Volume 9 No 1 June (2026)

e-ISSN: 2615-3270

p-ISSN: 2615-3599

Eigen Mathematics Journal

Homepage Journal: https://eigen.unram.ac.id/index.php/eigen

An Application of the Quantile Regression Model to the Relationship Between Digitalization and Productivity Growth in Indonesia

Ray Sastri[1], **Rofiq Nur Rizal**[1*]

[1] *STIS Polytechnic of Statistics, Indonesia*

[*] *Corresponding author: raysastri@stis.ac.id*

A B S T R A C T

Ordinary regression models are often inappropriate for economic performance metrics due to their tendency to have non-Gaussian distributions, heavy tails, and extreme outliers. This study analyzes the link between digitalization and provincial labor productivity growth in Indonesia using a Quantile Regression Model to capture the full, varied range of regional economic dynamics. The empirical framework assesses the combined influence of digital transformation and the underlying economic structures on productivity trajectories by using a panel data set of 34 provinces from 2017 to 2023. The baseline estimates suggest that the digital-productivity relationship is highly non-linear and more pronounced at the 50th quantile in which the direct effects of digital infrastructure, household consumption and sectoral value-added are statistically significant. Importantly, the inclusion of macro-digital interaction terms significantly changes the dynamics of the model. The results show that the marginal effect of digitalization on regional industrial upgrading is not marginal. Instead, it is highly conditional on a synergistic alignment between infrastructure, intensity of use, digital skills, and strong underlying economic baselines to effectively catalyze labor productivity gains.

Keywords: digitalization, productivity growth, quantile regression, emerging economies

Received : 23-04-2026;
Revised : 31-05-2026;
Accepted : 07-06-2026;
Published : 29-06-2026;

DOI: https://doi.org/10.29303/emj.v9i1.371

1. Introduction

The economic performance of regional economies are very heterogeneous and often exhibit non-Gaussian distributions, outliers and heavy tailed data [1]. These nuances are lost in standard mean-based regression models, risking overgeneralized policy recommendations. In this regard, this study employs a Quantile Regression Model (QRM) to investigate the heterogeneous impacts of digitalization on the conditional distribution of productivity performance. The main advantage of QRM is the possibility to provide a rich detailed description of the effect at different points of the distribution [2]. The methodology allows for the assessment of the relationship between two factors at different quantile. Due to the economic inequality between provinces in Indonesia [3], this is an indication that productivity growth is also not evenly spread. Therefore, QRM will be applied to modeled the relationship between productivity growth and its determinant.

In this study, productivity growth is defined as the sustained expansion of economic output relative to aggregate labor, which is driven by structural shifts, technological adoption, and efficiency gains [4], [5], [6]. It is highly related to industrial structure, which is affected by the rapid proliferation of digital technologies [7]. In the economic sphere, digital technologies are successfully integrated into the economy and become an integral part of its basic production processes [8]. For example, the use of these technologies at all stages of the agricultural cycle allows to rationalize the whole process from the preparation to the sale of finished products [9]. In the manufacturing sector, the use of technologies directly improves the production efficiency and competitiveness [10]. In the service sector, digital transformation can also allow firms to co-create value with all their stakeholders [11]. For instance, new industries such as fintech, e-commerce and gig economy are emerging as significant sources of employment and GDP [12].

According to the data from Statistics Indonesia (Badan Pusat Statistik - BPS), Indonesian labour productivity growth is 3.75 percent in 2025 [13]. At the same time, Indonesia has been actively and strategically leading digitalization [14], and has become the biggest digital economy and highly attractive investment destination in Southeast Asia [15] as evident by 72.78% internet access and 92.92% mobile phone ownership of households in 2024 [16]. In additions, there has been a substantial amount of public and private investment in improving physical and digital connectivity through national infrastructure projects. While connectivity has improved significantly, the national imperative has shifted from fixing the basic access gap to aggressively tackling disparities in skills, usage and outcomes [14]. However, there is a substantial gap in tangible evidence showing the impact of digitalization on productivity growth. According to the Asian Development Bank (ADB), the participation of Indonesia in the Global Value Chain (GVC) has been relatively marginal since 2010 around 10% and relatively lower than other Southeast Asian countries [17]. These data shows that Indonesia's economy is experiencing a productivity paradox, where the labor productivity is growing at the macro level, but integration in global value chains is stagnant. This divergence strongly suggests that the reported productivity growth is not a universal upward shift across provincial labor markets but is likely concentrated in a specific area. The structural fragmentation highlights the need of a quantile-based distributional analysis.

