Private Social Sciences Journal
E-ISSN 2798-6314
P-ISSN 2798-866X
https://doi.org/10.55942/pssj.v5i12.1040

Volume 5
Issue 12
December Edition 2025

Digital economy development in Eastern Indonesia: The infrastructure and socio-economic dimensions

I Made Jyotisa Adi Dwipatna*, Dirmansyah Darwin, Shadry Andriani, Putu Ananda Devi Nugraha, Andi Nur Wahyuningsih

Department of Economics, Faculty Economics and Business, State University of Makassar, South Sulawesi, Indonesia
e-mail: made.jyotisa@unm.ac.id

Received 13 October 2025
Revised 21 November 2025
Accepted 02 December 2025

ABSTRACT

The growth of the digital economy brings both challenges and opportunities for regional economic development, especially in areas where infrastructure and human resources are unevenly distributed. This study examines how digital infrastructure and socio-economic factors influence ICT competence, which is a key driver of digital economic progress in Eastern Indonesia. Using data from 13 provinces between 2016 and 2023, the study applied a Fixed Effects Model (FEM) to analyze regional and time-based differences. The results show that Internet access has a strong positive impact on ICT competence, highlighting the critical role of digital infrastructure in boosting participation and reducing the digital gap. Education also plays a significant role, with improved education helping to build digital literacy and better prepare the population for technological change. On the other hand, income does not seem to have a significant effect on ICT competence, suggesting that economic factors are not yet the main drivers of technological skills in the region. Overall, the findings emphasize that digital development in Eastern Indonesia is primarily influenced by the availability of infrastructure and the quality of human resources. To support inclusive and sustainable digital growth, policies should focus on ensuring equal access to the Internet and incorporating digital literacy into education.

Keywords: digital economy; public infrastructure; Internet services; education; personal income

1. INTRODUCTION

The growth of the digital economy in eastern Indonesia is a key part of regional transformation, linking infrastructure, social, and economic factors. While the region has significant natural resource potential, there are still major barriers to fully engaging in the digital economy, especially regarding digital infrastructure, education, and income levels. On the infrastructure front, there has been some progress, with Internet access increasing from 25.37% in 2016 to 53.73% in 2020, showing better access to digital services and connectivity (Anggoro et al., 2022). However, there is still a significant gap, as many provinces in the eastern region are highly vulnerable in terms of ICT, with notable disparities in technological readiness (Anggoro et al., 2022; Kharisma, 2022; Saputra et al., 2023). Key challenges remain, such as poor connectivity, high technology costs, and limited digital skills, which hinder effective use of ICT (Rahiem, 2020; Susanto, 2018). Consequently, improving digital infrastructure is essential for closing the digital divide, expanding reliable connectivity, and supporting human capital development. Investing in digital infrastructure not only facilitates information flow and innovation, but also lays the groundwork for boosting community participation and improving digital literacy (Saputra et al., 2023).

From a socio-economic perspective, digitalization in Eastern Indonesia holds significant potential for driving transformation. Digital platforms have given a boost to micro, small, and medium enterprises (MSMEs), helping them expand their market reach, improve efficiency, and foster innovation (Kushadiani et al., 2021; Rolando & Mulyono, 2025). However, the digital literacy gap and cybersecurity concerns remain major hurdles, particularly in rural areas where technology adoption is still low (Farliana et al., 2024; Rolando & Mulyono, 2025). Addressing these challenges will require comprehensive policies that focus on improving digital skills, promoting inclusive participation, and strengthening online security (Farliana et al., 2024). Economically, there's clear evidence that adopting digital technologies leads to higher Gross Regional Domestic Product (GRDP) per capita, highlighting the positive impact of digitalization on regional productivity and competitiveness (Ma et al., 2023; Novianti et al., 2025). The digital economy also plays a crucial role in diversifying industries, reducing regional isolation, and enhancing economic resilience, positioning Eastern Indonesia as a key area for inclusive growth (Ma et al., 2023; Suhendra et al., 2025). In this light, sustained investment in digital infrastructure, human resource development, and institutional capacity is essential to unlock the full potential of the digital economy and align it with national economic transformation goals.

While research on the digital economy in developing countries is growing, there is still a lack of empirical studies focused on the spatial and structural factors that influence digital economic development in Indonesia, especially in its eastern regions. These areas face significant gaps in infrastructure, education and income. Most existing studies have centered on the national level or urban areas like Java, where digital infrastructure and human resource quality are much more advanced (United Nations Development Program, 2023; World Bank, 2021). Consequently, they often overlook the regional differences that play a major role in digital transformation across Indonesia, leaving a gap in understanding how basic factors such as Internet infrastructure, education, and income levels affect digital economic performance in less developed regions.

