International Journal of Economics, Business and Innovation Research
https://e-journal.citakonsultindo.or.id/index.php/IJEBIR
E-ISSN : 2964-0865
IJEBIR

The Effect Of Physical Capital Accumulation, Human Capital And Ict Development Index On Labor Productivity In Indonesia As A Middle Income Trap Country

Atika Putri Sherlyanti[1], Marselina[2], Vitriyani Tri Purwaningsih[3]

[1,2,3] Faculty of Economics and Business, University of Lampung, Indonesia

Co-author: atikasherlyanti24@gmail.com

Abstract

Indonesia, as an upper middle-income country, continues to face the risk of falling into the middle income trap due to relatively low labor productivity, which has slowed economic growth and hindered the country's transition toward a developed economy. This research examines the effects of physical capital accumulation, human capital, and the Information and Communication Technology (ICT) Development Index on labor productivity across 34 provinces in Indonesia during 2019-2023. Using panel data analysis, physical capital is proxied by Gross Fixed Capital Formation (GFCF), while human capital is measured by mean years of schooling and life expectancy. The results show that GFCF, mean years of schooling, and life expectancy have positive and significant effects on labor productivity. Meanwhile, the ICT Development Index has a negative and insignificant effect, indicating that the impact of technology adoption on productivity may require a longer adjustment period and more effective utilization across regions. These findings suggest that strengthening investment and improving human capital quality are essential strategies for increasing labor productivity, enhancing economic competitiveness, and helping Indonesia escape the middle income trap.

Keywords: Labor Productivity, Physical Capital, Human Capital, ICT Development Index, Middle Income Trap

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

International Journal of Economics, Business and Innovation Research
https://e-journal.citakonsultindo.or.id/index.php/IJEBIR
E-ISSN : 2964-0865
IJEBIR

INTRODUCTION

Indonesia, as a developing country, continues to face major challenges in escaping the middle income trap. Countries categorized as middle income may face a middle income trap when economic growth slows and limits their progress toward developed-country status (Gill & Kharas, 2007). This condition is caused by the country's inability to maintain its competitive advantage in labor-intensive sectors based on low-cost labor due to rising wage levels, weak productivity growth, limited innovation, and the inability to develop high value-added industries (Paus, 2017). According to the World Bank (2023), Indonesia is currently categorized as an upper middle income country with a per capita income of US$4,940.5. However, Indonesia's economic growth has remained stagnant at around 5% in recent years, whereas achieving developed-country status requires sustainable economic growth of approximately 6-7% (Kementerian Koordinator Bidang Perekonomian Republik Indonesia, 2023). This condition indicates that Indonesia remains vulnerable to the middle income trap, particularly if it fails to improve labor productivity and national economic competitiveness.

Labor productivity is considered one of the main determinants of long-term economic growth because it reflects workers' ability to generate output or added value from labor inputs (McEachern W, 2000). Countries that successfully escape the middle income trap are generally able to increase productivity through structural transformation toward technology-based industries and innovation-driven sectors (Agénor, 2017). Conversely, stagnant productivity can weaken economic competitiveness and slow improvements in public welfare (Suyitno, 2023). Empirically, Indonesia's labor productivity remains relatively low compared to other middle-income countries. Data from World Development Indicators, the show that although Indonesia's labor productivity increased during 2019-2023, its growth remained slower than that of several other middle-income countries.

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

International Journal of Economics, Business and Innovation Research
https://e-journal.citakonsultindo.or.id/index.php/IJEBIR
E-ISSN : 2964-0865
IJEBIR

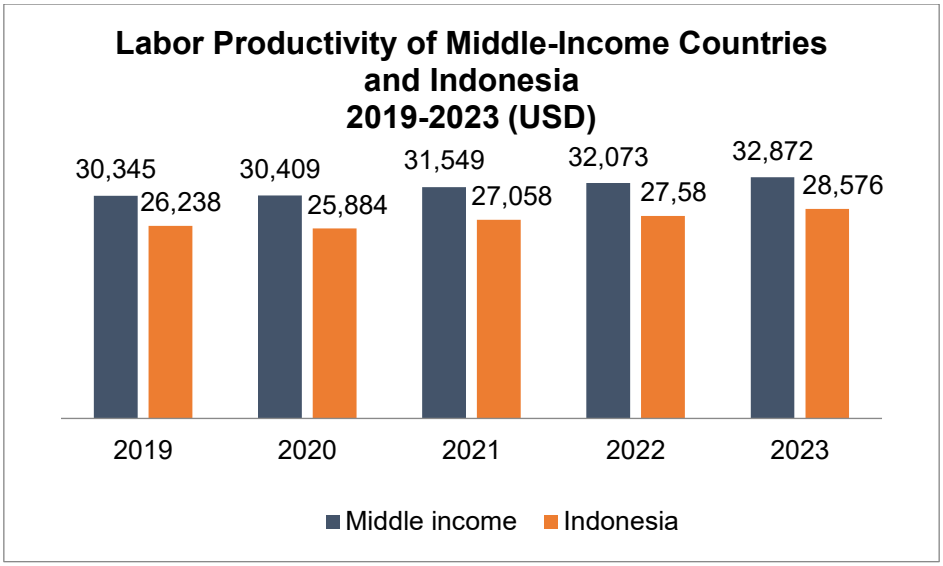


Figure 1. Labor Productivity of Middle-Income Countries and Indonesia (USD)