The prior literature has recently studied the relationship between digitalization and economic growth, with a focus on the role of digitalization as a fundamental determinant of economic development [18], [19], [20]. However, while some research has looked into the effects of technological innovation and market dynamics on this process [21], [5], the features of digitalization, such as the intensity of technology use and digital skills of the workforce, may be equally important in influencing the potential for productivity growth. However, the association between digital use and skill has not been examined in the literature about Indonesian productivity growth. Moreover, most of the studies on economic upgrading in Asia have focused on high-income economies, such as China and Korea, with little research on fast developing countries such as Indonesia. Furthermore, in addition to the individual contribution of single variables to productivity growth, the structural interdependence between these variables may bias the empirical estimates if not properly taken into account. However, the specific interaction terms remain unexamined in prior studies, leaving a distinct gap in our understanding of how these economic factors synergize to drive productivity growth.

The purpose of this study is to analyze the heterogeneous effect of digitalization on the productivity growth in Indonesia. This study specifically attempts to answer the following research questions.

1. How does digitalization affect productivity growth in Indonesia?

2. Is this relationship heterogeneous, and at what quantile of productivity growth do we observe the most pronounced effect of digitalization?
3. How does the interaction of economic factors affect productivity growth?

This study apply QRM to analyze the heterogeneous effect of digitalization on the productivity growth in Indonesia. The empirical model includes a rich set of control variables including important socioeconomic and demographic variables to disentangle the net effect of digital transformations. Besides that, this study introduces an interaction factor between the economic factors. This study contributes theoretically to the literature by providing empirical evidence on the particular role of digitalization, especially the role of utilization and skills on productivity growth in the Indonesian context. Practically, the result of this study can serve as a guideline for the formulation and policy making of an effective strategies in developing digital infrastructure, promoting vocational education, and designing labor market regulations that are responsive to the dynamics of the digital economy.

2. Research Methods

2.1. Data Source and Variable

This study employs panel data of 34 Indonesian provinces in the year 2017-2023. All variables are drawn from the official publication of BPS. Productivity growth (PRO) is the dependent variable in this research. Meanwhile, the independent variables are the digitalization factors, which include the digital infrastructure index (INF), digital use index (USE), and digital skill index (SKI). The control variables are foreign direct investment (FDI), gross domestic product (GDP), household consumption (HHC), size of the manufacturing sector (MAN) and size of the agricultural sector (AGR). The variables and measurements are shown in Table 1.

Table 1. List of Variables

Variable	Abb.	Measurement
Dependent Variable		
Productivity Growth	PRO	The growth of industrial productivity (%)
Independent Variables		
Digital Infrastructure	INF	ICT access and infrastructure index (0–100)
Digital Use	USE	ICT use index (0–100)
Digital Skill	SKL	ICT skill index (0–100)
Control Variables		
Foreign Direct Investment	FDI	Logarithm Natural of FDI
Gross Domestic Product	GDP	Logarithm Natural of per capita GDP
Household Consumption	HHC	Logarithm Natural of household consumption
Size of Manufacturing Sector	MAN	Logarithm Natural of manufacturing value added
Size of Agricultural Sector	AGR	Logarithm Natural of agricultural value added

2.2. Quantile Regression Model

The QRM is a robust econometric technique, especially when the data or residuals deviate substantially from a Gaussian distribution. QRM is more efficient than OLS in the case of non-normal residual series, and it provides results that are robust to outliers and heavy tailed distributions [1]. This model allows researchers to analyze the entire conditional distribution of the dependent variable, while OLS can only approximate the conditional mean [22]. This ability to explore different quantiles gives more insights into the effects of independent variables on different parts of the distribution of the dependent variable. Normality tests are often applied as a first step to investigate the distributional properties of the data to justify the use of QRM [22].

The analysis is built on the fundamental premise that the random variable's distribution function is precisely defined by Equation 1. The parameter τ which $0 < \tau < 1$ represent the proportion of data points that fall below the regression line compared to the entire data set. Based on this definition, the associated quantile function, $Q(\tau)$, serves to partition the data and is defined in Equation 2. Within the distribution of the dependent variable Y, a proportion of τ of the values are less than $Q(\tau)$, and a proportion of $1-\tau$ are greater than $Q(\tau)$. The associated probability density function (PDF) is defined in Equation 3, with μ as the parameter and $\rho_\tau(\mu)$ as the weighted relationship of the PDF when the sample point of y is below and above the τ-th quantile.

