Jurnal Akuntansi, Manajemen Dan Ekonomi Islam (JAM-EKIS)
Vol. 9, No. 1 / Jan 2026
Online ISSN: 2655-6359, Print ISSN: 2656-436X
DOI: https://doi.org/10.36085/jam-ekis

ANALYSIS OF HUMAN CAPITAL INVESTMENT AND INCOME INEQUALITY IN INDONESIA

Natasya Rahmayuli Irwin[1], Yulia Anas[2]
[12]Universitas Andalas
natasyarahmayulii@gmail.com , yuliaanas@eb.unand.ac.id

Padang, Sumatera Barat, Indonesia.
Corresponding email: natasyarahmayulii@gmail.com

How to cite: Irwin, Natasya Rahmayuli., Anas, Yulia. (2026). Analysis Of Human Capital Investment And Income Inequality In Indonesia. *Jurnal Ilmiah Akuntansi, Manajemen Dan Ekonomi Islam (JAM-EKIS), 9(1),* 152-161. https://doi.org/10.36085/jam-ekis.v9i1.9468

INFORMASI ARTIKEL

Article History:
Accepted : 22 Nov 2025
Revised : 9 Jan 2026
Approved : 15 Jan 2026

Keywords:
Income Inequality, Human Capital Investment, Education, Job Training, Health, Technology

Pages: 152-161

ABSTRACT

This study examines the heterogeneous effects of human capital investment—encompassing education, job training, health, and technology—on income inequality across districts and cities in Indonesia. Using individual microdata from the 2023 National Labor Force Survey (Sakernas) and the National Socio-Economic Survey (Susenas), the data are aggregated to the district/city level to capture regional disparities in income distribution. The analysis employs multiple linear regression with robust standard errors to address heteroscedasticity inherent in aggregated data.
The empirical results indicate that regional health conditions are associated with significantly lower income inequality, while job training participation and technology adoption exhibit positive and significant relationships with inequality. These findings challenge the conventional assumption that all forms of human capital investment uniformly reduce inequality and instead highlight a "digital paradox," whereby unequal regional access to skills development and technology intensifies income disparities. This study contributes to the literature by identifying job training and technology as potential drivers of inequality in the absence of inclusive regional access. The policy implications underscore the importance of targeted vocational programs and equitable digital infrastructure development in underdeveloped regions.

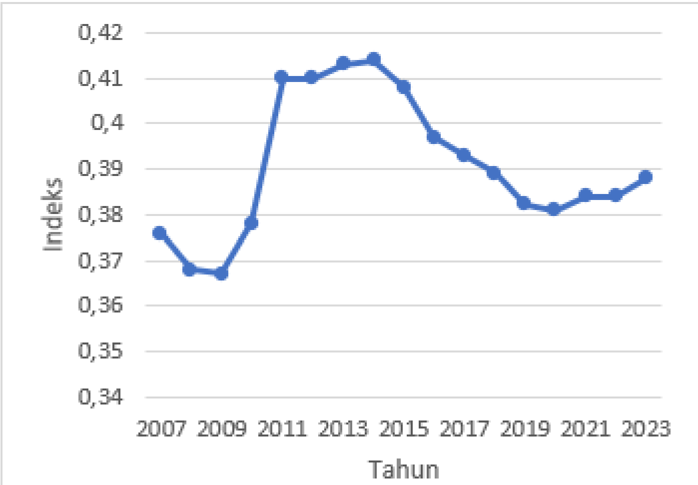
INTRODUCTION

Income inequality represents a major structural challenge for developing countries, including Indonesia, and constitutes a more complex issue than poverty alone (Wibowo,

Online ISSN: 2655-6359, Print ISSN: 2656-436X
DOI: https://doi.org/10.36085/jam-ekis

2016). The World Economic Forum (2014), as cited in Wibowo (2016), identifies severe income disparity as one of the most critical global risks, reflecting its broad economic and social consequences. Income inequality refers to the uneven distribution of welfare across the population, extending beyond the condition of the poor alone. High levels of inequality can impede economic growth, intensify social disparities, and restrict access to economic opportunities for low-income groups, thereby undermining inclusive and sustainable development. Patta (2012), as cited in Nursa Fitri et al. (2021), further argues that persistent inequality negatively affects both economic performance and societal welfare.