Source: World Development Indicators (2025)

In addition, substantial disparities in labor productivity persist across provinces in Indonesia. According to data from the Ministry of Manpower, average national labor productivity for the 2019-2023 period reached 85.58 million rupiah per worker. The province with the highest productivity was Jakarta, with an average of 391.95 million rupiah per worker. In contrast, East Nusa Tenggara is the province with the lowest level of labor productivity, with an average of 25.56 million rupiah per worker, well below the national average. The variation in labor productivity across regions reflects differences in the underlying determinants of productivity. Theoretically, labor productivity is influenced by physical capital accumulation, human capital quality, and technological development. Physical capital, proxied by Gross Fixed Capital Formation (GFCF), is expected to increase production capacity and labor efficiency. Human capital, represented by mean years of schooling and life expectancy, can improve workers' abilities, skills, and productivity (Becker, 1964). In addition, technological development can improve production efficiency, accelerate information access, and support innovation in economic activities.

However, improvements in investment, education, health, and technological development in Indonesia have not always been accompanied by optimal increases in

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

International Journal of Economics, Business and Innovation Research
https://e-journal.citakonsultindo.or.id/index.php/IJEBIR
E-ISSN : 2964-0865
IJEBIR

labor productivity. During the 2019-2023 period, substantial disparities in labor productivity persisted across provinces, indicating differences in the effectiveness of physical capital utilization, human capital quality, and technology adoption. Several provinces with relatively high physical capital investment, education, health, and technology indicators still recorded relatively low labor productivity. For example, North Maluku recorded an average Gross Fixed Capital Formation (GFCF) per worker of IDR 35.25 million, yet its labor productivity was only IDR 60.34 million per worker. This condition indicates that increases in physical investment have not been fully supported by efficient capital utilization and production efficiency (Hutami & Riani, 2022). Likewise, the Special Region of Yogyakarta showed relatively high levels of education, health, and ICT development, yet labor productivity in the province remained relatively low at only IDR 49.97 million per worker.

This suggests that improvements in education, health, and technology have not necessarily been followed by proportional increases in labor productivity, possibly due to skill mismatches between educational outcomes and labor market needs, unequal technology utilization, and the dominance of relatively low-productivity sectors (Putri & Kusreni, 2017). These conditions indicate that disparities in labor productivity across provinces are influenced not only by differences in investment and human capital accumulation, but also by variations in the effectiveness of resource utilization and regional economic structures in Indonesia.

METHODOLOGY

Variable	Symbol	Unit	Data Source
Labor Productivity	Y	Million Rupiah per Worker	Ministry of Manpower
Gross Fixed Capital Formation per Worker	X1	Million Rupiah per Worker	Central Statistics Agency
Mean Years of Schooling	X2	Years	Central Statistics Agency
Life Expectancy	X3	Years	Central Statistics Agency
ICT Development Index	X4	Scale	Central Statistics Agency

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

International Journal of Economics, Business and Innovation Research
https://e-journal.citakonsultindo.or.id/index.php/IJEBIR
E-ISSN : 2964-0865
IJEBIR

This study applies a quantitative panel data method using cross-sectional data from 34 provinces in Indonesia and annual data from 2019 to 2023. The data were obtained from the Central Statistics Agency and the Ministry of Manpower. In this study, labor productivity (PTK) serves as the dependent variable, while Gross Fixed Capital Formation (PMTB), Mean Years of Schooling (RLS), Life Expectancy (AHH), and the ICT Development Index (IPTIK) are treated as independent variables. To obtain a linear regression model and fulfill the classical assumptions, this study applies a semi-log transformation to the dependent variable. According to Junaidi (2015), a semi-log model applies logarithmic transformation to either the dependent or independent variable. The estimated regression model after transformation is expressed as follows:

$$\mathbf{LogPTK_{it}} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1 PMTB_{it}} + \boldsymbol{\beta_2 RLS_{it}} + \boldsymbol{\beta_3 AHH_{it}} + \boldsymbol{\beta_4 IPTIK_{it}} + \varepsilon_{it}$$

Where:

LogPTK	: Logarithm of Labor Productivity (Million Rupiah per Worker)
PMTB	: Gross Fixed Capital Formation per Worker (Million Rupiah per Worker)
RLS	: Mean Years of Schooling (Years)
AHH	: Life Expectancy (Years)
IPTIK	: ICT Development Index (Scale)
β_0	: Constant
$\beta_1, \beta_2, \beta_3$	: Regression coefficients
ε	: Error term
i	: Province
t	: Time period

Determination of the appropriate panel data regression model was conducted through several specification tests consisting of the Chow test, Hausman test, and Lagrange Multiplier test (Widarjono, 2018). These tests were used to select the most suitable model among the Common Effect Model, Fixed Effect Model, and Random Effect Model.

