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ECONOMICS

The Effects of Inward Investment, Education, Internet Access, and ICT Index on Unemployment in Indonesia

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HISTORY

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ABSTRACT

Purpose: This study examines the effects of inward investment, education level, internet access, and the Information and Communication Technology (ICT) Index on the unemployment rate in Indonesia.

Method: This study applies a quantitative approach using panel data regression across 34 Indonesian provinces from 2019 to 2023, yielding 170 observations. The data were obtained from Statistics Indonesia (BPS) and the Ministry of Communication and Digital Affairs (Komdigi). Model selection was conducted using the Chow and Hausman tests, which confirmed the Fixed Effects Model as the most appropriate estimation method.

Result: The findings show that inward investment and internet access negatively affect unemployment. This indicates that higher inward investment and broader internet access are associated with lower unemployment rates. Conversely, education level and the ICT Index positively affect unemployment, suggesting that improvements in education and ICT development have not yet been fully matched by labor market absorption across provinces.

Practical Implications for Economic Growth and Development: The study highlights the need to improve the quality of investment by directing it toward job creation. It also emphasizes the importance of strengthening vocational education, aligning educational outcomes with labor market demand, and improving workforce digital skills to support inclusive and sustainable economic development.

Originality/Value: This study integrates inward investment, education, internet access, and the ICT Index into a single analytical framework. Using provincial-level panel data, it offers a comprehensive perspective on unemployment dynamics, digital transformation, and regional labor market disparities in Indonesia.

Keywords: *Unemployment Rate, Inward Investment, Education Level, Internet Access, Information and Communication Technology Index, Panel Data*

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INTRODUCTION

Continuous population growth has contributed to a steady increase in the labor force. However, this growth has not always been followed by sufficient employment opportunities, either in quantity or quality. The imbalance between labor supply and labor demand has become a key driver of unemployment (Butkus et al., 2023; Thomas, 2023). This condition poses a serious challenge for developing countries, including Indonesia, especially in regions with rapid population growth but limited economic capacity to generate new jobs (Hawariyuni & Andrasari, 2022; Setiawana et al., 2024; Suparman & Muzakir, 2023).

In Indonesia, unemployment remains a persistent structural issue in economic development. The COVID-19 pandemic intensified this problem through economic contraction and widespread layoffs across several sectors (Sparrow et al., 2020). Provinces with strong industrial and service-based economies, such as DKI Jakarta, West Java, and Banten, experienced a sharp increase in unemployment during the period of mobility restrictions and declining business activity (Putra et al., 2023; Sabran et al., 2023). Although unemployment began to decline during the post-pandemic recovery period, the recovery process has remained gradual and uneven across provinces (Daud et al., 2024).

Data from Statistics Indonesia (BPS) show that the national open unemployment rate declined from 7.07 percent in 2020 to 5.32 percent in 2023 (BPS, 2024). Despite this improvement, interprovincial disparities remain evident. Banten recorded an unemployment rate of 7.52 percent, followed by West Java at 7.44 percent and DKI Jakarta at 6.53 percent. These rates remained above the national average. In contrast, several provinces dominated by primary-sector activities, such as Papua at 2.67 percent, Bali at 2.69 percent, and Central Sulawesi at 2.95 percent, reported lower unemployment rates. These differences indicate that regional economic structures influence labor absorption capacity.

The variation in unemployment across provinces reflects differences in economic structure and labor market characteristics (Suparman & Muzakir, 2023). Regions dominated by industrial and modern service sectors tend to be more sensitive to economic shocks than regions supported by primary-sector activities. In addition, the mismatch between workers' skills and labor market needs can slow employment recovery, particularly in industrial regions that require specific technical and digital competencies (Cvetkoska et al., 2025; Shi & Wang, 2022).

Education is widely recognized in labor economics as an important determinant of unemployment. Higher educational attainment can improve human capital, strengthen labor competitiveness, and expand access to employment. Mehmetaj and Xhindi (2022) and Tleppayev and Zeinolla (2025) found that education has a negative effect on unemployment. However, other studies show different results. Dimova and Stephan (2020), Esposito and Scicchitano (2022), and Dănăcică et al. (2023) argue that the expansion of higher education does not always lead to stronger labor absorption. When educational outcomes do not align with labor market demand, higher education may contribute to educated unemployment.