The unique aspect of this study is its regional and multidimensional approach, which analyzes the factors that influence digital economic development in eastern Indonesia by combining three key dimensions: infrastructure (Internet access), social capital (education), and economic capacity (income) into a single framework. Unlike previous studies that examined these factors separately or only at the national level, this study used panel data analysis to capture both spatial and temporal differences, offering a more detailed view of the structural dynamics behind regional digital transformation. By focusing on eastern Indonesia, this study contributes new theoretical insights into digital inclusivity and regional development, especially from a geographically diverse and underrepresented area. The findings are expected to inform policies aimed at bridging the digital divide and fostering inclusive and sustainable digital economic growth in Indonesia.

2. LITERATURE REVIEW

The theory of digital inclusivity, introduced by Warschauer (2003), highlights the need for equal access to, skills in, and use of Information and Communication Technology (ICT) across all segments of society. This idea builds on the concept of the digital divide, which not only points out the physical gaps in access to technology but also includes disparities in digital skills, meaningful use of technology, and institutional support (Garcia, 2003). When it comes to ICT competence, this perspective stresses that a person's ability to effectively use technology is deeply shaped by structural factors like the learning environment, training opportunities, and access to public digital services. Consequently, education policies and investments in digital infrastructure are key tools for promoting ICT literacy and skills development across all regions, ensuring a more even distribution of these capabilities.

Access to the Internet at the household level plays a crucial role in developing individual ICT skills, which in turn boosts social, economic, and educational participation. Reliable Internet access allows people to connect to information, online learning resources, and social networks, all of which help them adapt to technological changes. Therefore, household Internet access is not just a technical tool, but also a key factor in reducing digital exclusion by providing the necessary resources and environment to build ICT skills (Muñoz-Espinoza et al., 2025). Several studies have confirmed this, showing that household Internet access positively affects community ICT competence. Increased connectivity leads to better digital literacy, improved problem-solving skills using technology, and greater individual readiness for digital transformation (de Araujo et al., 2018; Formichella et al., 2020; Nash & Wakefield, 2025; Wamuyu, 2017). Based on this, the following hypothesis is proposed:

H1: Internet access positively affects ICT competence.

Formal education plays an important role as a systematic platform for developing ICT competence through a structured and integrated curriculum. In this context, educational institutions provide a learning environment that enables the implementation of digital technology and the use of Internet-based resources to improve the effectiveness of learning and student engagement (Blyznyuk & Hotsaniuk, 2024; Mochalina et al., 2025; Priimak & Razina, 2020). Formal education does more than transfer technical knowledge; it also plays a vital role in developing digital literacy, problem-solving skills, and critical thinking. These are essential for lifelong learning and adapting to the ever-changing global digital landscape (Ayyildiz et al., 2021; Javorcik, 2017). As noted by Formichella et al. (2020), this highlights that education level has a positive impact on community ICT competence. This shows that investing in education not only improves individuals' ability to use technology but also fosters more inclusive participation in the digital economy. Based on this, the following hypothesis can be proposed:

H2: Education has a positive effect on ICT competence

From an economic perspective, there is a clear link between socioeconomic status (SES) and ICT literacy. Individuals from higher SES groups tend to have better digital skills compared to those from lower-income backgrounds (Scherer & Siddiq, 2019). Income, a key component of SES, plays a significant role in providing access to devices, the Internet, and digital learning opportunities. For example, the income gap in China between urban and rural areas is strongly tied to differences in ICT adoption, like Internet usage and access to digital devices (Fong, 2009). This means that income not only affects people's ability to access technology but also influences their level of ICT competence. There's a positive relationship between income and ICT skills—higher income improves affordability and access to ICT training, ultimately enhancing digital skills (Ali et al., 2019; Park & Weng, 2020). Based on this, the following hypothesis is proposed:

H3: Income has a positive effect on ICT competence

3. METHOD

This study analyzed the digital economy development model in eastern Indonesia from infrastructure, social, and economic perspectives using panel data from 13 provinces from 2016 to 2023. A static panel data analysis was used to determine the most suitable model among pooled least squares (PLS), fixed effect model (FEM), and random effect model (REM), with the Chow and Hausman tests applied for selection.

