00

Note: Reject H0 if p-value < 0.05 (homoskedasticity); use clustered standard errors.

TABLE B4 Cross dependence

Pesaran CD (p-value)	total_neet	male_neet	female_neet
Infrastructure	0.93	0.34	0.69
Affordability	0.06	0.29	0.00
Consumer readiness	0.00	0.00	0.01
Content and services	0.18	0.17	0.05

Note: Reject H0 if p-value < 0.05; no cross-sectional dependence.

Appendix C: Robustness Checks

Robustness Check I: Fixed effects model with GDP per capita as control variable

TABLE C1 Infrastructure

Variable	total_neet	male_neet	female_neet
infra_nc	0.049	0.045	0.055
	(0.040)	(0.047)	(0.038)
infra_np	−0.030	0.003	−0.067
	(0.027)	(0.021)	(0.037)
infra_spec	−0.039	−0.052	−0.028
	(0.038)	(0.043)	(0.037)
loggdppc	−1.906	−1.216	−2.573*
	(0.999)	(1.141)	(1.114)
Constant	31.851	22.642	41.089
	(7.834)	(9.066)	(9.247)
Model	RE	RE	RE
Standard error type	Clustered	Clustered	Clustered
R^2	0.129	0.086	0.266
Wald χ^2	17.192	10.979	41.962
Observations	121	121	121

Note: (Applicable to tables C1–C4) Standard errors for all models are in parentheses. FE = fixed effects model; RE = random effects model. Wald χ^2 = Wald Chi-square statistics. The FE excludes a constant because it is absorbed by the country fixed effects.

*$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

TABLE C2 Affordability

Variable	total_neet	male_neet	female_neet
afford_mda	−0.078*	−0.052*	−0.105*
	(0.034)	(0.023)	(0.042)
afford_ha	0.048	0.059	0.049
	(0.037)	(0.044)	(0.038)
afford_tax	0.074	0.007	0.175**
	(0.061)	(0.059)	(0.053)
loggdppc	−2.628	−1.255	−6.985
	(1.430)	(1.380)	(4.738)
Constant	34.338	24.014	—
	(13.062)	(11.437)	—
Model	RE	RE	FE
Standard error type	Clustered	Clustered	Clustered
R^2	0.223	0.129	0.366
F-Statistic/ Wald χ^2	33.297	17.1583	15.267
Observations	121	121	121

Note: *p < 0.10, ** p < 0.05, ***p < 0.01.

TABLE C3 Consumer readiness

Variable	total_neet	male_neet	female_neet
read_bs	−0.035	0.018	−0.092*
	(0.033)	(0.036)	(0.042)
read_ge	0.005	0.013	−0.009
	(0.025)	(0.022)	(0.019)
read_mo	0.062	0.076	0.051***
	(0.039)	(0.049)	(0.008)
loggdppc	−2.460	−1.905	−3.396
	(1.052)	(1.187)	(3.759)
Constant	34.823	22.113	—
	(10.029)	(9.266)	—
Model	RE	RE	FE
Standard error type	Clustered	Clustered	Driscoll
R^2	0.128	0.125	0.233
F-Statistic/ Wald χ^2	17.022	16.630	8.039
Observations	121	121	121

Note: *p < 0.10, ** p < 0.05, ***p < 0.01.

TABLE C4 Content and services

Variable	total_neet	male_neet	female_neet
cons_lr	0.058	0.123	−0.083
	(0.078)	(0.086)	(0.083)
cons_os	−0.011	0.000	−0.023
	(0.035)	(0.033)	(0.040)
loggdppc	−3.190	−2.128	−4.357
	(5.380)	(4.972)	(5.953)
Model	FE	FE	FE
Standard error type	Clustered	Clustered	Clustered
R^2	0.022	0.063	0.103
F-Statistics/ Wald χ^2	0.821	2.390	4.082
Observations	121	121	121

Robustness Checks II: Random Effects to Fixed Effects Model

TABLE C5 Infrastructure

Variable	total_neet	male_neet	female_neet
infra_nc	0.045*	0.043*	0.049**
	(0.018)	(0.021)	(0.016)
infra_np	−0.034*	0.001	−0.072***
	(0.014)	(0.014)	(0.015)
infra_spec	−0.033	−0.042*	−0.025
	(0.021)	(0.020)	(0.025)
Model	FE	FE	FE
Standard error type	Driscoll	Driscoll	Driscoll
R^2	0.098	0.081	0.241
F-Statistics	3.861	3.1421	11.3246
Observations	121	121	121

Note: (Applicable to tables C5–C8) Standard errors for all models are in parentheses. The FE excludes a constant because it is absorbed by the country fixed effects.