The regression model was evaluated through normality, multicollinearity, heteroscedasticity, and autocorrelation tests. Furthermore, hypothesis testing employed the t-test, F-test, and coefficient of determination (R^2).

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

International Journal of Economics, Business and Innovation Research
https://e-journal.citakonsultindo.or.id/index.php/IJEBIR
E-ISSN : 2964-0865
IJEBIR

Results and Discussion

Descriptive Statistics Analysis

Descriptive statistics were applied to summarize the characteristics of the data used in this study, which consisted of 170 observations from 34 provinces in Indonesia during 2019-2023.

Tabel 1. Descriptive Statistics

Variabel	Obs	Mean	Std.Dev.	Min	Max
PTK	170	93.78165	73.03821	24.94	404.21
PMTB	170	30.24671	26.51099	11.08	153.98
RLS	170	9.150941	0.8276339	6.85	11.42
AHH	170	70.23841	2.475625	64.82	75.12
IPTIK	170	5.700706	0.738929	3.22	7.73

Source: Stata 14, Processed Data (2025)

Based on Table 1, labor productivity (PTK) has an average value of 93.78 million rupiah per worker, with the highest value recorded in DKI Jakarta and the lowest in East Nusa Tenggara. Gross Fixed Capital Formation (PMTB) per worker has an average value of 30.24 million rupiah per worker, with the highest value in DKI Jakarta and the lowest in East Nusa Tenggara. Mean Years of Schooling (RLS) averages 9.15 years, with the highest value recorded in DKI Jakarta and the lowest in Papua. Life Expectancy (AHH) has an average value of 70.23 years, with the highest value in Special Region of Yogyakarta and the lowest in West Sulawesi. Meanwhile, the ICT Development Index (IPTIK) averages 5.70 points, with the highest value recorded in DKI Jakarta and the lowest in Papua.

Selection of Analysis Model

Model selection in this study was carried out through the Chow, Hausman, and Lagrange Multiplier tests to identify the most suitable panel regression approach. The Chow test was first applied to compare the Common Effect Model and the Fixed Effect Model.

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

International Journal of Economics, Business and Innovation Research
https://e-journal.citakonsultindo.or.id/index.php/IJEBIR
E-ISSN : 2964-0865
IJEBIR

Table 2. Chow Test

F (33, 132)	Prob > F	Selected Model
197.32	0.0000	*Fixed Effect*

Source: Stata 14, Processed Data (2025)

A significance value of 0.0000 < 0.05 from the Chow test indicated that FEM was preferable to CEM.

Table 3. Hausman Test

Chi-square(4)	Prob. > Chi-square	Selected Model
6.87	0.1432	*Random Effect*

Source: Stata 14, Processed Data (2025)

A significance value of 0.1432 > 0.05 from the Hausman test indicated that REM was preferable to FEM.

Table 4. Lagrange Multiplier Test

Chibar2(01)	Prob. > Chibar2	Selected Model
309.13	0.0000	*Random Effect*

Source: Stata 14, Processed Data (2025)

With a significance value of 0.0000, which was below 0.05, the Lagrange Multiplier test indicated that the Random Effect Model (REM) was more appropriate than the Common Effect Model (CEM). Based on the overall model selection results, REM was selected as the final estimation model in this study.

Classical Assumption Test

Normality Test

The distribution of residuals was examined using the Skewness-Kurtosis approach to determine whether the residuals were normally distributed. According to Ghozali (2018) , residuals are considered normally distributed when the probability value exceeds 0.05.

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

International Journal of Economics, Business and Innovation Research
https://e-journal.citakonsultindo.or.id/index.php/IJEBIR
E-ISSN : 2964-0865
IJEBIR

Table 5. Normality Test

Variable	Obs	Pr(Skewness)	Pr(Kurtosis)	Adj. Chi-Sq.(2)	Prob. >Chi-Sq
Residual	170	0.8292	0.0463	4.07	0.1305

Source: Stata 14, Processed Data (2025)

The normality test results indicate a residual probability value of 0.1305, which is higher than the 0.05 significance level. Accordingly, the residuals are considered to be normally distributed, suggesting that the normality assumption has been satisfied. In addition, the skewness value of 0.8292 is within the acceptable range of -2 to +2, while the kurtosis value of 0.0463 is within the acceptable range of -3 to +3 (Ghozali, 2018). These results indicate that the residual distribution meets the normality criteria.

Multicollinearity Test

The Variance Inflation Factor (VIF) method was applied to detect potential multicollinearity among the independent variables.