Investment also plays a central role in employment creation. Higher investment can stimulate production expansion, infrastructure development, and broader economic activity, thereby increasing labor demand (Petrović et al., 2021; Sall & Burlea-Schiopoiu, 2021). This argument is consistent with the Harrod-Domar theory, which states that investment increases production capacity and supports employment expansion (Hoon et al., 2023). Therefore, inward investment is expected to contribute to unemployment reduction when it is directed toward labor-absorbing sectors.

The development of information and communication technology has also reshaped labor market dynamics. Digitalization through internet access, e-commerce, and digital platforms can create new employment opportunities and expand participation in economic activities (Avom et al., 2021; Huang, 2023). Abbasabadi and Soleimani (2021) and Rizqulloh (2021) found that digitalization contributes to job creation. However, the benefits of digital transformation are not evenly distributed. Matli and Wamba (2023) showed that disparities in digital infrastructure limit the inclusive impact of digitalization. Moreover, Hötte et al. (2023)

and Liang et al. (2025) explained that technological development may increase structural unemployment when workers lack the skills required to adapt to technological change.

Although many studies have examined the determinants of unemployment, several gaps remain. Mehmetaj and Xhindi (2022) and Tleppayev and Zeinolla (2025) focused mainly on education without incorporating digital transformation indicators such as internet access and the ICT Index. Petrović et al. (2021) and Sall and Burlea-Schiopoiu (2021) emphasized the role of investment in employment creation but did not examine how investment operates alongside regional digital disparities. Meanwhile, Abbasabadi and Soleimani (2021) and Hötte et al. (2023) analyzed digitalization and employment largely in cross-country or developed-country contexts. Their findings may not fully explain regional unemployment patterns in developing countries such as Indonesia.

In the Indonesian context, previous studies by Pasuria and Triwahyuningtyas (2022), Mufida and Nasir (2023), and Nisa and Sugiharti (2023) generally examined unemployment through separate macroeconomic, educational, or investment variables. Most of these studies also relied on national time-series data, which limits their ability to capture interprovincial differences. Therefore, this study offers novelty by integrating inward investment, education level, internet access, and the ICT Index into a single provincial-level panel data framework. This approach provides a more comprehensive explanation of unemployment dynamics, digital transformation, and regional labor market disparities in Indonesia. Its findings are expected to support the formulation of employment and economic development policies that are more responsive to regional conditions and the demands of digital transformation.

Hypotheses Development

Inward Investment on Unemployment Rate

In development economics, investment occupies a strategic position in promoting economic growth and employment creation. The Harrod–Domar growth theory explains that investment serves as a key driver of economic expansion by increasing production capacity through physical capital accumulation and infrastructure development (Hoon et al., 2023). Greater production capacity enables firms and industries to expand output, which in turn raises the demand for production factors, including labor. Consequently, higher investment is expected to create more employment opportunities and reduce unemployment.

This argument is also consistent with labor demand theory. Firms tend to increase labor demand when production activities expand as a response to higher investment (Elsby & Gottfries, 2022). Inward investment in a region is commonly associated with the establishment of new production facilities, expansion of industrial activities, and growth of business operations. These processes require additional workers and therefore strengthen labor absorption. Accordingly, inward investment is theoretically expected to reduce the unemployment rate. Based on this explanation, the following hypothesis is proposed:

H1: Inward investment has a negative effect on unemployment rate.

Education Level on Unemployment Rate

Education level represents an important determinant of human resource quality. In human capital theory, Becker conceptualizes education as an investment that improves workers' knowledge, skills, and productivity (Deming, 2022). Individuals with higher educational attainment are generally expected to possess stronger competencies, wider access to labor market information, and greater capacity to meet employment requirements. In this regard, education can enhance labor productivity, improve competitiveness, and increase the probability of obtaining employment (Indrawati & Kuncoro, 2021). Higher levels of education may also strengthen workers' ability to adapt to technological change and acquire new skills that are relevant to evolving labor market needs.

