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Toward a Digitalized Economy: The Impact of Digital Index Performance on The Economic Growth in Indonesia

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ABSTRACT: Amidst escalating global reliance on digitalisation, this study investigates its impact on economic growth in Indonesia through a panel data analysis of 32 provinces from 2017 to 2023. Employing both fixed-effects and dynamic panel data models, the study analyzes economic growth (dependent variable) in relation to capital stock, labour, and digitalisation (independent variables). Digitalisation is operationalised through three composite indicators: access and infrastructure, usage intensity, and digital skills proficiency. Empirical results indicate that capital stock, labour, and digital economic development exert statistically significant positive effects on provincial economic growth, accounting for observed heterogeneity across regions. Generalized Method Moment dynamic panel estimations show no significant long-term effects of digitalisation on growth, suggesting limitations in capturing structural dynamics or addressing endogeneity. These findings suggest three policy priorities: (1) augment physical capital investments strategically, (2) enhance human capital through targeted education, and (3) prioritize systemic ICT infrastructure upgrades.

Keywords: Digitalization, Dynamic Panel Model, Economic Growth.

ABSTRAK: *Penelitian ini bertujuan untuk menganalisis pengaruh digitalisasi terhadap pertumbuhan ekonomi di Indonesia. Penelitian ini menggunakan data panel dari 32 provinsi di Indonesia, mulai dari tahun 2017 hingga 2023. Penelitian ini menggunakan model panel tetap (fixed) dan dinamis (dynamic), dengan pertumbuhan ekonomi sebagai variabel dependen dan stok modal dan tenaga kerja digitalisasi sebagai variabel independen. Digitalisasi diproksikan oleh sub-indeks akses dan infrastruktur, sub-indeks penggunaan, dan sub-indeks keterampilan. Hasil estimasi menunjukkan bahwa variabel stok modal, tenaga kerja, dan pembangunan ekonomi digital di Indonesia berdampak positif pada pertumbuhan ekonomi, dan kami juga menemukan bahwa ada efek heterogenitas antara provinsi yang berbeda. Namun, tidak ada pengaruh signifikan pada model panel dinamis pada generalized method moment. Rekomendasi kebijakan dari hasil penelitian ini: meningkatkan investasi dalam stok modal fisik, meningkatkan kualitas modal manusia, dan mendorong kesiapan Teknologi Informasi dan Komunikasi (TIK).*

Kata Kunci: *Digitalisasi, Model Panel Dinamis, Pertumbuhan Ekonomi.*

INTRODUCTION

Recent studies confirm that technological advancements, particularly digitalisation, significantly drive economic growth (Heeks, 2017). The adoption of these technologies has profoundly influenced society, especially within economic systems. This transformation is closely tied to the rise of Information and Communication Technology (ICT), such as the internet and mobile telephone. These innovations have facilitated the creation of new products and processes, expanded market access, and increased organisational complexity, thereby driving further technological advancements (Myovella et al., 2020). Accordingly, the proliferation of technological progress requires the implementation of effective adoption strategies to fully harness its economic potential.

The impact of technological progress on economic growth can be viewed from several perspectives, with infrastructure as a key element. Increased investment in ICT infrastructure correlates with higher scores in the infrastructure and access sub-index, promoting greater ICT adoption. This, in turn, boosts employment opportunities and firm productivity, contributing positively to economic growth (Pradhan et al., 2021). Advances in ICT infrastructure have played a pivotal role in job creation and the emergence of new digital industries, both of which contribute to enhanced economic performance. Moreover, sustained high economic growth amplifies the demand for ICT innovations, driven by the imperative for market expansion and productivity enhancements. Technological progress bolsters productivity by streamlining production processes and improving efficiency. ICT, in turn, fosters economic growth by enhancing resource accessibility, improving operational efficiency, and strengthening the capacity of economic actors to leverage knowledge and access markets (Arvin et al., 2021).

Indonesia's open economic system and active participation in international agreements necessitate prioritizing the development of information and communication technology (ICT). This requirement has become even more acute following the COVID-19 pandemic, which has increased reliance on technological solutions in daily life.

Digitalization marks a transformative milestone in human civilization and has gained significant momentum over the past two decades. It has reshaped nearly every aspect of modern life, including consumer behavior, global business practices, employment patterns, and communication methods. As the foundation of digitalization, technology has the potential to drive economic recovery—an essential consideration amid the economic challenges brought by the COVID-19 pandemic.