Table 6. Multicollinearity Test

Variable	VIF	Multicollinearity
PMTB	1.58	Low
RLS	2.62	Low
AHH	2.10	Low
IPTIK	3.70	Low

Source: Stata 14, Processed Data (2025)

The multicollinearity test shows that the VIF values of all independent variables are lower than 5, indicating that multicollinearity is not a serious issue. This means that the independent variables do not exhibit strong correlations with one another within the regression model.

Heteroscedasticity Test

The heteroscedasticity test was performed using the Breusch-Pagan test to check whether the variance of the residuals remains constant across all observations (Widarjono, 2018).

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

International Journal of Economics, Business and Innovation Research
https://e-journal.citakonsultindo.or.id/index.php/IJEBIR
E-ISSN : 2964-0865
IJEBIR

Table 7. Heteroscedasticity Test

Chi.Sq.(1)	Prob. > Chi.Sq	Conclusion
1.59	0.2072	Accept H_0

Source: Stata 14, Processed Data (2025)

The probability value obtained from the heteroscedasticity test is 0.2072, exceeding the 0.05 significance level. Therefore, the regression model can be considered free from heteroscedasticity problems..

Autocorrelation Test

To identify the presence of correlation between residuals over time, the autocorrelation test was carried out using the Breusch-Godfrey LM approach.

Table 8. Autocorrelation Test

lags (*p*)	Chi.Sq	df	Prob. > Chi.Sq
1	3.818	1	0.0507

Source: Stata 14, Processed Data (2025)

The probability value obtained from the autocorrelation test is 0.0507, exceeding the 0.05 significance threshold. Therefore, it can be concluded that no autocorrelation issue is present in the regression model.

Random Effect Model (REM) Regression

The overall test results supported the use of the Random Effect Model (REM) for estimating the panel regression. The estimation outcomes are presented as follows.

Table 9. Random Effect Model Regression Results

Variable	Coef	Std. Err	Prob.	Description
Cons	-0.533328	1.048288	0.611	
PMTB	0.0116981	0.00106	0.000	Positive and significant
RLS	0.078642	0.0466161	0.092	Positive and significant

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

International Journal of Economics, Business and Innovation Research
https://e-journal.citakonsultindo.or.id/index.php/IJEBIR
E-ISSN : 2964-0865
IJEBIR

AHH	0.0571467	0.0176192	0.001	Positive and significant
IPTIK	0.0348895	0.0226059	0.123	Negative and insignificant

Source: Stata 14, Processed Data (2025)

Based on the estimation results, the regression equation is formulated as follows:

$$LogPTK_{it} = -0.533328 + 0.0116981PMTB_{it}^{*} + 0.078642RLS_{it}^{**} + 0.0571467AHH_{it}^{*} - 0.0348895IPTIK_{it}^{*}$$

Note: *Significant at α=5%
**Significant at α=10%

The regression results suggest that Gross Fixed Capital Formation (PMTB) contributed positively and significantly to labor productivity with a coefficient of 0.0116981, indicating that every one-million rupiah increase in PMTB per worker increases labor productivity by 1.1%. Average Years of Schooling (RLS) also has a positive and significant effect with a coefficient of 0.078642, meaning that every additional one year of schooling increases labor productivity by 7.8%. Furthermore, Life Expectancy (AHH) has a positive and significant influence with a coefficient of 0.0571467, where every one-year increase in life expectancy raises labor productivity by 5.7%. Meanwhile, the ICT Development Index (IPTIK) has a negative and insignificant effect with a coefficient of -0.0348895, indicating that every one-point increase in the ICT Development Index decreases labor productivity by 3.4%.

t-statistic test

The t-statistic test, commonly referred to as the partial test, was employed to analyze the individual effect of each independent variable on the dependent variable. The purpose of this test is to evaluate the partial significance of the regression coefficients.

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

International Journal of Economics, Business and Innovation Research
https://e-journal.citakonsultindo.or.id/index.php/IJEBIR
E-ISSN : 2964-0865
IJEBIR

Table 10. t-Statistic Test Results

Variable	Coef	z	P > |z|	Conclusion
PMTB	0.0116981	11.04	0.000	Reject H_0
RLS	0.078642	1.69	0.092	Reject H_0
AHH	0.0571467	3.24	0.001	Reject H_0
IPTIK	0.0348895	-1.54	0.123	Accept H_0

Source: Stata 14, Processed Data (2025)

The t-test results show that Gross Fixed Capital Formation (PMTB) had a positive and significant effect on labor productivity, with a coefficient of 0.0116981 and a probability value of 0.000, which was significant at the 5% level. Mean Years of Schooling (RLS) also showed a positive effect and was significant at the 10% level, with a coefficient of 0.078642 and a probability value of 0.092. Likewise, Life Expectancy (AHH) positively affected labor productivity, as reflected by a coefficient of 0.0571467 and a probability value of 0.001, indicating significance at the 5% level. In contrast, the ICT Development Index (IPTIK) showed a negative coefficient of -0.0348895 and was not statistically significant, with a probability value of 0.123.