However, the relationship between education and unemployment is not always linear. Several studies indicate that higher educational attainment may increase educated unemployment when labor markets fail to absorb graduates with specific qualifications or when educational outcomes do not match industry demand (Dănăcică et al., 2023; Dimova & Stephan, 2020; Esposito & Scicchitano, 2022). This condition is common in developing countries, including Indonesia, where the expansion of education is not always followed by sufficient growth in formal employment opportunities. Such a mismatch may reduce the immediate employment benefits of higher education.

Despite these mixed findings, this study predicts a negative relationship between education level and the unemployment rate. This prediction is grounded in human capital theory, which emphasizes the role of education in improving productivity, adaptability, and labor market competitiveness in the long term (Leoni, 2025). During the post-pandemic recovery and digital transformation period, workers with higher educational attainment are expected to adapt more effectively to changing labor market demands and technological development. Therefore, higher education levels are expected to contribute to lower unemployment rates. Based on this explanation, the following hypothesis is proposed:

H2: Education level has a negative effect on unemployment rate.

Internet Access on Unemployment Rate

The development of digital technology has significantly transformed labor market structures. From the perspective of digital economy theory, internet access can improve labor market efficiency by expanding access to employment information, strengthening economic connectivity, and creating new forms of digital-based work (Yu et al., 2023). Through internet access, individuals can search for job vacancies, participate in online recruitment processes, develop digital businesses, and improve their competencies through online learning platforms (Tiwasing et al., 2022).

Internet access also supports the growth of the digital economy, including e-commerce, platform-based services, and technology-driven creative industries (Ortiz-Ospino et al., 2025). The expansion of these sectors creates new employment opportunities that are not always available in conventional labor markets. In regions with broader internet access, workers and entrepreneurs have greater opportunities to participate in digital economic activities. As a result, internet access is expected to strengthen labor absorption and reduce unemployment. Based on this theoretical explanation, the following hypothesis is proposed:

H3: Internet access has a negative effect on unemployment rate.

ICT Index on Unemployment Rate

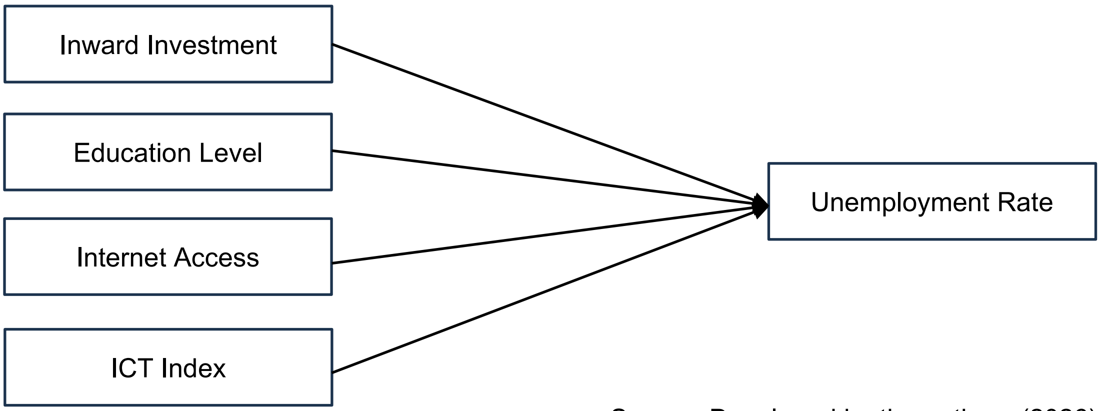
The development of information and communication technology (ICT) has substantial implications for the dynamics of the modern labor market. In the theory of technological change, technological advancement can improve productivity by increasing automation, operational efficiency, and production capacity (Damioli et al., 2021). Higher productivity may stimulate economic expansion and create new employment opportunities, particularly in technology-based sectors.