$$F(y) = P(Y \leq y), \tag{1}$$

$$Q(\tau) = \inf y : F(y) \geq \tau, \tag{2}$$

$$\rho_\tau(\mu) = \begin{cases} \tau\mu, & ; Y_i \geq X_i'\beta \\ (\tau-1)\mu, & ; Y_i < X_i'\beta \end{cases}. \tag{3}$$

Generally, the QRM is specified in Equation 4, which estimate the minimum absolute deviation sum of dependent variable at the Q-th quantile, as expressed in Equation 5. Consequently, parameter estimation for any τ-th quantile minimizes the sum of squares of the absolute values of weighted errors, given by Equation 6. The QRM in this study is expressed in Equation 7.

$$\hat{y}_Q = \alpha_Q + \beta_Q x, \tag{4}$$

$$\min_\beta \sum_i \left| y_i - \alpha_Q - \beta_Q x_i \right| \rho_{iQ}, \tag{5}$$

$$\hat{\beta}(\tau) = \arg\min_\beta \left[\sum_{i:Y_i \geq X_i'\beta} \tau \left| y_i - x_i'\beta \right| + \sum_{i:Y_i < X_i'\beta} (1-\tau) \left| y_i - x_i'\beta \right| \right], \tag{6}$$

$$\begin{aligned} Q(\text{PROIUP}_{it}) = {} & \beta_0 + \beta_1 \text{INF}_{it} + \beta_2 \text{USE}_{it} + \beta_3 \text{SKL}_{it} + \beta_4 \text{FDI}_{it} + \beta_5 \text{GDP}_{it} + \beta_6 \text{HHC}_{it} + \\ & \beta_7 \text{MAN}_{it} + \beta_8 \text{AGR}_{it} + \beta_9 \text{INF}_{it} \cdot \text{GDP}_{it} + \beta_{10} \text{USE}_{it} \cdot \text{FDI}_{it} + \\ & \beta_{11} \text{SKL}_{it} \cdot textGDP_{it} + \varepsilon_{it}. \end{aligned} \tag{7}$$

3. Result and Discussion

3.1. Descriptive Statistics

Table 2 presents the descriptive statistics for the variables used in this study, showing the characteristics of productivity growth and its potential determinants across Indonesian provinces. The productivity growth shows a wide range, from -13.42 to 86.57, with a mean of 6.02 and a standard deviation of 8.81. This statistics indicate significant variation in productivity performance among provinces. The digitalization variable exhibit different levels of dispersion. While the digital infrastructure (INF) and digital skill (SKL) shows a small dispersion, the digital utilization (USE) has a wider dispersion. Other explanatory variables also show varied distributions.

Table 2. Descriptive Statistics

Variable	Obs	Min	Max	Mean	Standard Deviation
PRO	238	-13.42	86.57	6.02	8.81
INF	238	3.38	8.31	5.88	0.81
USE	238	2.15	7.65	4.85	1.14
SKL	238	4.65	7.77	6.07	0.55
FDI	238	1.87	9.02	5.90	1.62
GDP	238	9.75	12.68	10.92	0.58
HHC	238	16.44	21.48	18.59	1.20
MAN	238	7.04	13.91	10.28	1.72
AGR	238	7.63	12.69	10.49	1.07

3.2. Normality and Statistical Distribution

Figure 1 shows histograms for the descriptive statistics and distributional properties of productivity growth. The histogram displays a long right tail and a cluster of data points between -17 and 32 percent, suggesting dominance of lower productivity growth. This observation implies that most provinces are at relatively low levels of productivity growth and a subset of higher values leads to the observed right skewness. This histogram pattern is consistent with the results of the normality tests in Table 2, which indicates a significant deviations from normality. Table 2 demonstrates the results of the normality testing of the industrial upgrading by using three different statistical tests, Anderson-Darling (AD), Shapiro-Wilk (SW) and Kolmogorov-Smirnov (KS). The table shows the distribution of the variable significantly deviates from a normal distribution at the 99% confidence level. The result shows that the industrial upgrading does not obey the normal distribution, and thus the ordinary regression model cannot be used for modeling.