F-statistic test

The simultaneous test assessed the combined contribution of all independent variables to the dependent variable. Within the panel data regression framework, this assessment can be identified through the Wald Chi-Square value.

Table 11. F-Statistic Test Results

Wald chi2(4)	Prob. > Chi2	Conclusion
195.97	0.0000	Menolak H_0

Source: Stata 14, Processed Data (2025)

The test results reveal that PMTB, RLS, AHH, and IPTIK simultaneously have a significant effect on labor productivity in 34 provinces in Indonesia during 2019-2023.

Coefficient of Determination Test

The R-square value shows how much variation in the dependent variable can be explained by the independent variables. The R-square ranges from 0 to 1, where a lower

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

value suggests that the explanatory power of the independent variables is limited, while a higher value indicates a stronger ability of the model to explain changes in the dependent variable.

Table 12. Coefficient of Determination Test Results

Selected Model	R-sq: within	R-sq: between	R-sq: overall
Random Effect	0.4715	0.7155	0.7129

Source: Stata 14, Processed Data (2025)

The coefficient of determination results indicate that the R-squared value is 0.7129. This suggests that 71.29% of the variation in labor productivity can be explained by PMTB, Mean Years of Schooling, Life Expectancy, and the ICT Development Index. The remaining 28.71% is influenced by other variables outside the model.

Analysis Discussion

Effect of Gross Fixed Capital Formation on Labor Productivity in 34 Provinces in Indonesia (2019-2023)

The results indicate that Gross Fixed Capital Formation (GFCF) has a positive and significant effect on labor productivity in 34 provinces in Indonesia during 2019-2023. The positive coefficient of 0.0116981 indicates that every one-million-rupiah increase in GFCF per worker tends to increase labor productivity by approximately 1.1%, ceteris paribus. This finding suggests that investment in physical capital contributes to expanding production capacity and improving work efficiency.

This result is consistent with the Solow-Swan Growth Theory, which explains that physical capital accumulation is an important determinant of output and labor productivity (Solow, 1956). Higher investment in machinery, infrastructure, and production facilities enables workers to produce output more efficiently. In addition, Barro (1990) stated that investment in physical capital and infrastructure can support productivity improvement and long-term economic growth.

Previous studies by Hidayat & Yuniasih (2023) and Yanto & Azizah (2023) also reported similar results, which found that GFCF positively and significantly affects labor productivity. Higher investment increases production capacity and supports productivity growth across regions.

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

However, in the context of the Middle Income Trap (MIT), the effectiveness of investment depends not only on its quantity but also on its quality and allocation. Data from Badan Pusat Statistik show that Indonesia's GFCF remains dominated by investment in buildings, accounting for 63.95% of total GFCF in 2022, while investment in machinery and equipment accounted for only 16.22%, and intellectual property products represented only 1.92%. This indicates that investment is still concentrated in physical construction rather than technology- and innovation-based sectors that generate higher value added. As a result, increases in GFCF have not fully encouraged structural transformation toward modern manufacturing and technology-intensive industries.

According to the World Bank (2024), middle-income countries are vulnerable to economic stagnation when economic growth relies mainly on physical investment without being accompanied by technological innovation and productivity improvement. International experiences such as South Korea and Singapore show that successful structural transformation requires investment directed toward manufacturing industries, innovation, and technology development.

Empirically, disparities in GFCF across provinces also reflect differences in labor productivity levels. Provinces with relatively high investment levels, such as DKI Jakarta, tend to record higher labor productivity because they are supported by better infrastructure and the dominance of modern economic sectors. In contrast, provinces with relatively low investment levels, such as East Nusa Tenggara, tend to have lower labor productivity due to limited infrastructure and lower industrial development. These conditions indicate that unequal investment distribution and differences in regional economic structures continue to influence labor productivity disparities across provinces in Indonesia.

Therefore, although GFCF positively affects labor productivity, its effectiveness depends on investment quality, sectoral allocation, and equitable distribution across regions. Investment policies should not only focus on increasing the quantity of investment, but also prioritize productive sectors with high value added, technology adoption, and innovation development to support sustainable productivity growth and accelerate Indonesia's economic transformation in escaping the middle income trap.

Effect of Mean Years of Schooling on Labor Productivity in 34 Provinces in Indonesia (2019-2023)

The results indicate that Mean Years of Schooling (MYS) positively influenced labor productivity across 34 provinces in Indonesia during 2019-2023. The estimated

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

coefficient of 0.078642 implies that an additional year of schooling was associated with an increase of approximately 7.8% in labor productivity, assuming other variables remained constant. These findings reflect the important role of education in improving workers' capabilities, skills, and productivity.