However, technological advancement may also generate technological unemployment. This occurs when technology replaces human labor in certain occupations, especially routine and low-skilled jobs. When technological development progresses faster than the workforce’s ability to adapt, unemployment may increase in the short term (Szabó-Szentgróti et al., 2021). Automation and digital transformation can reduce labor demand in specific sectors and contribute to structural unemployment when workers lack the skills required by new technologies (Hötte et al., 2023; Liang et al., 2025).

Despite this potential risk, this study predicts that ICT development has a negative effect on the unemployment rate. Improved ICT infrastructure and digital connectivity can support economic growth by increasing productivity, efficiency, and market access (Sarangi & Pradhan, 2020). ICT development also encourages the emergence of new economic activities, such as e-commerce, digital services, creative industries, and platform-based work, which may generate additional employment opportunities. Furthermore, ICT can improve labor market efficiency by facilitating job matching, online recruitment, and digital skills development (Atasoy et al., 2021). In the long term, the employment creation effect of ICT development is expected to outweigh the short-term displacement effect caused by automation. Based on this explanation, the following hypothesis is proposed:

H4: ICT Index has a negative effect on unemployment rate.

Figure 1. Research Framework



Source: Developed by the authors (2026)

METHOD

This study employed a quantitative approach to examine the determinants of unemployment rates in Indonesia. A quantitative design was considered appropriate because it allows the analysis of causal relationships between independent and dependent variables using numerical data and inferential statistical procedures (Ghanad, 2023). The study specifically analyzed the effects of inward investment, education level, internet access, and the Information and Communication Technology (ICT) Index on provincial unemployment rates in Indonesia. The scope of this study covered 34 provinces in Indonesia during the 2019–2023 period. A census sampling technique was used because all provinces in the population were included as units of analysis (Hossan et al., 2023). This approach enables the study to provide a comprehensive picture of labor market variation across regions.

This study used secondary data obtained from official government sources, namely Statistics Indonesia, or Badan Pusat Statistik (BPS), and the Ministry of Communication and Digital Affairs, or Komdigi. Data on unemployment rates, inward investment, education level, and internet access were obtained from BPS publications and statistical databases, including the National Labor Force Survey, Statistics Indonesia reports, and provincial statistical publications for the 2019–2024 period. Meanwhile, data on the ICT Index were obtained from Komdigi through ICT Development Index publications and digital development reports for the same period. The data structure combines cross-sectional and time-series dimensions, thereby forming panel data. Panel data are useful because they allow the analysis of changes over time while also capturing differences in characteristics across provinces (Zyphur et al., 2020). With 34 provinces observed over five years, the total number of observations in this study was 170.

Data were collected using the documentation technique by compiling statistical data officially published by relevant government institutions. The dependent variable in this study was the unemployment rate, while the independent variables consisted of inward investment, education level, internet access, and the ICT Index. The operational definitions and measurements of each variable are presented in Table 1.

Table 1. Research Variables

Variable	Operational Definition	Unit	Source
Unemployment Rate	The percentage of the labor force that is unemployed and actively seeking work at the provincial level.	Percent (%)	BPS
Inward Investment	The total realized investment entering each province, consisting of Domestic Investment (PMDN), used as an indicator of regional economic activity and capital inflows.	Billion Rupiah	BPS
Education Level	The percentage of the population graduating from senior high school or equivalent.	Percent (%)	BPS
Internet Access	The percentage of the population using the internet in daily activities.	Percent (%)	BPS
ICT Index	The information and communication technology development index reflects ICT infrastructure, usage, and skills.	Index	Komdigi

Source: Compiled by the authors (2026)

Data analysis was conducted using panel data regression. Three estimation approaches were considered, namely the Pooled Least Squares (PLS), Fixed Effects Model (FEM), and Random Effects Model (REM) (Baltagi, 2021). The most appropriate estimation model was selected through a sequential testing procedure. First, the Chow test was used to compare the PLS and FEM models. Second, the Hausman test was applied to determine the more appropriate model between FEM and REM.