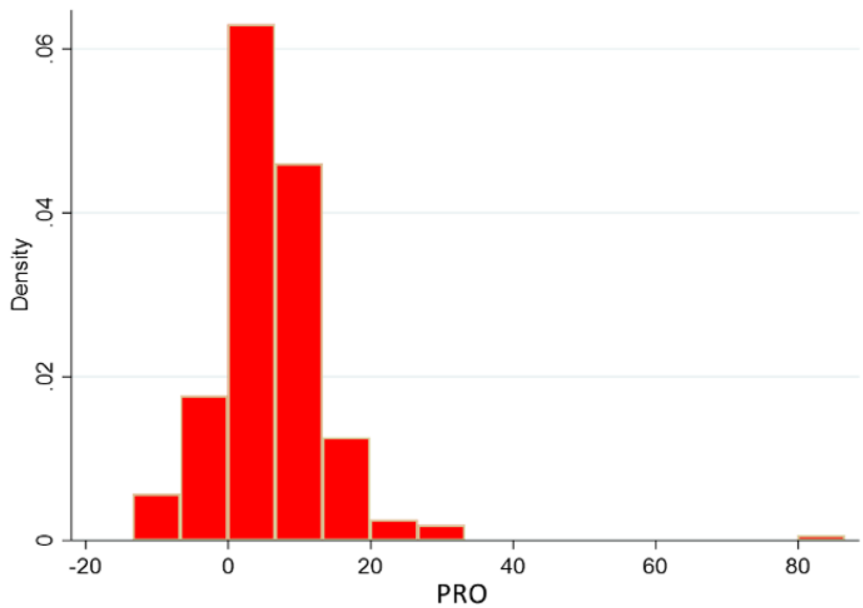

Figure 1. Histogram of Productivity Growth

Table 3. Normality Test

Variable	AD	SW	KS
PRO	6.944***	0.788***	0.152***

Note: In Table 3, the (*), (**), and (***) means not follow normality at CI of 90% level, not follow normality at CI of 95% level, and not follow normality at CI of 99% level, respectively.

3.3. Correlation Coefficient Test

Table 3 presents the correlation coefficients, revealing a spectrum of weak to moderate associations among the variables. A strong positive correlation was observed between household consumption and the value added of the manufacturing sector (ρ = 0.840), and between infrastructure and use index (ρ = 0.822). This finding suggests a potential trade-off where a heightened digitalization impact on productivity growth is related to the interaction between variables.

Table 4. Coefficient Correlation

Variable	PRO	INF	USE	SKL	FDI	GD	HHC	MAN	AGR
PRO	1.000								
INF	-0.037	1.000							
USE	-0.030	0.822	1.000						
SKL	0.068	0.498	0.361	1.000					
FDI	0.081	0.190	0.207	-0.151	1.000				
GDP	0.012	0.467	0.555	0.140	0.381	1.000			
HHC	-0.094	0.398	0.337	-0.115	0.638	0.239	1.000		
MAN	-0.027	0.466	0.481	-0.054	0.662	0.492	0.840	1.000	
AGR	-0.058	-0.157	-0.017	-0.255	0.281	-0.144	0.532	0.500	1.000

3.4. Quantile Regression Model

In view of the observed departures from normality, the data were analyzed by a QRM. Table 4 reports the regression results of different quantiles. The model with 8 independent variables and control variables revealed the pseudo R2 value of the 90th quantile was the highest (0.1957) indicating the better goodness-of-fit for this model. But the model at the 50th quantile showed the higher number of statistically significant variables .

Table 5. Parameter Estimation

Variable	Q10	Q30	Q50	Q70	Q90
INF	-8.266	-6.705*	-5.778*	-4.890	-3.271
	(-1.35)	(-1.88)	(-1.82)	(-1.22)	(-0.47)
USE	1.510	-0.411	-1.552	-2.645	-4.638
	(0.35)	(-0.16)	(-0.68)	(-0.93)	(-0.94)
SKL	-34.927	-9.662	5.353	19.733	45.933
	(-1.32)	(-0.63)	(0.40)	(1.15)	(1.53)
FDI	0.628	1.214	1.563	1.897	2.505
	(0.34)	(1.12)	(1.63)	(1.57)	(1.20)
GDP	-13.560	-7.723	-4.231	-0.887	5.207
	(-0.77)	(-0.75)	(-0.46)	(-0.08)	(0.26)
HHC	-9.617	-23.326	-31.474**	-39.278**	-53.494*
	(-0.36)	(-1.48)	(-2.25)	(-2.22)	(-1.75)
MAN	6.547	7.472	8.021**	8.548*	9.506
	(0.84)	(1.64)	(1.98)	(1.68)	(1.08)
AGR	42.180**	36.089***	32.471***	29.006**	22.693
	(2.02)	(2.95)	(2.99)	(2.13)	(0.96)
Pseudo R-sq	0.0592	0.0149	0.0283	0.0537	0.1597

Note: β, value in parenthesis ( ) is z value, *significant in 90% of confidence level, **significant in 95% of confidence level, and ***significant in 99% of confidence level.