In Indonesia, income inequality varies substantially across regions and is commonly measured using the Gini Ratio. According to Statistics Indonesia (Badan Pusat Statistik, 2024), the Gini coefficient ranges from 0 to 1, with higher values indicating greater inequality. Countries with high income inequality typically exhibit Gini coefficients between 0.50 and 0.75, whereas those with more equitable income distribution fall within the range of 0.20 to 0.35 (Wijayanti et al., 2023). This regional variation underscores the importance of identifying structural factors—such as disparities in human capital development—that contribute to unequal income distribution across districts and cities in Indonesia.



Pict 1. Gini Ratio of Indonesia

Source : Badan Pusat Statistik, 2024 (processed)

Based on Figure 1, Indonesia exhibits a moderate level of income inequality, with Gini values fluctuating between 0.30 and 0.50. The sharp increase during 2011–2012 reflects uneven economic growth across regions, while the decline between 2015 and 2020 was partly driven by the economic slowdown during the COVID-19 pandemic. The subsequent rise in 2022–2023 suggests that post-pandemic economic recovery has not yet been evenly distributed across districts and cities. These dynamics indicate persistent inter-regional income disparities (Shinetiara & Adry, 2023).

One of the key factors frequently associated with regional income inequality is the uneven development of human capital, encompassing education, skills, health, and technological capacity. Alisjahbana (2012) argues that inequality is a long-term structural issue requiring comprehensive policies focused on improving the quality of human resources across regions. Investment in education, job training, health, and technology has the potential to enhance regional productivity and economic opportunities. Frank and Bernanke (2007) emphasize the role of human capital in driving productivity and innovation, while Todaro and Smith (2020) highlight the importance of education and health in strengthening economic capacity at the regional level.

Regions with higher average educational attainment and skill levels tend to be better positioned to attract productive economic activities, while regions with healthier populations are more likely to sustain labor participation and economic growth. Technological capability further differentiates regional economic performance in the digital era, as areas with better access to technology and digital skills can achieve higher productivity and income growth. Endogenous growth theory underscores the role of human capital in fostering innovation and knowledge-based development (Romer, 1990), suggesting that unequal regional access to human capital may reinforce income disparities (Adriani, 2019).

Despite the extensive literature on human capital and inequality, most studies in Indonesia primarily focus on education and health as aggregate indicators (e.g., Ghifara et al., 2022; Adan et al., 2023), while relatively little attention is given to job training and technology adoption as distinct components of human capital. Moreover, existing studies often overlook the skill-biased nature of recent human capital investments. This study addresses these gaps by explicitly examining the roles of job training and technology adoption alongside education and health in explaining inter-regional income inequality. By utilizing district/city-level data from 2023, this research captures post-pandemic labor market conditions and provides new evidence on how unequal access to skills and technology shapes income distribution in Indonesia.

Accordingly, this study aims to analyze the effects of human capital investment—covering education, job training, health, technology, age structure, gender composition, work experience, and regional classification—on income inequality across districts and cities in Indonesia using cross-sectional data from 2023 and an Ordinary Least Squares (OLS) regression framework.

LITERATURE REVIEW

Theoretical Framework

The relationship between human capital and income inequality is rooted in Human Capital Theory, which posits that individual income is determined by productivity-enhancing investments such as education, training, health, and technological proficiency (Becker, 1993; Borjas, 2013). According to Mincer (1974), disparities in earnings are largely driven by differences in the accumulation of these human capital stocks. Individuals with higher education and skills command a premium in the labor market, while those with limited access remain in lower income brackets. This framework intersects with Kuznets' (1955) inverted-U hypothesis, which suggests that inequality initially rises during the early stages of development as returns to skills increase, but eventually declines as access to education becomes more widespread. However, Borjas (2013) argues that if the distribution of human capital remains unequal—particularly in terms of quality and access—income inequality will persist or even worsen, creating a structural barrier to inclusive growth.