After the best model was selected, hypothesis testing was conducted using both simultaneous and partial tests. The F-test was used to examine the simultaneous effect of inward investment, education level, internet access, and the ICT Index on the unemployment rate. Meanwhile, the t-test was used to analyze the partial effect of each independent variable on the dependent variable. All stages of data processing and statistical analysis were performed using EViews 13 software.

The empirical panel regression model used in this study is formulated as follows:

$$UR_{it} = \beta_0 + \beta_1 II_{it} + \beta_2 EL_{it} + \beta_3 IA_{it} + \beta_4 ICT_{it} + \varepsilon_{it}$$

Where:

UR_{it} : Unemployment rate in province *i* at time *t*
II_{it} : Inward investment in province *i* at time *t*
EL_{it} : Education level in province *i* at time *t*
IA_{it} : Internet access in province *i* at time *t*
ICT_{it} : Information and Communication Technology index in province *i* at time *t*
β_0 : Constant
$\beta_1 - \beta_4$: Regression coefficients of each independent variable
ε_{it} : Error term

RESULT AND DISCUSSION

Result

After estimating the panel data regression using three alternative approaches, model selection tests were conducted to identify the most appropriate estimation model. The Chow test was first applied to compare the Pooled Least Squares (PLS) model and the Fixed Effects Model (FEM). Subsequently, the Hausman test was used to determine whether the Fixed Effects Model (FEM) or the Random Effects Model (REM) was more suitable for the analysis. The Chow test results presented in Table 2 show a Cross-section F statistic of 6.656 with a probability value of 0.000, which is lower than the 5 percent significance level. This result indicates that the Fixed Effects Model is more appropriate than the Pooled Least Squares model. Furthermore, the Hausman test produces a chi-square statistic of 13.661 with a probability value of 0.009. Since this value is also lower than 0.05, the null hypothesis is rejected. This finding suggests that the Random Effects Model is not appropriate, thereby confirming that the Fixed Effects Model is the most suitable estimation model for this study.

Table 2. Estimation Results of Panel Data Models and Model Selection Tests

Variable	PLS Coefficient & Prob.	FEM Coefficient & Prob.	REM Coefficient & Prob.
C	−1.626 (0.121)	0.423 (0.867)	0.627 (0.691)
II	0.472 (0.000)*	−0.308 (0.058)***	−0.053 (0.694)
EL	0.059 (0.001)*	0.059 (0.002)*	0.057 (0.001)*
IA	−0.019 (0.438)	−0.102 (0.006)*	−0.077 (0.003)*
ICT	0.048 (0.925)	2.064 (0.018)**	1.309 (0.029)**
R^2	0.264	0.864	0.143
Adjusted R^2	0.246	0.826	0.121
F-statistic	14.381	22.631	6.656
Prob. F-statistic	0.000	0.000	0.000
Chow Test: Cross-section F = 6.656; Prob. F = 0.000 Hausman Test: Cross-section random χ^2 = 13.661; Prob. χ^2 = 0.009			

*Note: *Significant at α = 0.01; **significant at α = 0.05; ***significant at α = 0.10.*

Source: Processed data (2026)

Based on these test results, the Fixed Effects Model was selected as the best model because it is able to account for unobserved heterogeneity across provinces in Indonesia. This model is more appropriate for capturing province-specific characteristics that may influence unemployment rates but remain constant over time. Compared with the PLS and REM models, FEM provides a more accurate estimation when individual effects are correlated with the explanatory variables (Hill et al., 2020; Breuer & DeHaan, 2024). The estimation results of the Fixed Effects Model are presented in Table 3.