Based on the model performance, the 50th quantile is chosen for further analysis, as it has a higher explanatory power with four significant variables. The digital infrastructure index, household consumption, the value added of the manufacturing sector and the value added of the agricultural sector have significant effects on industrial upgrading in the selected quantile. In addition, because of high correlations between some variables, interaction terms were included in the model to evaluate conditional effects. Table 5 analyzes the effect of different digitalization factors on productivity growth, focusing on the 50th quantile. The analysis is done in a series of models, to isolate the influence of different variables and their interactions[

Table 6. Parameter Estimation for Model with Interaction at Q50

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
INF	-5.778*	-112.477***	-5.666*	-5.593	-201.090***
	(-1.82)	(-3.63)	(-1.69)	(-1.09)	(-3.78)
USE	-1.552	0.450	-2.125	-1.015	5.655*
	(-0.68)	(0.19)	(-0.66)	(-0.27)	(1.74)
SKL	5.353	10.718	4.835	-77.764	167.389*
	(0.40)	(0.72)	(0.35)	(-0.82)	(1.78)
FDI	1.563	1.001	0.961	1.300	5.966***
	(1.63)	(0.99)	(0.47)	(0.83)	(2.57)
GDP	-4.231	-44.728***	-4.303	-45.155	-5.323
	(-0.46)	(-4.05)	(-0.48)	(-0.96)	(-0.18)
HHC	-31.474**	-52.898***	-31.940**	-37.001	-57.791***
	(-2.25)	(-3.44)	(-2.23)	(-1.62)	(-3.98)
MAN	8.021**	6.065	7.885*	5.274	10.522**
	(1.98)	(1.50)	(1.92)	(0.75)	(2.36)
AGR	32.471***	25.630**	32.063***	28.444	25.167**
	(2.99)	(2.13)	(2.94)	(1.53)	(2.35)
INF×GDP		9.805***			17.847***
		(3.47)			(3.65)
USE×FDI			0.124		-1.007**
			(0.30)		(-2.22)
SKL×GDP				7.920	-13.882*
				(0.89)	(-1.65)
Pseudo R-sq	0.0283	0.0312	0.0288	0.0298	0.0451

Note: β, value in parenthesis ( ) is z value, *significant in 90% of confidence level, **significant in 95% of confidence level, and ***significant in 99% of confidence level.

Model 1 in Table 5 includes only the single independent variables. The results indicate that digital infrastructure is the only digitalization factor that significantly affects productivity growth. Some control variables, such as household consumption, manufacturing sector value added, and agricultural value added, also demonstrate a significant impact. Whereas, Model 2 introduces the interaction between digital infrastructure index and percapita GDP. The inclusion of this term not only increases the significance of digital infrastructure but also renders percapita GDP and the interaction term itself statistically significant. Meanwhile, Model 3 incorporates the interaction between the digital use and FDI. Neither the single digital use variable nor its interaction with FDI is found to be significant, although some other explanatory variables remain significant. Meanwhile, Model 4 adds the interaction between digital skill and percapita GDP. In a stark contrast to the preceding models, the inclusion of this interaction term causes all previously significant variables to become insignificant, suggesting a significant moderating effect.

The Model 5 integrates all single independent variables along with all three interaction terms. The results from this model shows that ten out of eleven variables are statistically significant, suggesting that the combined effects of these factors are crucial for understanding productivity growth. Only per capita GDP remains insignificant, while GDP interactions with digital infrastructure and skills are highly significant. In Model 5, digital infrastructure and household consumption exhibit negative relationship with productivity growth with parameter estimation of $\beta = -201.090$ and $\beta = -57.791$, respectively. Conversely, digital use and skill have positive coefficients of $\beta = 5.655$ and $\beta = 167.389$, respectively. This finding suggests that skill in using digital products has the largest positive effect on productivity growth among the digitalization factors. Additionally, FDI and the size of the manufacturing and agricultural industries also have positive coefficients, indicating their positive role in provincial productivity growth in Indonesia. Interestingly, while digital infrastructure and percapita

GDP show a negative relationship with productivity growth in isolation, their interaction term has the largest positive coefficient among all interaction terms which $\beta = 17.847$.