Online ISSN: 2655-6359, Print ISSN: 2656-436X
DOI: https://doi.org/10.36085/jam-ekis

Components of Human Capital Investment

Human capital investment encompasses four critical dimensions. First, education acts as the primary signal of productivity, ideally enabling individuals to secure higher wages (Psacharopoulos & Patrinos, 2018). Second, job training complements formal education by updating workforce skills to match industrial needs, although its benefits are often skewed toward formal sector workers (Autor, 2014). Third, health is a fundamental prerequisite for productivity; as noted by Grossman (1972) and Bloom and Canning (2005), better health status extends productive life and enhances work intensity. Fourth, in the modern economy, technological proficiency has emerged as a decisive factor. Romer (1990) and Acemoglu and Restrepo (2018) emphasize that technology can be "skill-biased," disproportionately benefiting those with digital literacy while displacing low-skilled labor, thereby potentially exacerbating inequality.

Empirical Evidence and Research Gap

Empirical studies on the determinants of inequality yield mixed results depending on the region and variables analyzed. In the context of Indonesia, Ghifara et al. (2022) found that improvements in the aggregate Human Development Index (HDI) significantly reduce income inequality. Similarly, Adan et al. (2023) observed in Kenya that health expenditure and HDI negatively affect inequality, confirming the equalizing role of basic human capital. However, other studies highlight the complexity of these relationships. Moyo et al. (2022) found that in South Africa, increased educational attainment was paradoxically correlated with higher inequality, attributing this to unequal access to quality education.

Specific to labor market segmentation, Satria and Wulandari (2018) revealed that income inequality in Indonesia is driven more by inter-sectoral discrimination (formal vs. informal) than by productivity differences alone. Sari and Sugiarto (2024) further emphasized that variables such as job training and work experience are significant determinants of income for informal workers. Despite these extensive studies, a gap remains in analyzing these factors simultaneously. Most previous research focuses on aggregate indicators like HDI or separates education from health. This study aims to fill this void by integrating job training and technology adoption alongside education and health, providing a comprehensive analysis of how specific human capital components influence income distribution in Indonesia's post-pandemic economy.

RESEARCH METHOD

This study employs a quantitative research design utilizing secondary data in the form of individual microdata sourced from Statistics Indonesia (BPS) through two national surveys: the National Labor Force Survey (SAKERNAS) August 2023 and the National Socio-Economic Survey (SUSENAS) 2023. SAKERNAS data is utilized to obtain information regarding employment and human capital variables, such as education level, work experience, training participation, technology usage, age, gender, and regional classification (urban or rural). Meanwhile, SUSENAS data is used to capture health variables, as these indicators are not available in SAKERNAS.

After merging the individual-level data from both surveys, the data are aggregated to the district/city level ($n = 514$) to analyze the relationship between human capital investment and inter-regional income inequality in Indonesia. This

Online ISSN: 2655-6359, Print ISSN: 2656-436X
DOI: https://doi.org/10.36085/jam-ekis

aggregation strategy is methodologically necessary, as income inequality in this study is measured using the Gini Ratio, which is defined at the regional level rather than at the individual level. Nevertheless, aggregating microdata into regional units introduces statistical implications, particularly the potential for heteroscedasticity arising from differences in population size and variance across districts. To address this issue and ensure valid statistical inference, this study employs Ordinary Least Squares (OLS) regression with Huber–White robust standard errors, which provide consistent standard errors even when the assumption of homoscedasticity is violated.