3.1 Chow Test

The Chow test was used to determine whether the data could be combined in a single PLS model or if there were significant differences between groups that required separate models. This test examined the null hypothesis that the regression coefficients had the same across all groups (e.g., region, sector, or time) (Granger & Newbold, 1974). If the test results reject the null hypothesis, then the PLS model cannot be used, and it is recommended that separate models (such as the Fixed Effects Model (FEM) or Random Effects Model (REM)) be used.
In the context of this test:
H_0 : Regression coefficients are the same across groups (pooled model is valid)
H_1 : Regression coefficients differs across groups (separate models are more appropriate)
If the Chow Test p-value < 0.05, the null hypothesis was rejected and choose a model separate group (e.g., FEM or REM)

3.2 Hausman Test

The Hausman test was used to determine the most appropriate model between FEM and REM by testing whether there is a correlation between unique errors (individual effects) and independent variables in the model. If the individual effects are correlated with the independent variables, then the FEM model is more appropriate to use, as it can control for unobserved individual effects, thereby producing consistent estimates. Conversely, if the individual effects are not correlated with the independent variables, then the REM model is more efficient, as it does not require additional estimates to control for individual variation and produces estimates with smaller variance. As a result, the Hausman Test serves as a tool to ensure the selection of a panel data model that is not only statistically efficient but also theoretically consistent in representing the relationship between the research variables (Frondel & Vance, 2010).
In the context of this test:
H_0 : There is no correlation between the individual effects and independent variables (REM is more efficient).
H_1 : There is a correlation between individual effects and independence (FEM is more appropriate).
If the p-value of the Hausman Test is < 0.05, the null hypothesis is rejected, and the FEM is selected. Conversely, if p-value > 0.05, the REM is considered a more efficient choice.

Furthermore, classical assumption tests – namely, multicollinearity, heteroskedasticity, and autocorrelation tests—were conducted to ensure the absence of these issues, thereby confirming that the model and empirical results are free from bias.

Table 1. Description of Variable

No	Variables	Indicator	Units	Source
Dependent Variable				
1	ICT Competence (ictcomp)	Proportion of population with ICT skills	Percentage (%)	Central Bureau of Statistics (Indonesian
Independent Variables				
2	Internet Access (inetacc)	Proportion of households that have accessed the Internet in the last three months	Percentage (%)	Central Bureau of Statistics (Indonesian

3	Education (educ)	Rate of school participations	Percentage (%)	Central Bureau of Statistics (Indonesian
4	Income (income)	GRDP per capita	Thousand Rupiahs	Central Bureau of Statistics (Indonesian

As shown in Table 1, the dependent variable used to assess the digital economy is ICT competence (ICTcomp), measured by the proportion of the population possessing ICT skills. To represent the infrastructural, social, and economic dimensions, the independent variables employed include Internet access (inetacc), education (educ), and income (income). Accordingly, the analytical model used in this study can be formulated as follows:

$$ICTcomp_{it} = \beta_0 + \beta_1 inetacc_{it} + \beta_2 educ_{it} + \beta_3 lnincome_{it} + \delta_{it} \quad (1)$$

where:

ICTcomp : ICT Competence
Inetacc : Internet Access
educ : Education
lnincome : logarithm of natural income
β_0 : Intersep
$\beta_1, \beta_2, \beta_3$: Coefficient of Regression
δ : random error (noise)
i : 1-13 cross-sectional data of province
t : 1-8 time series data from 2016 to 2023

4. RESULT AND DISCUSSION

4.1 Result

4.1.1 Descriptive Statistics

Table 2. Descriptive Statistics

Variables	N	Mean	Std. Dev.	Min	Max
ICTcomp	104	49.00	17.30	15,00	84.03
inetacc	104	63.60	18.52	19.26	91.21
educ	104	74.41	3.927	61.89	79.92
income	104	31.254	13.522	11.469	71.924

Table 2 presents the descriptive statistics for the four key variables analyzed in this study: ICT competence (ICTcomp), Internet access (inetacc), education level (educ), and income (income). The average ICT competence score is 49.00, with a standard deviation of 17.30, showing that there is a wide range of digital skills across different regions. Internet access had a mean of 63.60 and a standard deviation of 18.52, highlighting significant differences in both the availability and quality of Internet connectivity between provinces. The average education level is 74.41, with a standard deviation of 3.93, indicating that most regions have relatively high education levels, but there are still noticeable regional differences. Income has an average of 31.254 with a standard deviation of 13.522, ranging from 11.469 to 71.924, indicating significant income inequality between areas. Overall, these statistics point to clear socio-economic disparities that could affect the results of the model, suggesting the need to address issues such as multicollinearity and heterogeneity in the analysis.

4.1.2 Best Model Choices

In the panel data analysis, the Chow and Hausman tests were used to determine the best model among PLS, FEM, and REM (Arellano & Bond, 1991; Ciarreta et al., 2019; Verbeek, 2021). First, the The Chow test was applied to compare the PLS and FEM. The results showed a Prob > F value of 0.000 (<0.05), leading to the rejection of the null hypothesis, which means FEM was chosen over PLS. The Hausman test was then performed to decide between FEM and REM. The estimation resulted in a Prob > Chi² value of 0.000 (<0.05), leading to the rejection of the null hypothesis again. Therefore, FEM was confirmed as the preferred model. In conclusion, the Fixed Effects Model (FEM) was determined to be the most appropriate model for this study.