3.5. Discussion

The distribution of productivity growth data contains severe outliers, reflecting localized and exceptionally high growth spikes in specific regions. For this case, the ordinary regression model cannot be applied due to the sensitivity to outliers [1]. The result from 50th quantile or median gives a clear picture of the relationship between digitalization and productivity growth, which is more robust especially when confronted with different economic conditions across regions. The most important contribution of this study is the non-linearity of the relationship between digitalization and productivity growth as evidenced by the significance of the interaction terms. This finding aligns with [23], who found the non-linear effect of economic indicator on total factor productivity.

The outcome of an independent digital infrastructure with a substantially negative association with productivity growth appears to contradict earlier literature [24] that commonly posits a positive association between the internet and economic development. The negative coefficient includes the large initial investment cost in infrastructure and the time lag associated with training the required workforce. Such upfront costs and disruptions may outweigh productivity gains in the short run. This view is consistent with the perspective of [25] who emphasize the crucial mediating role of complementary factors in converting infrastructure into positive economic outcomes such as technological innovation. On the other hand, the positive and significant coefficient of the interaction term between digital infrastructure and percapita GDP offsets the negative effect of the standalone term. The result suggests that the contribution of infrastructure is significantly positive, but only at a higher level of economic development. The richer provinces have the necessary conditions to deploy and use infrastructure for industrial gain, given the established institutions, the higher human capital base and the ready access to capital. This result is consistent with the argument of [26] that institutional quality is crucial for infrastructure development to boost economic growth.

The results also show that infrastructures are not enough alone and the effective use and skills of digitalization are also the drivers of economic upgrading. The widespread use of digital technology that enables e-commerce, better communication and digital business practices, contributes positively and significantly to productivity growth. This finding confirms the results of [19] who reported a positive direct effect of digitalization on economic growth and financial development. Furthermore, a workforce that is more digitally literate is a direct and major catalyst for upgrading productivity. This variable reflects the ability of the workforce to use sophisticated digital tools, which translates into high productivity and the creation of higher value-added industries. This finding is consistent with the productivity-enhancing effect of digital skills as shown by [27]. Moreover, the interaction between digital use and FDI shows a positive effect. The results indicate that the positive effect of FDI on productivity is higher when combined with a high level of digital adoption. Finally, the significant positive correlation of the control variables, FDI, RGDPP, household consumption, and size of the manufacturing and agricultural sectors, confirms their established role as fundamental preconditions of successful economic growth [28], [29], [30].

4. Conclusions

This study explores the effects of digitalization on productivity growth in Indonesia at the provincial level over the period 2017–2023 utilizing a QRM to identify the heterogeneous effects across the distribution. The empirical results show that digital infrastructure has negative effect on productivity growth, while digital utilization and digital skills have strong and highly significant positive effects. This relationship is strongest at the 50th quantile, both structurally and geographically. Ten of the eleven variables were statistically significant, which strongly suggests that the synergy of these factors is the key to a holistic understanding of regional productivity upgrading. Moreover, the model also validates the importance of interactive dynamics. Particularly, the interaction terms of digital infrastructure and GRDP, digital utilization and FDI, and digital skills and GRDP are all highly significant.

This research has important theoretical implications as it reveals the core drivers of productivity growth and shifts the theoretical focus from digital access to effective digital utilization. This finding theoretically suggests that policy measures to improve digital literacy and the popularization of e-commerce are more powerful drivers for industrial upgrading than mere investments in infrastructure development. Moreover, the interaction between digital use and FDI has a synergetic effect, providing a theoretical basis for amplification. This result suggests that the positive effects of global technology transfer through FDI are not passively received but are greatly amplified when the host economy has a high level of digital fluency and adoption. Furthermore, productivity promotion efforts should not only be focused on developing digital infrastructure, but also on developing human capital and creating a conducive environment for the adoption of technology and foreign investment.

The main limitations of the present research are connected to the scope of the data and the nature of the econometric model. The absence of a long enough time series precludes the firm from testing and quantifying the time-lag that is needed for infrastructure investments to generate positive returns. Moreover, the study concentrated on economic development and FDI as the main complementary factors. However, the interaction analysis did not fully consider other potential relevant factors, such as institutional quality, access to finance or credit, or specific policy measures. Some points will be focused on in future research given the limitations and significant findings. The time-lag of the positive returns of digital infrastructure investment to be fully realized and the length of the negative drag from digital infrastructure investment should be explicitly modeled and estimated using dynamic panel data models with a longer time series. Moreover, the future research needs to quantify the role of institutional quality by including interaction with digitalization factors.