Table 3. Fixed Effects Model (FEM) Estimation Results

Variable	Coefficient	Std. Error	t-Statistic	Probability
C	0.423	2.520	0.168	0.867
II	−0.308***	0.161	−1.916	0.058
EL	0.059*	0.019	3.151	0.002
IA	−0.102*	0.036	−2.816	0.006
ICT	2.064**	0.864	2.389	0.018
R^2 = 0.864; Adjusted R^2 = 0.826; F-Statistic = 22.631; Prob. F-Statistic = 0.000				

*Note: *Significant at α = 0.01; **significant at α = 0.05; ***significant at α = 0.10.*

Source: Processed data (2026)

Based on the Fixed Effects Model (FEM) estimation results presented in Table 3, the model shows an R^2 value of 0.864, an F-statistic of 22.631, and a Prob. F-statistic of 0.000. Since the probability value of the F-statistic is lower than the 5 percent significance level, the results indicate that inward investment, education level, internet access, and the Information and Communication Technology (ICT) Index jointly have a statistically significant effect on the unemployment rate in Indonesia. The R^2 value of 0.864 indicates that 86.4 percent of the variation in unemployment rates across Indonesian provinces can be explained by the independent variables included in the model. Meanwhile, the remaining 13.6 percent is explained by other factors outside the model, such as regional wage levels, industrial structure, labor market flexibility, government employment policies, demographic conditions, and sectoral economic growth.

Table 4. Partial Test Results (t-Test) of the Fixed Effects Model

Variable	Coefficient	Probability	Statistical Significance	Conclusion
II	−0.308***	0.058	Significant at $\alpha = 0.10$	II has a negative effect on UR.
EL	0.059*	0.002	Significant at $\alpha = 0.01$	EL has a positive effect on UR.
IA	−0.102*	0.006	Significant at $\alpha = 0.01$	IA has a negative effect on UR.
ICT	2.064**	0.018	Significant at $\alpha = 0.05$	ICT has a positive effect on UR.

*Note: *Significant at α = 0.01; **significant at α = 0.05; ***significant at α = 0.10.*

Source: Processed data (2026)

The hypothesis testing results using the t-test, as presented in Table 4, show that inward investment and internet access have a negative effect on the unemployment rate in Indonesia. In contrast, education level and the ICT Index have a positive effect on the unemployment rate. The coefficient of inward investment (II) is −0.308, with a probability value of 0.058. Since this value is lower than the 10 percent significance level, inward investment has a negative and statistically significant effect on unemployment. This finding indicates that, assuming inward investment is measured in billion rupiahs, an increase of one billion rupiahs in inward investment is associated with a decrease in the unemployment rate by 0.308 percentage points. This result suggests that higher investment can stimulate economic expansion through increased production capacity, industrial development, and infrastructure growth, thereby creating additional employment opportunities. The coefficient of education level (EL) is 0.059, with a probability value of 0.002. This value is significant at the 1 percent level, indicating that education level has a positive and statistically significant effect on unemployment. This result implies that a one-percentage-point increase in the proportion of the population graduating from senior high school or its equivalent is associated with an increase in the unemployment rate by 0.059 percentage points. This finding may reflect the presence of skills mismatch, where the increase in educated labor is not fully matched by the availability of jobs that correspond to graduates' qualifications and competencies.

The coefficient of internet access (IA) is −0.102, with a probability value of 0.006. Since this value is significant at the 1 percent level, internet access has a negative and statistically significant effect on unemployment. This result indicates that a one-percentage-point increase in internet access is associated with a decrease in the unemployment rate by 0.102 percentage points. Broader internet access may improve labor market efficiency by facilitating access to job vacancy information, supporting online learning, and expanding digital-based business opportunities. The coefficient of the ICT Index (ICT) is 2.064, with a probability value of 0.018. This value is significant at the 5 percent level, indicating that the ICT Index has a positive and statistically significant effect on unemployment. This result implies that a one-point increase in the ICT Index is associated with an increase in the unemployment rate by

2.064 percentage points. In the short term, ICT development may contribute to technological displacement, particularly when automation and digital technologies replace certain routine and low-skilled jobs. This finding suggests that ICT advancement must be accompanied by workforce reskilling, digital literacy improvement, and labor market adaptation policies to prevent structural unemployment.