4.1.3 Classical Assumption Test

In econometric analysis, it's essential to test classical assumptions to ensure the regression model used for data analysis is both valid and reliable. In this study, two key diagnostic tests were conducted: the multicollinearity test and the heteroskedasticity test. Multicollinearity happens when two or more independent variables in a regression model are highly correlated, which can distort the estimation of regression coefficients. In the fixed effects model, multicollinearity can be spotted by checking the correlation matrix of the independent variables. If the correlation coefficient exceeds 0.75, it suggests potential multicollinearity (Goodman, 2013). Heteroskedasticity occurs when the variance of the residuals changes across observations, leading to inefficient estimates and biased standard errors (Yang, 2021). To check for heteroskedasticity in the fixed effects model, the study used the Kezdi test (Kezdi, 2005; Uchôa et al., 2014).

Table 3. Correlation between Independent Variables

	inetacc	**educ**	**lnincome**
inetacc	1.000		
educ	0.4962	1.000	
lnincome	0.1791	-0.1852	1.000

Source: Author (processed data) (2025)

As presented in Table 3, the correlation values among the independent variables—ICT competence (ICTcomp), education (educ), and log of income (lnincome)—do not exceed 0.75. This indicates that the model is free from multicollinearity issues. Table 4 presents the results of the heteroskedasticity test.

Table 4. Kezdi Test (Heteroskedasticity Test)

Test for	Statistic	P-value
H1 vs. H_0	5.811	0.562
H2 vs. H_0	11.548	0.116
H3 vs. H_0	8.726	0.273

H_1: Cross-sectional homoskedasticity
H_2: Serially uncorrelated: e_it, x_it or both
H_3: Homoskedasticity and serially uncorrelated
H_0: Heteroskedasticity

Source: Author (processed data) (2025)

The results of the Kézdi test in Table 4 show that the p-values for all comparisons (H1 vs. H0, H2 vs. H0, and H3 vs. H0) are greater than 0.05. This indicates there isn't enough evidence to reject the null hypothesis, meaning there's no significant heteroskedasticity or autocorrelation in the Fixed Effects Model. As a result, the model's estimated coefficients are considered efficient, and the model is not influenced by the non-constant error variances.

Table 5. Comparison of PLS, FEM, and REM Estimation

Variables	PLS	FEM	REM
inetacc	0.939***	0.972***	0.979***
	(0.0221)	(0.0240)	(0.0198)
educ	-0.312***	1.305**	-0.298
	(0.105)	(0.611)	(0.196)
lnincome	1.592*	-3.481	0.387
	(0.827)	(2.630)	(1.514)
Constant	-3.833	-74.17	4.907
	(12.54)	(51.94)	(23.15)
Observations	104	104	104
R-squared	0.962	0.977	
Number of Prov		13	13

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: Author (processed data) (2025)

Based on the model selection process (Table 5), the Fixed Effects Model (FEM) was chosen as the most suitable specification. The relationships between the variables are summarized in Table 5 (Column 3, FEM). The model's R-squared value of 0.977 indicates that 97.7% of the variation in ICT competence (ICTcomp) is explained by the independent variables: Internet access (inetacc), education (educ), and income (lnincome). The remaining 2.3% is due to factors not included in the model.

Internet access (inetacc) has a strong positive and statistically significant effect, with a coefficient of 0.972 at the 1% significance level ($p < 0.01$). This means that a 1% increase in Internet access leads to a 0.972% increase in ICT competence. Education (educ) also has a positive and significant impact, with a coefficient of 1.305 at the 5% significance level ($p < 0.05$), suggesting that a 1% improvement in education results in a 1.305% increase in ICT competence. On the other hand, income (lnincome) does not show a significant effect, as its p-value is above 0.10, indicating that income doesn't play a major role in determining ICT competence in this model.

4.2 Discussion

The estimation results show that Internet access has a strong positive and significant effect on ICT competence. Having access to the Internet opens up digital resources and additional learning materials, which help improve both academic performance and technological skills. Students with Internet access at home tend to perform better in subjects like mathematics and reading (Formichella et al., 2020; Rodríguez Arenas & Gamboa, 2024), highlighting how connectivity contributes to better learning outcomes and stronger ICT skills. Additionally, Internet access boosts self-confidence in using technology, which further enhances ICT competence. Professional development programs for teachers, supported by Internet access, have also been found to improve their digital self-efficacy and ICT skills (Murwaningsih, 2025).