*$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

TABLE C6 Affordability

Variable	male_neet
afford_mda	−0.049***
	(0.011)
afford_ha	0.058***
	(0.014)
afford_tax	0.045
	(0.029)
Model	FE
Standard error type	Driscoll
R^2	0.135
F-Statistics	5.554
Observations	121

Note: *p < 0.1, ** p < 0.05, ***p < 0.01.

TABLE C7 Consumer readiness

Variable	female_neet
read_bs	−0.108**
	(0.035)
read_ge	−0.018
	(0.022)
read_mo	0.043***
	(0.006)
Model	FE
Standard error type	Driscoll
R^2	0.218
F-Statistics	9.942
Observations	121

Note: *p < 0.1, ** p < 0.05, ***p < 0.01.

TABLE C8 Content and services

Variable	female_neet
cons_lr	−0.054*
	(0.022)
cons_os	−0.029
	(0.020)
Model	FE
Standard error type	Driscoll
R^2	0.083
F-Statistics	4.874
Observations	121

Note: *p < 0.10, ** p < 0.05, ***p < 0.01.

Robustness Checks III: Two Way Fixed Effects Model

TABLE C9 Infrastructure

Variable	total_neet	male_neet	female_neet
infra_nc	−0.003	0.004	0.009
	(0.0501)	(0.059)	(0.045)
infra_np	−0.036	−0.024	−0.051
	(0.037)	(0.038)	(0.050)
infra_spec	−0.077	−0.068	−0.088
	(0.038)	(0.037)	(0.048)
Model	FE	FE	FE
Standard error type	Driscoll	Driscoll	Driscoll
R^2	0.106	0.070	0.130
F-Statistic	3.844	2.425	4.833
Observations	121	121	121

Note: (Applicable to tables C9–C12) Standard errors for all models are in parentheses. The FE model excludes a constant because it is absorbed by the country fixed effects

TABLE C10 Affordability

Variable	total_neet	male_neet	female_neet
afford_mda	−0.076*	−0.051	−0.104*
	(0.037)	(0.033)	(0.043)
afford_ha	0.044	0.046	0.042
	(0.031)	(0.033)	(0.031)
afford_tax	0.093*	0.047	0.152***
	(0.037)	(0.046)	(0.030)
Model	FE	FE	FE
Standard error type	Driscoll	Driscoll	Driscoll
R^2	0.187	0.103	0.276
F-Statistic	7.416	3.715	12.313
Observations	121	121	121

Note: * p < 0.10, ** p < 0.05, ***p < 0.01.

TABLE C11 Consumer readiness

Variable	total_neet	male_neet	female_neet
read_bs	0.013	-0.037	-0.012
	(0.034)	(0.046)	(0.025)
read_ge	0.036*	0.034*	-0.040
	(0.017)	(0.016)	(0.022)
read_mo	0.107*	0.103	0.112*
	(0.047)	(0.057)	(0.043)
Model	FE	FE	FE
Type	Driscoll	Driscoll	Driscoll
R^2	0.190	0.142	0.209
F-Statistic	7.598	5.373	8.536
Observations	121	121	121

Note: *p < 0.10, ** p < 0.05, ***p < 0.01.

TABLE C12 Content and services

Variable	total_neet	male_neet	female_neet
cons_lr	0.041	0.019	0.073
	(0.097)	(0.097)	(0.129)
cons_os	−0.003	-0.003	−0.002
	(0.034)	(0.039)	(0.033)
Model	FE	FE	FE
Type	Driscoll	Driscoll	Driscoll
R^2	0.002	0.001	0.005
F-Statistic	0.093	0.027	0.233
Observations	121	121	121

Note: *p < 0.10, ** p < 0.05, ***p < 0.01.

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