References

[1] E. Waldmann, "Quantile regression: A short story on how and why," *Statistical Modelling*, vol. 18, no. 3–4, pp. 203–218, 2018. https://doi.org/10.1177/1471082X18759142.

[2] F. Javed, T. Kiss, and P. Österholm, "Performance analysis of nowcasting of gdp growth when allowing for conditional heteroscedasticity and non-gaussianity," *Applied Economics*, vol. 54, no. 58, pp. 6669–6686, 2022. https://doi.org/10.1080/00036846.2022.2075823.

[3] C. Hornok and D. G. S. Raeskyesa, "Economic zones and local income inequality: Evidence from indonesia," *The Journal of Economic Inequality*, vol. 22, pp. 66–100, 2024. https://doi.org/10.1007/s10888-023-09581-x.

[4] H. Q. Vu, N. H. M. Tram, and L. T. Thung, "Digital transformation and economic growth: empirical evidence from vietnam," *Post-Communist Economies*, vol. 37, no. 7, pp. 910–932, 2025. https://doi.org/10.1080/14631377.2025.2511511.

[5] S. Gomes and J. M. Lopes, "Ict access and entrepreneurship in the open innovation dynamic context: Evidence from oecd countries," *Journal of Open Innovation: Technology, Market, and Complexity*, vol. 8, no. 2, p. 102, 2022. https://www.sciencedirect.com/science/article/pii/S2199853122000439.

[6] W. XU, X. WANG, and Z. ZHANG, "The role of the information technology in the industrial structure optimization and upgrading in china," *The Singapore Economic Review*, vol. 67, no. 06, pp. 2023–2048, 2022. https://doi.org/10.1142/S0217590822500333.

[7] Y. Wang and L. Li, "Digital economy, industrial structure upgrading, and residents' consumption: Empirical evidence from prefecture-level cities in china," *International Review of Economics & Finance*, vol. 92, no. C, pp. 1045–1058, 2024. https://doi.org/10.1016/j.iref.2024.02.069.

[8] I. Belikova, N. B. Chernobay, R. V. Kron, V. A. Zhukova, and A. F. Dolgopolova, *Digitalization in Agriculture—A New Step in the Development of Agro-industrial Complex*. Springer Nature Singapore, 2022. https://doi.org/10.1007/978-981-16-7633-8_8.

[9] I. F. Gorlov, G. V. Fedotova, A. V. Glushchenko, M. I. Slozhenkina, and N. I. Mosolova, "Digital technologies in the development of the agro-industrial complex," in *Digital Economy: Complexity and Variety vs. Rationality*, pp. 220–229, Springer International Publishing, 2020. https://doi.org/10.1007/978-3-030-29586-8_26.

[10] A. Shabur, A. Shahriar, and A. Ara, "From automation to collaboration: exploring the impact of industry 5.0 on sustainable manufacturing," *Journal of Discover Sustainability*, vol. 6, no. 1, 2025. https://doi.org/10.1007/s43621-025-01201-0.

[11] J. S. Rha and H.-H. Lee, "Research trends in digital transformation in the service sector: a review based on network text analysis," *Journal of Service Business*, vol. 16, no. 1, 2022. https://doi.org/10.1007/s11628-022-00481-0.

[12] H. Zhong and X. Wang, "Spatial mobility of china's population in the digital economy," *Journal of Asian Economics*, vol. 99, p. 101, 2025. https://doi.org/10.1016/j.asieco.2025.101941.

[13] B. P. Statistik, "Statistical yearbook of indonesia 2026," 2026. https://www.bps.go.id/en/publication/2026/02/27/a43f03f45543dc4e9942f44c/statistical-yearbook-of-indonesia-2026.html, Last accessed on 2026-05-01.

[14] E. Aminullah, T. Fizzanty, N. Nawawi, J. Suryanto, N. Pranata, I. Maulana, L. Ariyani, A. Wicaksono, I. Suardi, N. L. L. Azis, and A. P. Budiatri, "Interactive components of digital msmes ecosystem for inclusive digital economy in indonesia," *Journal of the Knowledge Economy*, vol. 15, no. 1, 2024. https://doi.org/10.1007/s13132-022-01086-8.

[15] M. S. Sapulette and P. A. Muchtar, "Redefining indonesia's digital economy," ERIA Policy Brief 2022-06, Economic Research Institute for ASEAN and East Asia (ERIA), jan 2023. https://www.eria.org/research/redefining-indonesias-digital-economy.