Discussion

The findings indicate that inward investment has a negative effect on unemployment in Indonesia. Thus, the first hypothesis (H1) is accepted. This result suggests that higher realized investment contributes to job creation through the expansion of productive economic sectors. In the Indonesian context, investment flows are commonly directed toward manufacturing, infrastructure, and service sectors, which generally have relatively high labor absorption capacity. Investment also increases production capacity and strengthens labor demand (Gherghina et al., 2020). This finding supports Petrović et al. (2021) and Sall and Burlea-Schiopoiu (2021), who found that higher investment is associated with lower unemployment. During the 2019–2023 period, inward investment played an important role in supporting post-pandemic economic recovery and employment creation in Indonesia. After the economic contraction caused by the COVID-19 pandemic, the government strengthened investment-oriented policies through infrastructure development, industrial downstreaming, and incentives for strategic sectors, including manufacturing, transportation, digital services, and renewable energy. Investment projects in labor-intensive industries, particularly manufacturing and construction, increased labor absorption in provinces with strong industrial bases, such as West Java, Central Java, and Banten. In addition, investment in infrastructure and digital sectors stimulated supporting economic activities and created indirect employment in trade, logistics, and small-scale services. Therefore, inward investment not only increased production capacity but also accelerated labor market recovery during the post-pandemic period.

The findings also show that education level has a positive effect on unemployment. Therefore, the second hypothesis (H2) is rejected. Theoretically, education is a major component of human capital formation because it improves productivity, adaptability, and labor competitiveness (Indrawati & Kuncoro, 2021). However, the empirical result indicates a skills mismatch between graduates' competencies and labor market needs. The increase in educated workers has not been followed by sufficient employment opportunities that match their qualifications. This condition contributes to educated unemployment, particularly among senior high school and university graduates (Azzahra et al., 2024). This result is consistent with Esposito and Scicchitano (2022) and Dănăcică et al. (2023), who emphasized that skills mismatch plays an important role in educated unemployment. Dimova and Stephan (2020) also showed that formal education does not automatically reduce unemployment without practical and market-relevant skills. This condition reflects the structure of Indonesia's labor market, where improvements in educational attainment have not been fully aligned with industrial labor demand. Many graduates, especially those from senior high schools and non-technical university programs, face difficulties entering the labor market because their competencies do not correspond to the needs of industries undergoing digital and technological transformation. At the same time, educational institutions and vocational training centers still face challenges related to curriculum relevance, practical training quality, and collaboration with industry (Zukna & Sassi, 2024). As a result, many firms prefer workers with specific technical and digital skills, while many graduates remain dominated by theoretical competencies. Moreover, job creation in the formal sector during the post-pandemic recovery period has not been sufficient to absorb the growing number of educated workers. Therefore, strengthening vocational education, industry-based curriculum design, internship programs, and market-oriented skills development is essential to reduce labor market mismatch in Indonesia.

Internet access has a negative effect on unemployment in Indonesia. Thus, the third hypothesis (H3) is accepted. Internet access improves labor market efficiency by accelerating access to job vacancy information, expanding opportunities for skills development through online learning, and creating digital business opportunities. The growth of Indonesia's digital economy, including e-commerce, freelance platforms, and creative industries, provides alternative sources of income outside the formal sector. Denzer et al. (2021) found that the internet improves job-search efficiency, while Tiwasing et al. (2022) emphasized its role in promoting digital entrepreneurship. Therefore, wider internet penetration not only broadens access to information but also supports the formation of a new economic ecosystem that can absorb labor.

The ICT Index has a positive effect on open unemployment in Indonesia. Therefore, the fourth hypothesis (H4) is rejected. This finding indicates that technological development does not always reduce unemployment in the short term. One possible explanation is technological displacement, where automation and digital systems replace routine tasks previously performed by human labor. Digital transformation across various sectors may improve production efficiency, but it can also reduce labor demand for repetitive and low-skilled jobs (Damioli et al., 2021). This finding supports Grigoli et al. (2020), who showed that technological progress can reduce labor participation in certain sectors. Hötte et al. (2023) and Liang et al. (2025) also confirmed that the labor market impact of technology depends strongly on workers' adaptability. In Indonesia, limited digital literacy and technological skills remain key barriers to maximizing the benefits of digital transformation. Without sufficient improvement in human capital quality, ICT development may increase unemployment.