This result is consistent with Human Capital Theory, which explains that education improves workers' competencies and adaptability to technological change and innovation. Similar results were reported by MS et al. (2022) and Puspasari & Handayani (2020), who also found that education contributed positively to labor productivity. Nevertheless, the contribution of education to productivity in Indonesia may vary across regions due to skill mismatch and differences in economic structures. Dina et al. (2024) argued that educational attainment does not automatically increase productivity when workers' skills are not aligned with industrial needs.

In addition, Indonesia's labor structure remains dominated by low-productivity sectors. This condition is reflected in the substantial disparities in labor productivity across provinces. Provinces with more modern economic structures, such as DKI Jakarta, Riau, and East Kalimantan, tend to achieve higher labor productivity due to stronger industrial activities, higher investment concentration, and better infrastructure development. In contrast, provinces dominated by traditional sectors, such as East Nusa Tenggara and West Nusa Tenggara, tend to exhibit lower productivity levels despite improvements in schooling duration. These findings indicate that the relationship between education and labor productivity is strongly influenced by regional economic structures and industrial characteristics (Rodrik, 2016). Therefore, improving schooling duration alone is insufficient. Educational policies should also prioritize learning quality, vocational education, and stronger integration between education systems and labor market needs to support productivity growth and Indonesia's transition out of the middle income trap.

Effect of Life Expectancy on Labor Productivity in 34 Provinces in Indonesia (2019-2023)

The results indicate that life expectancy has a positive and significant effect on labor productivity in 34 provinces in Indonesia during 2019-2023. The coefficient value of 0.0571467 indicates that every one-year increase in life expectancy tends to increase labor productivity by approximately 5.7%, assuming other variables remain constant (ceteris paribus).

This finding is consistent with Human Capital Theory, which considers health as an important component of human capital alongside education. Better health conditions

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

improve workers' physical endurance, cognitive ability, and work efficiency, thereby increasing output per worker. This result is also in line with studies conducted by Ezoji et al. (2019) and Mehmood et al. (2022) which found that health improvements contribute positively to labor productivity.

In the Indonesian context, rising life expectancy reflects improving access to healthcare services, nutrition, and public health programs. However, within the context of the Middle Income Trap (MIT), increasing life expectancy alone is insufficient to optimally improve productivity. According to World Health Organization (2023), although Indonesia's life expectancy has reached around 71 years, healthy life expectancy remains approximately around 62 years. This indicates that a considerable proportion of the population lives longer but not entirely in healthy and productive conditions.

In comparison, Japan has a life expectancy of approximately 84 years with a healthy life expectancy of around 74 years (World Health Organization, 2023). Higher life expectancy accompanied by better health quality enables the population to remain active and productive even at older ages. In addition, labor policies in Japan encourage elderly workforce participation, allowing longer life expectancy to directly contribute to national productivity. This comparison demonstrates that productivity improvement depends not only on longevity but also on productive health quality.

Regional disparities also influence the relationship between health and productivity. Provinces with better healthcare access and more modern economic structures, such as DKI Jakarta and East Kalimantan, tend to record higher productivity levels. Data from Badan Pusat Statistik (2023) show that DKI Jakarta recorded one of the highest life expectancy levels in Indonesia, reaching around 74 years, accompanied by the highest labor productivity of 404.21 million rupiah per worker in 2023. Similarly, East Kalimantan recorded relatively high life expectancy and labor productivity due to the dominance of mining and industrial sectors. In contrast, provinces such as East Nusa Tenggara and West Sulawesi, which have lower life expectancy and are still dominated by traditional agricultural sectors, recorded lower labor productivity levels. These conditions indicate that health quality, healthcare access, and regional economic structures jointly influence labor productivity across provinces in Indonesia.

Therefore, improving life expectancy should be accompanied by policies that enhance productive health quality through preventive healthcare services, nutrition improvement, and better healthcare access. These efforts are important to support sustainable productivity growth and help Indonesia avoid the Middle Income Trap.

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

International Journal of Economics, Business and Innovation Research
https://e-journal.citakonsultindo.or.id/index.php/IJEBIR
E-ISSN : 2964-0865
IJEBIR

Effect of ICT Development Index on Labor Productivity in 34 Provinces in Indonesia (2019-2023)

The results indicate that the ICT Development Index does not significantly affect labor productivity in 34 provinces in Indonesia during the 2019-2023 period. This is reflected by the significance value of 0.123, which is higher than the significance level of 0.05. In addition, the negative regression coefficient of -0.0348895 indicates that every one-point increase in the ICT Development Index tends to reduce labor productivity by approximately 3.4%, ceteris paribus. These findings suggest that improvements in ICT development do not automatically increase labor productivity.

Theoretically, technological advancement is expected to improve efficiency and increase labor productivity. However, in the Indonesian context, ICT development demonstrates a negative and insignificant relationship with labor productivity. Wijayanti & Turgel (2021), also found that digitalization did not positively affect labor productivity. This result differs from neoclassical growth theory, which identifies technology as a major driver of productivity growth, and also contrasts with the finding of Coreynen et al. (2016), who found that digitalization significantly increased productivity in developed countries.