Furthermore, education shows a strong positive and significant link to ICT competence. It plays a crucial role in developing the digital skills needed for effective technology use. Students with higher digital literacy are more likely to use technology successfully for academic purposes (Shima & Jaupaj, 2025). Educational programs and ICT-focused training initiatives have been proven to improve digital competence among both students and teachers, as seen in Vietnam and China (Thao et al., 2024; Xiong & Lim, 2015). These findings highlight that investing in education not only strengthens individual tech skills but also supports broader, more inclusive participation in the digital economy (Formichella et al., 2020).

However, income does not have a statistically significant impact on ICT competence. This finding contrasts with some theoretical expectations and previous studies that suggested that a higher economic status would boost digital skills. However, this effect seems to be influenced more by other factors, especially education and technology access. For example, a study in Bangladesh showed that while wealthier women were more likely to acquire ICT skills, about 85% of this effect was explained by their level of education (Islam & Uthso, 2024). This suggests that while income may help with accessing devices and Internet connectivity, ICT competence is more strongly shaped by education and effective use of technology than by financial resources alone. This highlights that policy efforts focused only on increasing income, without simultaneous improvements in education and digital infrastructure, are unlikely to produce the best results for the elderly.

5. CONCLUSION

This study examines how digital infrastructure and socio-economic factors affect ICT competence as a measure of digital economic development in eastern Indonesia, using panel data at the provincial level. The results show that Internet access has a positive and significant impact on ICT competence, highlighting the essential role of digital infrastructure in developing digital capacity. Education also plays a significant role, reinforcing the importance of improving the quality and equity of education to strengthen digital literacy and skills. However, income does not appear to have a significant effect, suggesting that economic conditions aren't yet a major driver of technological proficiency in the region.

Given these findings, digital economic development in eastern Indonesia is mainly driven by the availability of digital infrastructure and the quality of human resources, not economic factors. Policymakers should focus on expanding equitable digital infrastructure across all provinces, especially in areas with limited Internet access. It's also crucial to integrate digital literacy into both formal and non-formal education systems to build ICT competence from an early age. Capacity-building programs should target lower- and middle-income communities to ensure inclusive participation in digital transformation. Additionally, while efforts to increase income are important, they should be paired with policies that promote the productive use of technology in agriculture. The key to achieving inclusive and sustainable digital economic growth in Eastern Indonesia lies in the combined efforts of infrastructure development, educational improvement, and economic empowerment policies.

6. LIMITATION

This study has some limitations that should be considered when interpreting the results and planning future research. The static panel data model used may not fully capture the long-term dynamics between digital infrastructure, education, income, and ICT competence in Eastern Indonesia. Therefore, future studies should consider using dynamic panel methods, such as the Generalized Method of Moments (GMM) or spatial panel models, to better account for temporal changes and the interactions between regions.

Additionally, using provincial-level data may overlook variations within provinces, especially the differences between urban and rural areas, which can vary significantly in terms of geography and infrastructure. This research also does not include important variables such as local government policies, the quality of educational infrastructure, ICT sector investments, or sociocultural factors that could influence how technology is adopted and mastered. Future research should expand the range of variables considered, extend the observation period, and incorporate both quantitative and qualitative methods for a more comprehensive understanding of the factors driving digital economic development, particularly in Eastern Indonesia.

Ethical Approval and Informed Consent Statement

This study used secondary data from publicly available and verified institutional sources. Since no human subjects were involved and no personal or identifiable information was collected, ethical approval or informed consent was not necessary according to institutional guidelines. All data were handled in accordance with research ethics standards, ensuring integrity, confidentiality, and responsible use for academic purposes only. This study adhered to the ethical principles set out in the Declaration of Helsinki and institutional policies on the use of secondary data.

Authors' Contributions

IMJAD contributed to the conceptualization, formal analysis, and methodology. DD, SA, and PADN contributed to validation. DD, SA, and ANW provided resources. IMJAD, DD, and SA contributed to the writing of the original draft. Meanwhile, IMJAD, PADN, and ANW contributed in writing – review and editing,

Disclosure Statement

The authors declare that there is no conflict of interest related to the research, authorship, or publication of this article, which focuses on the development of the digital economy in Eastern Indonesia.

Data Availability Statement

The data and resources used in this study on digital economy development in eastern Indonesia were sourced from the Indonesian Central Bureau of Statistics. These data are publicly available and officially published by the Indonesian government, ensuring their reliability, transparency, and verifiability for replication and further research by others.

Funding

No funding.

Notes on Contributors

I Made Jyotisa Adi Dwipatna

https://orcid.org/0009-0000-0758-1563

I Made Jyotisa Adi Dwipatna, S.E., M.SE., is a lecturer in the Department of Economics at the Faculty of Economics and Business, State University of Makassar. His research interests span Public Economics, Tourism Economics, Digital Economics, and Education Economics, with a focus on how policy, technology, and education impact sustainable regional and national development. He is actively involved in both teaching and research, contributing to the advancement of knowledge and evidence-based policymaking in Indonesia.