The different effects of internet access and the ICT Index indicate that digitalization influences the labor market through distinct mechanisms. Internet access mainly reflects individuals' ability to connect to digital networks and participate in online economic activities. Wider internet access enables people to search for jobs, join online learning, engage in e-commerce, and develop digital entrepreneurship. These mechanisms directly support employment opportunities at the household and microeconomic levels. In contrast, the ICT Index reflects broader technological development, including digital infrastructure, technological sophistication, and the intensity of technology adoption across sectors. Higher ICT development is often associated with automation, digital integration, and the replacement of routine jobs with technology-based systems.

In Indonesia, provinces with rapid ICT development are often regions with stronger industrial and service modernization. In these regions, firms increasingly adopt automation and digital operational systems to improve efficiency. Although these changes increase productivity, they may reduce demand for low-skilled and routine labor in the short term. Therefore, internet access tends to generate more inclusive employment opportunities, while ICT development at the industrial and institutional levels may initially create labor displacement before new technology-based jobs are fully absorbed by the labor market (Halla et al., 2020). This explains why internet access reduces unemployment, whereas the ICT Index is positively associated with unemployment during the observation period.

CONCLUSION

This study examines the effects of inward investment, education level, internet access, and the Information and Communication Technology (ICT) Index on unemployment in Indonesia. The findings show that inward investment and internet access have a negative effect on unemployment, whereas education level and the ICT Index have a positive effect. Based on these findings, several policy implications can be formulated for relevant stakeholders.

For the central government, employment policy should prioritize the expansion of labor-intensive and inclusive investment, particularly in the manufacturing, infrastructure, and digital economy sectors. These sectors have strong potential to generate broad employment opportunities across regions. The central government also needs to strengthen industrial policies that support downstreaming and productive sector development in order to increase labor absorption during the post-pandemic recovery period.

For local governments, policy efforts should focus on improving the regional investment climate, expanding employment opportunities based on local economic potential, and strengthening workforce competencies through vocational training and skills development programs that correspond to regional labor market needs. Local governments also need to improve digital infrastructure accessibility, especially in relatively underdeveloped provinces, to reduce disparities in labor market access and participation in the digital economy.

For educational institutions, curriculum reform is required to ensure that educational outcomes are aligned with labor market and industrial needs. Universities and vocational schools should strengthen practical learning, internship programs, digital skills training, and collaboration with industry. These efforts are important to reduce skills mismatch and improve graduates' competitiveness. Educational institutions should also promote entrepreneurship- and innovation-based learning to prepare graduates for the demands of the digital economy.

For policymakers in the digital sector, the findings suggest that digital transformation policies should not focus solely on technological expansion and automation. They should also emphasize workforce adaptation and inclusiveness. Therefore, ICT development needs to be accompanied by reskilling and upskilling programs, digital literacy improvement, and job transition assistance for workers vulnerable to technological disruption. This approach is necessary to ensure that ICT development contributes to employment creation rather than increasing structural unemployment.

This study has several limitations. First, the observation period is relatively short because it covers only five years. Thus, it may not fully capture the long-term dynamics of Indonesia's labor market. Second, the explanatory variables are limited to inward investment, education level, internet access, and the ICT Index. Other potential determinants, such as economic growth, industrial structure, institutional quality, wage levels, and labor market policies, are not included in the model. Third, this study does not conduct robustness tests using alternative model specifications to verify the consistency of the estimation results. Fourth, potential endogeneity problems, such as bidirectional causality between unemployment, investment, and digital development, are not specifically addressed. Fifth, this study does not examine spatial dependence or interregional spillover effects, although unemployment and digital development in one province may influence labor market conditions in neighboring provinces.

Future studies are therefore encouraged to use a longer observation period and include more comprehensive explanatory variables. Further research may also apply more advanced econometric methods, such as dynamic panel models, instrumental variable estimation, or the Generalized Method of Moments (GMM), to address potential endogeneity. In addition, spatial econometric models can be used to examine interregional interactions and spatial spillover effects in unemployment dynamics across Indonesian provinces.

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