One possible explanation is that technological adoption in developing countries often creates substitution between labor and capital, particularly for low-skilled workers. Zeira (1998) argued that technology may replace labor when workers do not possess adequate skills to adapt to technological changes. Similarly, the International Labour Organization (2020) reported that approximately 56% of Indonesian workers face a high risk of automation, especially those employed in routine and administrative occupations. Under these conditions, digitalization may generate labor displacement rather than productivity improvement.

In addition, the negative and insignificant result may also be explained by the relatively short observation period used in this study. The impact of technology adoption on labor productivity generally requires a longer adjustment process because firms and workers need time to adapt to digital transformation, develop technological capabilities, and improve workforce skills. Therefore, the 2019-2023 period may not be sufficient to fully capture the long-term contribution of ICT development to productivity growth.

Furthermore, the benefits of ICT development in Indonesia may not yet be fully realized because digital transformation requires substantial adjustment costs and workforce readiness. Let et al. (2018) explained that firms in developing countries often face high investment costs related to digital infrastructure, systems, equipment, and worker training, which can delay productivity gains in the short term.

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

Low digital literacy and the dominance of informal employment also limit the effectiveness of ICT development in increasing productivity. According to Badan Pusat Statistik, around 60% of Indonesian workers are still engaged in informal jobs that generally require lower skill levels and limited technological capability. As a result, improvements in ICT infrastructure have not necessarily been followed by productive technology utilization across regions.

Empirically, provinces with relatively high ICT Development Index values, such as DKI Jakarta and Riau Islands, generally record higher labor productivity. However, this relationship is not consistent across all provinces. The Special Region of Yogyakarta, for example, has relatively high ICT development but relatively low labor productivity. This indicates that ICT improvement alone is insufficient to increase productivity without being supported by adequate human capital quality and technological adaptation capacity.

From the perspective of the Middle Income Trap, these findings indicate that digital transformation alone cannot automatically accelerate productivity growth. Escaping the Middle Income Trap requires not only ICT infrastructure development but also improvements in human capital quality, digital literacy, innovation capacity, and structural economic transformation. Therefore, ICT policies should prioritize labour-augmenting technology that complements workers, strengthens workforce skills, and supports innovation-based industrial development in order to improve labor productivity sustainably.

CONCLUSION

This study analyzes the effects of physical capital accumulation, human capital, and the ICT Development Index on labor productivity across 34 provinces in Indonesia during 2019-2023. The results show that physical capital accumulation, proxied by Gross Fixed Capital Formation (GFCF), has a positive and significant effect on labor productivity. This finding indicates that higher investment contributes to increasing production capacity, improving work efficiency, and supporting productivity growth across regions. However, investment should not only focus on quantity, but also be directed toward productive sectors with high added value, such as manufacturing, technology, and innovation-based industries, to support Indonesia's transition out of the middle income trap.

Human capital, represented by mean years of schooling and life expectancy, also has a positive and significant effect on labor productivity. These findings indicate that improvements in education and health contribute to enhancing workers' knowledge, skills,

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

work capacity, and adaptability to technological change. Nevertheless, disparities in regional economic structures and labor market conditions cause the contribution of education to productivity to vary across provinces. Therefore, policies aimed at increasing labor productivity should not only emphasize longer schooling duration, but also focus on improving educational quality, vocational training, and the alignment between workforce skills and industrial needs.

Meanwhile, the ICT Development Index has a negative and insignificant effect on labor productivity, indicating that digital transformation in Indonesia has not yet been fully effective in increasing productivity growth. This condition may reflect unequal technological readiness, limited digital literacy, and the dominance of low-productivity sectors, particularly in regions with limited industrial development and infrastructure. Therefore, improving labor productivity requires not only expanding ICT infrastructure, but also strengthening innovation capacity, workforce digital skills, and structural transformation toward more modern and technology-based economic sectors.

REFERENCES

Agénor, P. R. (2017). Caught in the Middle? the Economics of Middle-Income Traps. Journal of Economic Surveys, 31(3), 771–791.

Barro, R. J. (1990). Government Spending in a Simple Model of Endogenous Growth. Journal of Political Economy, 98(5), 103–126.

Coreynen, W., Matthyssens, P., & Van Bockhaven, W. (2016). Boosting servitization through digitization: Pathways and dynamic resource configurations for manufacturers. Industrial Marketing Management, 60, 12.

Dina, L., Harafah, L. O. M., & Rachmasari, A. W. O. (2024). Pengaruh Kualitas Sumber Daya Manusia Terhadap Produktivitas Tenaga Kerja Di Kota Kendari. Jurnal Ekonomi (JE), 9, 48–56.