The analytical method employed is multiple linear regression using cross-sectional data from 2023 to examine the influence of human capital investment on income inequality. The dependent variable in this study is income inequality (Y), measured by the district/city-level Gini Ratio. The main independent variables include education (X_1), job training (X_2), health (X_3), and technology (X_4), along with control variables consisting of age (Z_1), gender (Z_2), work experience (Z_3), and regional classification (Z_4). The econometric model is specified as follows:

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \gamma_1 Z_1 + \gamma_2 Z_2 + \gamma_3 Z_3 + \gamma_4 Z_4 + \epsilon$$

where:
Y = Income inequality (Gini Ratio)
X_1 = Education (1 = senior high school/vocational or higher, 0 = others)
X_2 = Job training (1 = participated, 0 = did not participate)
X_3 = Health (1 = healthy, 0 = unhealthy)
X_4 = Technology (1 = user, 0 = non-user)
Z_1 = Age (years)
Z_2 = Gender (1 = male, 0 = female)
Z_3 = Work experience (1 = has worked, 0 = has not worked)
Z_4 = Regional classification (1 = urban, 0 = rural)
α = Constant
β, γ = Regression coefficients
ϵ = error term

All regression estimations were performed using Stata software. Prior to estimation, diagnostic tests for multicollinearity and residual normality were conducted. Although heteroscedasticity was detected, the use of robust standard errors ensures that the inference remains valid.

Diagnostic Tests

Prior to interpreting the regression estimates, classical assumption tests were conducted to ensure the validity of the Ordinary Least Squares (OLS) model. The multicollinearity test yielded an average Variance Inflation Factor (VIF) of 2.63, with all individual variables exhibiting VIF values well below the threshold of 10, indicating the absence of severe multicollinearity. Regarding heteroscedasticity, the Breusch–Pagan test rejected the null hypothesis of homoscedasticity ($\chi^2 = 14.09, p = 0.0002$). To address this issue and ensure valid statistical inference, the regression model was estimated using Huber–White robust standard errors. Finally, although the Shapiro–Wilk test indicates that the residuals are not normally distributed ($p = 0.000$), the relatively large sample size ($n = 514$) implies that the sampling distribution of the OLS estimators converges to normality according to the Central Limit Theorem (CLT),

Jurnal Akuntansi, Manajemen Dan Ekonomi Islam (JAM-EKIS)
Vol. 9, No. 1 / Jan 2026
Online ISSN: 2655-6359, Print ISSN: 2656-436X
DOI: https://doi.org/10.36085/jam-ekis

thereby ensuring the validity of hypothesis testing (Stock & Watson, 2020).

RESEARCH RESULTS AND DISCUSSION

Regression Analysis

Table 4 presents the estimation results of the influence of human capital investment on income inequality using the robust OLS method.

Table 4. Regression Results

Variabel	Koefisien	Std. Error	t-Statistik	p-Value	Kesimpulan
Education	0.0155	0.0387	0.40	0.690	Not significant
Job Training	0.1443	0.0589	2.45	0.015	Positive significant
Health	-0.1008	0.0352	-2.86	0.004	Negative significant
Technology	0.1840	0.0831	2.21	0.027	Positive significant
Age	0.0014	0.0013	1.05	0.293	Not significant
Gender	-0.9889	0.1318	-7.50	0.000	Negative significant
Regional Classification	-0.0734	0.0121	-6.09	0.000	Negative significant
Work Experience	-0.0113	0.0240	-0.47	0.638	Not significant

Source: Stata Output (processed), 2025

The regression estimates indicate heterogeneous effects of human capital components on income inequality. Job Training ($\beta = 0.1443$, $p = 0.015$) and Technology ($\beta = 0.1840$, $p = 0.027$) exhibit positive and statistically significant coefficients, indicating that districts with higher levels of training participation and technology usage tend to experience higher income inequality. In contrast, Health demonstrates a statistically significant negative effect ($\beta = -0.1008$, $p = 0.004$), suggesting that better health outcomes are associated with lower levels of income inequality.

Among the control variables, Gender and Regional Classification show statistically significant negative coefficients, implying that regions with higher proportions of male workers and urban populations are associated with lower income inequality. Meanwhile, Education, Age, and Work Experience do not exhibit statistically significant effects on income inequality in this aggregate model.