[16] Badan Pusat Statistik, *Telecommunication Statistics in Indonesia 2024*. BPS-Statistics Indonesia, 2025. https://www.bps.go.id/en/publication/2025/08/29/beaa2be400eda6ce6c636ef8/telecommunication-statistics-in-indonesia-2024.html,Lastaccessedon2026-05-01.

[17] A. D. Bank, *ASEAN and Global Value Chains: Locking in Resilience and Sustainability*. Mandaluyong City, Philippines: Asian Development Bank, 2023. https://doi.org/10.22617/SPR230100-2.

[18] B. Behera, A. Haldar, and N. Sethi, "Investigating the direct and indirect effects of information and communication technology on economic growth in the emerging economies: role of financial development, foreign direct investment, innovation, and institutional quality," *Information Technology for Development*, vol. 30, no. 1, pp. 33–56, 2024. https://doi.org/10.1080/02681102.2023.2233463.

[19] C. S. Saba, N. Ngepah, and N. M. Odhiambo, "The nexus between ict diffusion, financial development, industrialization and economic growth: Evidence from sub-saharan african countries," *Journal of African Business*, vol. 26, no. 2, pp. 454–478, 2025. https://doi.org/10.1080/15228916.2025.2451550.

[20] U. F. Saeed, R. Kamil, and I. Wiredu, "The roles of ict and governance quality in the finance-growth nexus of developing countries: a dynamic gmm approach," *Cogent Economics & Finance*, vol. 13, no. 1, p. 2448228, 2025. https://doi.org/10.1080/23322039.2024.2448228.

[21] H. Fang and K. Iqbal, “Information and communication technology, upgrading of industrial structure and spatial spillover effect,” *Scientific Reports*, vol. 15, no. 1, 2025. https://doi.org/10.1038/s41598-025-02957-1.

[22] Z. Lv and T. Xu, “A panel data quantile regression analysis of the impact of corruption on tourism,” *Current Issues in Tourism*, vol. 20, no. 6, pp. 603–616, 2017. https://doi.org/10.1080/13683500.2016.1209164.

[23] Y. Yu, Q. Zhang, and F. Song, “Non-linear impacts and spatial spillover of digital finance on green total factor productivity: An empirical study of smart cities in china,” *Sustainability*, vol. 15, no. 12, 2023. https://doi.org/10.3390/su15129260.

[24] Y. A. Purnama and H. Mitomo, “The impact of ict on regional economic growth: Empirical evidence from 34 provinces of indonesia,” in *29th European Regional Conference of the International Telecommunications Society (ITS): "Towards a Digital Future: Turning Technology into Markets?"*, International Telecommunications Society (ITS), International Telecommunications Society (ITS), August 2018. https://hdl.handle.net/10419/184963.

[25] P. Zhang, J. Wang, M. Li, and F. Xiao, “Research on the mechanism of information infrastructure affecting industrial structure upgrading,” *Scientific Reports*, vol. 12, no. 1, 2022. https://doi.org/10.1038/s41598-022-24507-9.

[26] R. P. Pradhan, M. B. Arvin, M. Nair, J. H. Hall, and S. E. Bennett, “Institutional development in an information-driven economy: can icts enhance economic growth for low- and lower middle-income countries?,” *Information Technology for Development*, vol. 28, no. 3, pp. 468–487, 2022. https://doi.org/10.1080/02681102.2022.2051417.

[27] G. Cette, S. Nevoux, and L. Py, “The impact of icts and digitalization on productivity and labor share: Evidence from french firms,” *Economics of Innovation and New Technology*, vol. 31, no. 8, pp. 669–692, 2022. https://doi.org/10.1080/10438599.2020.1849967.

[28] A. A. Bello, J. Renai, A. Hassan, S. S. Akadiri, and A. R. Itari, “Synergy effects of ict diffusion and foreign direct investment on inclusive growth in sub-saharan africa,” *Environmental Science and Pollution Research*, vol. 30, no. 4, pp. 9428–9444, 2023. https://doi.org/10.1007/s11356-022-22689-3.

[29] B. Xi and P. Zhai, “Economic growth, industrial structure upgrading and environmental pollution: evidence from china,” *Kybernetes*, vol. 52, pp. 518–553, 07 2022. https://doi.org/10.1108/K-02-2022-0279.

[30] D. Zhang, X. Ma, J. Zhang, and Q. Deng, “Can consumption drive industrial upgrades? evidence from chinese household and firm matching data,” *Emerging Markets Finance and Trade*, vol. 56, no. 2, pp. 409–426, 2020. https://doi.org/10.1080/1540496X.2019.1610878.