Ezoji, A., Assari, A., Mahdavi, M. R. V., & Jahangard, E. (2019). The Impact of Human Capital (Health and Education) on Labor Productivity; a Composite Model Approach-a Case Study of Iran. Iranian Economic Review, 23(2), 373–397.

Ghozali, I. (2018). Aplikasi Analisis Multivariate Dengan Pogram IBM SPSS (9th ed.). Badan Penerbit Universitas Diponegoro.

Gill, I. S., & Kharas, H. (2007). An East Asian Renaissance : Ideas for Economic Growth. World Bank.

Hidayat, A. S., & Yuniasih, A. F. (2023). Aplikasi Regresi Data Panel Untuk Menganalisis Produktivitas Tenaga Kerja di Sulawesi Barat 2011-2023. 2023, 959–968.

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

Hutami, R. Y., & Riani, N. Z. (2022). Peran Investasi Modal Manusia dan Modal Fisik dalam Meningkatkan Pertumbuhan Produktivitas Tenaga Kerja di Indonesia. Ecosains: Jurnal Ilmiah Ekonomi Dan Pembangunan, 11(1), 30.

International Labour Organization. (2020). Gender diversity and inclusion in the future of work in Indonesia.

Junaidi. (2015). Bentuk Fungsional Regresi Linear (Aplikasi Model dengan Program SPSS). Fakultas Ekonomi dan Bisnis, Universitas Jambi.

Kementerian Koordinator Bidang Perekonomian Republik Indonesia. (2023). Menko Airlangga Tegaskan Keberlanjutan Kebijakan Reformasi Ekonomi untuk Menjadikan Indonesia Salah Satu Negara Maju pada 2045. Kementerian Koordinator Bidang Perekonomian Republik Indonesia.

Let, H. S., Hamzah, H. Z., Yusop, Z., & Mazlan, N. S. (2018). ICT Adoption Drives Productivity in Developed and Developing Countries. Jurnal Ekonomi Malaysia, 52(3), 205–217.

McEachern W, A. (2000). Ekonomi Makro: Pendekatan Kontemporer. Salemba Empat.

Mehmood, A., Siddique, H. M. A., & Ali, A. (2022). Impact of Health on Worker Productivity: Evidence from South Asia. MPRA.

MS, M. Z., Syukri, M., Budiningtyas, D. P., & Hasibuan, N. V. (2022). Pengaruh Tingkat Pendidikan dan Kesehatan terhadap Produktivitas Tenaga Kerja di Provinsi Jambi. J-MAS (Jurnal Manajemen Dan Sains), 7(2).

Paus, E. (2017). Escaping The Middle-Income Trap: Innovate or Perish (Issue 685). Asian Development Bank Institute.

Puspasari, D. A., & Handayani, H. R. (2020). Analisis Pengaruh Pendidikan, Kesehatan dan Upah Terhadap Produktivitas Tenaga Kerja di Provinsi Jawa Tengah. Jurnal Dinamika Ekonomi Pembangunan, 3(1), 65–76.

Putri, Y. A. K. D., & Kusreni, S. (2017). Analisis Pengaruh Tingkat Kesehatan, Tingkat Pendidikan, Dan Upah Terhadap Produktivitas Tenaga Kerja Di Indonesia. Jurnal Ilmu Ekonomi Dan Pembangunan, 17(2).

Rodrik, D. (2016). Premature deindustrialization. Journal of Economic Growth, 21(1).

Solow, R. M. (1956). A Contribution to the Theory of Economic Growth. The Quartely Journal of Economics, 70(1), 65–94.

Suyitno, S. L. P. (2023). Transformasi Ekonomi Indonesia: Keluar Dari Middle Income Trap (MIT) Menuju Indonesia Emas 2045. In Bappenas Working Papers (Vol. 6, Issue 3).

Widarjono, A. (2018). Ekonometrika (5th ed.). UPP STIM YKPN.

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

Wijayanti, F., & Turgel, I. D. (2021). The Consequences of Digitalization of the Labor Market in Developing Countries: Case Study in Indonesia. Proceedings of the XV International Conference “Russian Regions in the Focus of Changes” (ICRRFC 2020), 162(Icrrfc 2020), 96–105.

World Bank. (2023). World Bank Group country classifications by income level for FY24 (July 1, 2023- June 30, 2024). World Bank.

World Bank. (2024). “Middle-Income Trap” Hinders Progress in 108 Developing Countries. World Bank Group.

World Health Organization. (2023). World health statistics 2023: monitoring health for the SDGs, Sustainable Development Goals.

Yanto, & Azizah. (2023). The Influence of Education, Health, and Gross Fixed Capital Formation (PMTB) on Labor Productivity In West Kalimantan Province. Jurnal Pembangunan Dan Pemerataan, 12(2), 1–27.

Zeira, J. (1998). Workers, machines, and economic growth. The Quarterly Journal of Economics, November, 1091–1117.

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.