Education and Income Inequality

At the regional level, the education variable (X_1) exhibits a positive but statistically insignificant coefficient, indicating that differences in average educational attainment across districts/cities do not significantly explain variations in income inequality in Indonesia. This suggests that regions with higher average education levels do not necessarily experience more equal income distribution. This finding is consistent with Diyanty and Siregar (2021), who emphasize the persistence of skills mismatch at the regional labor market level, and with Hanushek and Woessmann (2008), who argue that education quality matters more than years of schooling. Furthermore, Moyo et al. (2022) show that regional inequality may persist when access to high-quality education remains concentrated in economically advantaged areas. In line with the capital–skill complementarity framework (Goldin & Katz, 1998), education can contribute to reducing regional income inequality only when improvements in attainment are accompanied by equitable access, quality enhancement, and alignment with local labor market demand.

Job Training and Income Inequality

Job training (X_2) shows a positive and statistically significant effect on income inequality at the district/city level. This result contradicts the initial hypothesis that training expansion would reduce inequality and instead indicates that regions with higher participation in job training tend to experience greater income inequality. This pattern reflects unequal regional access to training programs, where economically developed districts—particularly those dominated by formal employment—benefit more from training opportunities. This outcome aligns with the skill-biased technological change framework (Acemoglu & Autor, 2011), which suggests that training disproportionately enhances the productivity of already-skilled labor. Moreover, firm-based training programs are typically concentrated in formal-sector clusters (Autor, 2014), reinforcing inter-regional inequality. Empirical evidence from Sari and Sugiarto (2024) and Satria and Wulandari (2018) similarly demonstrates that uneven training distribution across regions can amplify income gaps.

Health and Income Inequality

Health (X_3) has a negative and statistically significant coefficient, indicating that districts with better average health conditions tend to exhibit lower income inequality. This finding supports the hypothesis that health improvements function as an equalizing force at the regional level. Consistent with Grossman's (1972) human capital theory and subsequent empirical studies by Bloom and Canning (2005) and Weil (2007), healthier populations enhance regional productivity and labor participation. However, persistent disparities in access to health services across districts—particularly between urban and rural areas—limit the equalizing potential of health improvements (World Bank, 2022; Gertler et al., 2014).

Technology and Income Inequality

Technology adoption (X_4) shows a positive and statistically significant relationship with income inequality at the district/city level. This indicates that regions with higher levels of technology usage tend to experience greater income inequality. This outcome is consistent with the skill-biased technological change (SBTC) hypothesis proposed by Acemoglu and Restrepo (2018), which posits that technological progress disproportionately benefits regions with a higher concentration of skilled labor. The winner-takes-all dynamics described by Brynjolfsson and McAfee (2014) further explain how technologically advanced districts gain disproportionate economic advantages. In Indonesia, digital infrastructure and digital skills remain heavily concentrated in urban areas (Bappenas, 2023), exacerbating inter-regional inequality.

Other Variables and Income Inequality

Among the control variables, gender composition and regional classification significantly affect income inequality at the district/city level, while age and work experience do not. Districts with a higher proportion of male workers tend to exhibit lower

Jurnal Akuntansi, Manajemen Dan Ekonomi Islam (JAM-EKIS)
Vol. 9, No. 1 / Jan 2026
Online ISSN: 2655-6359, Print ISSN: 2656-436X
DOI: https://doi.org/10.36085/jam-ekis

income inequality, reflecting persistent gender-based disparities in regional labor markets, as documented by Blau and Kahn (2017) and Wijayanto and Sari (2020). Additionally, urban districts tend to have lower income inequality than rural districts due to better access to infrastructure, education, and economic opportunities (Kanbur & Venables, 2005; Suryahadi et al., 2012). In contrast, age and work experience do not significantly influence income inequality across regions, indicating that structural factors dominate demographic characteristics in explaining regional inequality patterns.

Policy Implications

The finding that job training and technology act as drivers of regional income inequality suggests the need for a reorientation of policy design. First, vocational training programs should be restructured to specifically target informal-sector workers in lagging regions through affirmative instruments such as upskilling vouchers. Second, technology policy should move beyond infrastructure provision toward the development of regional digital capabilities, including community-based digital literacy centers in rural and underdeveloped areas. Without such targeted interventions, the process of skill-biased technological change is likely to perpetuate and exacerbate regional income inequality in Indonesia.