Dirmansyah Darwin

https://orcid.org/0000-0002-1153-365X

Dirmansyah Darwin, S.E., M.Si., is currently a lecturer in the Development Economics Study Program at the Faculty of Economics and Business, Makassar State University. His contributions to the human development paradigm are seen from multiple perspectives, not just from a single theory, but also through social phenomena, capital relations, the role of government, and technological development—factors that all play a significant role in shaping human progress.

Shadry Andriani

https://orcid.org/0009-0008-2754-1751

Shadry Andriani, S.Pd., M.Si., is a lecturer in the Development Economics Study Program at the Faculty of Economics and Business, Makassar State University. Her expertise in labour economics has been invaluable to this research, particularly in analyzing labour market dynamics, wage structures, and policies aimed at improving labour productivity. Shadry's dedication to advancing studies in labour economics and her commitment to fostering an inclusive and sustainable labour market are evident in her extensive academic work and contributions to the field.

Putu Ananda Devi Nugraha
https://orcid.org/0009-0009-6325-6154
Putu Ananda Devi Nugraha, S.IP., M.E., is a lecturer and researcher in the Department of Economics at the Faculty of Economics and Business, State University of Makassar. Her academic interests cover development studies, political economy, international economics, and cultural economics. Her research examines how governance, policy, and cultural dynamics intersect to shape sustainable and inclusive development. She is particularly focused on understanding how cultural values and institutional structures influence economic transformation in developing countries, with a special emphasis on the Southeast Asian context.

Andi Nur Wahyuningsih
https://orcid.org/0009-0004-5033-3329
Andi Nur Wahyuningsih, S.E., M.Si., is a lecturer in the Department of Economics at the Faculty of Economics and Business, State University of Makassar. Her academic and research interests include Human Resource Economics, Population Economics, Labor Economics, and Development Economics, with a focus on how demographic and labor dynamics drive sustainable economic growth. She is actively involved in teaching, research, and community service, contributing to the advancement of economic scholarship and the development of evidence-based policies in Indonesia.

REFERENCES

Ali, M. A., Alam, K., Taylor, B., & Rafiq, S. (2019). Do income distribution and socio-economic inequality affect ICT affordability? Evidence from Australian household panel data. *Economic Analysis and Policy*, *64*, 317–328. https://doi.org/10.1016/j.eap.2019.10.003

Anggoro, F., Caraka, R. E., Prasetyo, F. A., Ramadhani, M., Gio, P. U., Chen, R.-C., & Pardamean, B. (2022). Revisiting Cluster Vulnerabilities towards Information and Communication Technologies in the Eastern Island of Indonesia Using Fuzzy C Means. *Sustainability*, *14*(6), 3428. https://doi.org/10.3390/su14063428

Arellano, M., & Bond, S. (1991). Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. *The Review of Economic Studies*, *58*(2), 277. https://doi.org/10.2307/2297968

Ayyildiz, P., Yilmaz, A., & Baltaci, H. S. (2021). Exploring Digital Literacy Levels and Technology Integration Competence of Turkish Academics. *International Journal of Educational Methodology*, *7*, 15–31. https://doi.org/10.12973/ijem.7.1.15

Blyznyuk, O., & Hotsaniuk, T. (2024). DIGITAL COMPETENCE AMONG THE KEY COMPONENTS OF FUTURE MASTERS OF PRIMARY EDUCATION PROFESSIONAL TRAINING: THEORETICAL INTERPRETATIONS. *Journal of Vasyl Stefanyk Precarpathian National University*, *11*, 164–172. https://doi.org/10.15330/jpnu.11.1.164-172

Ciarreta, A., Espinosa, M. P., & Zarraga, A. (2019). Panel Data Analysis. In *Encyclopedia of Law and Economics* (pp. 1549–1550). Springer New York. https://doi.org/10.1007/978-1-4614-7753-2_360

de Araujo, M. H., Reinhard, N., & Cunha, M. A. (2018). Electronic government services in Brazil: An analysis based on measures of access and users' Internet skills. *Revista de Administracao Publica*, *52*, 676–694. https://doi.org/10.1590/0034-7612171925

Farliana, N., Murniawaty, I., & Hardianto, H. (2024). Sustainability of the Digital Economy in Indonesia: Opportunities, Challenges and Future Development. *Review of Business and Economics Studies*, *11*(4), 21–28. https://doi.org/10.26794/2308-944X-2023-11-4-21-28

Fong, M. W. L. (2009). Digital Divide Between Urban and Rural Regions in China. *The Electronic Journal Ff Information Systems in Developing Countries*, *36*(1), 1–12. https://doi.org/10.1002/j.1681-4835.2009.tb00253.x