CONCLUSION

This study examines the relationship between human capital investment and income inequality across districts and cities in Indonesia by incorporating education, job training, health, and technology as core explanatory variables, alongside demographic and regional controls. The empirical findings reveal that job training participation and technology adoption are positively and significantly associated with regional income inequality, indicating that access to these forms of human capital remains uneven across districts. In contrast, health conditions exhibit a negative and significant relationship with income inequality, suggesting that improvements in population health function as an equalizing force at the regional level. Meanwhile, education, age structure, and work experience do not show statistically significant effects on income inequality during the observation period.

Additionally, gender composition and regional classification remain important determinants of inequality, with rural districts and regions with lower female labor market outcomes experiencing higher levels of income disparity. Overall, these results highlight that not all forms of human capital investment automatically promote equality; without inclusive access, job training and technological progress may instead reinforce existing regional disparities. This study contributes to the literature by providing evidence that the distributional effects of human capital investment depend critically on regional access and institutional context.

Future research is encouraged to employ panel or longitudinal data to capture the dynamic effects of human capital investment on income inequality over time and to explore potential spatial spillovers across regions.

REFERENCE

Acemoglu, D., & Autor, D. H. (2011). Skills, tasks and technologies: Implications for employment and earnings. *Handbook of Labor Economics*, 4, 1043–1171. https://doi.org/10.1016/B978-0-44-453532-1.00009-9

Adan, M. A., Muriithi, D. K., & Mbaabu, O. (2023). Effect of human capital investment on income inequality in Kenya. *European Journal of Development Studies*, 3(4), 30–40. https://doi.org/10.24018/ejdevelop.2023.3.4.288

Adriani, E. (2019). Pengukuran modal manusia (suatu studi literatur). *J-MAS (Jurnal Manajemen dan Sains)*, 4(1), 176. https://doi.org/10.33087/jmas.v4i1.86

Badan Pusat Statistik. (2023). *Statistik Indonesia 2023: Data sosial dan ekonomi*. Badan Pusat Statistik. https://www.bps.go.id

Badan Pusat Statistik. (2024). *Gini ratio menurut provinsi dan daerah*. Badan Pusat Statistik. https://www.bps.go.id/id/statistics-table/2/OTgjMg==/gini-ratio-menurut-provinsi-dan-daerah.html

Bappenas. (2023). *Rencana Pembangunan Jangka Panjang Nasional (RPJPN) 2025–2045: Indonesia Emas 2045*. Kementerian PPN/Bappenas. https://www.bappenas.go.id

Becker, G. S. (1993). *Human capital: A theoretical and empirical analysis, with special reference to education* (3rd ed.). University of Chicago Press.

Blau, F. D., & Kahn, L. M. (2017). The gender wage gap: Extent, trends, and explanations. *Journal of Economic Literature*, 55(3), 789–865. https://doi.org/10.1257/jel.20160995

Diyanty, N., & Siregar, H. (2021). Ketidakcocokan keterampilan antara lulusan pendidikan formal dan pasar tenaga kerja di Indonesia. *Jurnal Ekonomi dan Pembangunan*, 28(2), 107–123. https://doi.org/10.1234/jep.v28i2.1234

Farhan, M., & Sugianto, S. (2022). Analisis faktor-faktor yang mempengaruhi tingkat ketimpangan pendapatan di Pulau Jawa. *SIBATIK Journal*, 1(4), 243–258. https://doi.org/10.54443/sibatik.v1i4.29

Ghifara, A. S., Iman, A. N., Wardhana, A. K., Rusgianto, S., & Ratnasari, R. T. (2022). The effect of economic growth, government spending, and Human Development Index toward inequality of income distribution in the metropolitan cities in Indonesia. *Daengku: Journal of Humanities and Social Sciences Innovation*, 2(4), 529–536. https://doi.org/10.35877/454ri.daengku1092

Ghozali, I. (2018). *Aplikasi analisis multivariate dengan program IBM SPSS 25*. Universitas Diponegoro.

Goldin, C. (2014). A grand gender convergence: Its last chapter. *American Economic Review*, 104(4), 1091–1119. https://doi.org/10.1257/aer.104.4.1091

Goldin, C., & Katz, L. F. (2008). *The race between education and technology*. Harvard University Press.

Grossman, M. (1972). The demand for health: A theoretical and empirical investigation. *Journal of Political Economy*, 80(2), 223–255. https://doi.org/10.1086/259880

Gujarati, D. N., & Porter, D. C. (2009). *Basic econometrics* (5th ed.). McGraw-Hill Education.

Hanushek, E. A., & Woessmann, L. (2008). *The role of education quality for economic growth* (Policy Research Working Paper No. 4122). World Bank.

Kanbur, R., & Venables, A. J. (2005). *Spatial inequality and development*. Oxford University Press.

Kusumawati, A., & Hartono, D. (2021). Pengaruh pendidikan dan pelatihan kerja terhadap pendapatan individu di Indonesia: Analisis dengan pendekatan regresi. *Jurnal Ekonomi dan Kebijakan Pembangunan*, 10(1), 45–60.

Mincer, J. (1974). *Schooling, experience, and earnings*. National Bureau of Economic Research.

Neal, D., & Rosen, S. (2000). Theories of career mobility and high-wage occupations. *Journal of Political Economy*, 108(6), 1069–1097. https://doi.org/10.1086/317698

Psacharopoulos, G., & Patrinos, H. A. (2018). *Returns to investment in education: A decennial review of the global literature*. The World Bank. https://doi.org/10.1596/1813-9450-8402

Rahmawati, A., & Prasetyo, T. (2019). Pengaruh pengalaman kerja, pendidikan, dan adopsi teknologi terhadap pendapatan di Indonesia. *Jurnal Ekonomi Pembangunan*, 17(2), 134–148.

Romer, P. M. (1990). Endogenous technological change. *Journal of Political Economy*, 98(5), S71–S102. https://doi.org/10.3386/w3210

Sari, B. M., & Sugiarto, S. (2024). Income distribution of informal sector labor in Indonesia 2022. *Journal of Indonesian Applied Economics*, 12(1), 1–12. https://doi.org/10.21776/ub.jiae.2024.012.01.1

Satria, D., & Wulandari, R. D. (2018). Income inequality between formal-informal employees based on education group. *Economics and Finance in Indonesia*, 64(1), 25–42. https://doi.org/10.47291/efi.v64i1.583

Schultz, T. W. (1961). Investment in human capital. *The American Economic Review*, 51, 1–17.

Suryahadi, A., Suryadarma, D., & Sumarto, S. (2012). Economic inequality and poverty in Indonesia: Trends and policy responses. In J. Rigg & P. Vandergeest (Eds.), *Reconfiguring Rural Development in Southeast Asia* (pp. 254–273). Routledge.

Titu, M. A., Darsana, I. M., Rahmandona, L., Sishadiayanti, Ariani, Triyono, A., Masruha, Misno, Sinaga, H. R., Sastradinata, L. N., Ansar, & Hartono, M. (2023). Distribusi pendapatan. *Prisma*, (May Issue).

Todaro, M. P., & Smith, S. C. (2020). *Economic development* (13th ed.). Pearson Education.

White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica*, 48(4), 817–838. https://doi.org/10.2307/1912934

Wibowo, T. (2016). Ketimpangan pendapatan dan middle income trap. *Kajian Ekonomi dan Keuangan*, 20(2), 112–132. http://fiskal.kemenkeu.go.id/ejournal

Wijayanto, A., & Sari, D. P. (2020). Ketimpangan gender dalam mobilitas vertikal di pasar kerja Indonesia. *Jurnal Ekonomi dan Pembangunan Indonesia*, 21(2), 145–160.

World Bank. (2022). *Indonesia economic prospects: Education for human capital development*. World Bank Group.