Formichella, M. M., Alderete, M. V., & Di Meglio, G. (2020). New technologies in households: Is there an educational payoff? evidence from Argentina. *Education in the Knowledge Society*, *21*, 181–1814. https://doi.org/10.14201/eks.23553

Frondel, M., & Vance, C. (2010). Fixed, random, or something in between? A variant of Hausman's specification test for panel data estimators. *Economics Letters*, *107*(3), 327–329. https://doi.org/10.1016/j.econlet.2010.02.007

Garcia, D. L. (2003). Technology and Social Inclusion: Rethinking the Digital Divide . By Mark Warschauer. Cambridge, Mass.: MIT Press, 2003. Pp. xii+260. . *American Journal of Sociology*, *109*, 767–768. https://doi.org/10.1086/381987

Goodman, R. J. B. (2013). Econometrics. In *Applications of Mathematics in Economics* (pp. 75–90). The Mathematical Association of America. https://doi.org/10.5948/9781614443179.009

Granger, C. W. J., & Newbold, P. (1974). Spurious regressions in econometrics. *Journal of Econometrics*, *2*(2), 111–120. https://doi.org/10.1016/0304-4076(74)90034-7

Islam, T., & Uthso, N. A. (2024). Investigating the causal relationship between wealth index and ICT skills: a mediation analysis approach. *Scientific Reports*, *14*(1), 19786. https://doi.org/10.1038/s41598-024-71090-2

Javorcik, T. (2017). PLE as a Tool for the Development of the Learning to Learn Competence. *Proceedings of the European Conference on E-Learning*. https://www.researchgate.net/publication/322665614_PLE_as_a_Tool_for_the_Development_of_the_Learning_to_Learn_Competence

Kezdi, G. (2005). Robus Standard Error Estimation in Fixed-Effects Panel Models. In *Econometrics* (Vol. 0508018). University Library of Munich. https://econwpa.ub.uni-muenchen.de/econ-wp/em/papers/0508/0508018.pdf

Kharisma, B. (2022). Surfing alone? The Internet and social capital: evidence from Indonesia. *Journal of Economic Structures*, *11*(1), 8. https://doi.org/10.1186/s40008-022-00267-7

Kushadiani, S. K., Nugroho, B., Mardian, S., Muhammad-Bello, B., & Hermawan, A. (2021). Evaluating Digital Economy in the Covid-19 Pandemic Era: A Review. *6th International Conference on Sustainable Information Engineering and Technology 2021*, 80–85. https://doi.org/10.1145/3479645.3479653

Ma, R., Zhu, M., Sun, J., & Zhang, X. (2023). Spatial Distribution of Digital Economy Model in Zhejiang Province, China. *Tropical Geography*, *43*(4), 745–757. https://doi.org/10.13284/j.cnki.rddl.003662

Mochalina, M. V., Gruzdeva, M. L., Smirnova, Z. V., Chaykina, Z. V., & Tsapina, T. N. (2025). The Role of the Educational Space in the Process of Informatization of Society. In *Advances in Science, Technology and Innovation: Vol. Part F354* (pp. 183–188). Springer Nature. https://doi.org/10.1007/978-3-031-83041-9_31

Muñoz-Espinoza, K., Gutiérrez-Aguado, A., Caballero-Montes, A., & Angeles-Donayre, M. (2025). Disparities in access to and knowledge of ICT among health sciences students in Peru: The National Household Survey on Living Conditions and Poverty (ENAHO) 2022. *Educacion Medica*, *26*. https://doi.org/10.1016/j.edumed.2024.100976

Murwaningsih, T. (2025). The Impact of Teachers' Professional Development on The Internet Self-Efficacy and ICT Competencies. *Data and Metadata*, *4*, 531. https://doi.org/10.56294/dm2025531

Nash, K., & Wakefield, R. (2025). Mapping the Pathways: Stigmergy Theory as a Lens for Analyzing e-Participation. *International Journal of Public Administration*. https://doi.org/10.1080/01900692.2025.2466658

Novianti, T., 'Ilmi, S. W., Muhibuddin, F. W., Chasanah, A., Inayah, I., Hadiarto, A., & Utami, A. D. (2025). How Mobile Internet and E-Commerce Drive Economic Growth: District-Level Insights From Indonesia. *International Journal of Economics and Finance Studies*, *17*(1), 146–169. https://doi.org/10.34109/ijefs.202517109

Park, S., & Weng, W. (2020). The relationship between ICT-related factors and student academic achievement and the moderating effect of country economic indexes across 39 countries: Using multilevel structural equation modelling. *Educational Technology and Society*, *23*(3), 1–15. https://www.jstor.org/stable/26926422?seq=1

Priimak, E. V., & Razina, I. S. (2020). Information and communication technology in the professional activity of higher school teachers. *Journal of Physics: Conference Series*, *1691*. https://doi.org/10.1088/1742-6596/1691/1/012077

Rahiem, M. D. H. (2020). Technological Barriers and Challenges in the Use of ICT during the COVID-19 Emergency Remote Learning. *Universal Journal of Educational Research*, *8*(11B), 6124–6133. https://doi.org/10.13189/ujer.2020.082248

Rodríguez Arenas, J. L., & Gamboa, L. F. (2024). Does access to ICTs equally matter for men and women in terms of academic exam performance? The case of middle education in Colombia. *Revista de Economía Del Rosario*, *26*(2), 1–32. https://doi.org/10.12804/revistas.urosario.edu.co/economia/a.14427

Rolando, B., & Mulyono, H. (2025). E-Commerce as a Catalyst for Digital Economy Development: A Study of Marketing Strategies and Their Impact. *Journal of Distribution Science*, *23*(4), 61–79. https://doi.org/10.15722/jds.23.04.202504.61

Saputra, F. T., Indrabudi, T., Dirgahayu, D., Karman, & Mudjiyanto, B. (2023). Initiatives of the Indonesian Government for Digital Transformation in Rural Areas. *E3S Web of Conferences*, *444*, 03001. https://doi.org/10.1051/e3sconf/202344403001

Scherer, R., & Siddiq, F. (2019). The relation between students' socioeconomic status and ICT literacy: Findings from a meta-analysis. *Computers & Education*, *138*, 13–32. https://doi.org/10.1016/j.compedu.2019.04.011

Shima, B., & Jaupaj, A. (2025). The Impact of Digital Competencies on Students' Attitudes towards the Use of Information and Communication Technology. *Wseas Transactions on Environment and Development*, *21*, 714–728. https://doi.org/10.37394/232015.2025.21.59

Suhendra, I., Istikomah, N., Anwar, C. J., Supriadi, A., Wakhid, A. A., Purwanda, E., & Salim, A. (2025). Influence of the digital economy on economic growth: empirical study of a region in Indonesia. *Cogent Economics & Finance*, *13*(1). https://doi.org/10.1080/23322039.2025.2457477

Susanto, A. (2018). The Digital Poverty and Empowerment Issue in Indonesia. *2018 International Conference on ICT for Rural Development (IC-ICTRuDev)*, 137–141. https://doi.org/10.1109/ICICTR.2018.8706859

Thao, T. T. P., Thi-Nga, H., Hang, N. T. T., Minh Thai, D. T., Linh, H. T. K., Hong Nhung, N. Do, Huong Giang, N. Do, & Dinh, N. Van. (2024). The Influence of Gender and Training Sector on the ICT Competency of Pre-Service Teachers in Vietnam: Using the UNESCO ICT Competency Framework. *International Journal of Learning, Teaching and Educational Research*, *23*(3), 411–427. https://doi.org/10.26803/ijlter.23.3.20

Uchôa, C. F. A., Cribari-Neto, F., & Menezes, T. A. (2014). Testing inference in heteroskedastic fixed effects models. *European Journal of Operational Research*, *235*(3), 660–670. https://doi.org/10.1016/j.ejor.2014.01.032

United Nations Development Programme. (2023). *UNDP Policy Volume: Indonesia Needs a Strong Digital Inclusivity Index*. https://www.undp.org/indonesia/press-releases/undp-policy-volume-indonesia-needs-strong-digital-inclusivity-index

Verbeek, M. (2021). *Panel Methods for Finance*. De Gruyter. https://doi.org/10.1515/9783110660739

Wamuyu, P. K. (2017). Bridging the digital divide among low income urban communities. Leveraging use of Community Technology Centers. *Telematics and Informatics*, *34*, 1709–1720. https://doi.org/10.1016/j.tele.2017.08.004

Warschauer, M. (2003). Technology and social inclusion : rethinking the digital divide. In *https://books.google.co.id/books?id=nU4zz1O88mAC&printsec=copyright&hl=id#v=onepage&q&f=false*. MIT Press.

World Bank. (2021). *Beyond Unicorns: Harnessing Digital Technologies for Inclusion in Indonesia*. https://www.worldbank.org/en/country/indonesia/publication/beyond-unicorns-harnessing-digital-technologies-for-inclusion-in-indonesia

Xiong, X. B., & Lim, C. P. (2015). Curriculum Leadership and the Development of ICT in Education Competencies of Pre-service Teachers in South China. *The Asia-Pacific Education Researcher*, *24*(3), 515–524. https://doi.org/10.1007/s40299-015-0238-1

Yang, Z. (2021). Joint tests for dynamic and spatial effects in short panels with fixed effects and heteroskedasticity. *Empirical Economics*, *60*(1), 51–92. https://doi.org/10.1007/s00181-020-01935-y