Demographic trends further highlight Indonesia's pressing need for technological advancement. The country's population continues to grow, accompanied by a steady rise in internet users, mobile phone subscribers, and participants in electronic commerce. Over the past decade, internet usage has increased by 19.04%, reaching 205 million users as of January 2022 (KEPIOS, 2022).

Indonesia's internet infrastructure, a key enabler of its digital economy, has been driven by widespread mobile technology adoption. As of January 2022, mobile phone usage rose by 3.6% year-on-year. KEPIOS (2022) reports 370.1 million cellular subscriptions in Indonesia—surpassing the total population by 133.3%—indicating widespread multi-device ownership. This proliferation of internet-enabled devices has transformed social interactions and business practices, especially in e-commerce.

E-commerce expansion signals strong economic potential, marked by consistent, robust growth. In 2021, Indonesia led globally in e-commerce user penetration, with 88.1% of its internet users engaging in online shopping (Statista, 2022). Over five years, average annual e-commerce users reached 19.06 million, with projections suggesting a rise to 189.6 million by 2024. Statistics Indonesia (2021) notes a spike in digital transactions, averaging over IDR 16 billion monthly from January 2020 to January 2021 and peaking at IDR 22.14 billion in December 2020. These trends underscore the merging of social, commercial, and financial activities in Indonesia's digital transformation.

Niebel (2018) examines the relationship between information and communication technology (ICT) and economic growth in developing and developed countries. Using regression analysis of panel data from 59 nations (1995–2010), the study identifies a significant positive link between ICT development and economic growth. It also finds that technology's impact on growth is comparable across both country groups, suggesting developing economies can achieve substantial gains through technological adoption. These results align with Myovella et al. (2020), who further affirm ICT's role in driving economic development.

Mura and Donath (2023), analyse digitalisation's effect on economic growth in the European Union using balanced panel data (2000–2021). Their analysis, controlling for multiple factors, confirms digitalisation's positive impact. The authors call for governments to harmonise digital policies and promote innovative, digitally driven business models to maximise transformation benefits. Similarly, Lechman & Anacka (2022) study low- and lower-middle-income economies (1990–2019), showing digitalisation not only boosts growth but also reduces economic disparities between nations.

Donou-Adonsou (2019), employing the First-Differenced Generalised Method of Moments (FD GMM), finds that internet access significantly drives economic growth in countries with higher education levels, unlike mobile phones. This suggests education is pivotal for the internet to stimulate growth, while non-internet mobile phones show negligible impact. However, smartphones—which typically integrate internet access—may still deliver economic benefits.

Lefophane and Kalaba (2020) investigate whether post-1994 policy reforms in South Africa's manufacturing sector, alongside ICT adoption, explain rising labour productivity. Using regression analysis and a Differences-in-Differences (DD) approach on 1970–2016 data, they compare pre- and post-reform periods with dummy variables. Results indicate higher productivity after ICT interventions post-reform, a finding supported by Irtyshcheva et al. (2021), who reinforce ICT's role in productivity gains.

Economic growth, a key measure of national progress, is typically assessed through annual GDP changes. Growth theories have evolved from classical to neoclassical, historical, and contemporary models. Classical theorist Adam Smith linked growth to population expansion, which drives output increases. He emphasised education's role in enhancing labour quality, arguing that broader educational access improves workforce expertise and productivity (Bianchi & Labory, 2022). Smith also introduced foundational concepts like institutional stability, the invisible hand, and trade openness (Ucak, 2015), with his labour value theory aligning with liberal capitalist principles (Robinson & Subrick, 2021).

While classical theory prioritised capital and labour as growth drivers, neoclassical frameworks added technological advancement. Here, technology includes not only tools but also innovative methods. Joseph Schumpeter viewed innovation—particularly through entrepreneurship—as vital for overcoming competition and fostering growth (Tülüce & Yurtkur, 2015). He proposed cyclical growth: initial innovations trigger expansion, followed by creative destruction that replaces outdated practices, spurring further innovation (de Groot et al., 2022). Similarly, the Solow-Swan model positioned technological progress as central to growth, often framed within endogenous growth theory (Kadigi et al., 2022; Munguía et al., 2019).

Historically and in contemporary thought, growth is depicted as societal evolution-from agrarian economies to advanced societies characterised by high consumption and industrial strength. This transition occurs in phases, with increasing focus on environmental sustainability (Calvano & Polo, 2021; Chu, 2022). Technology and innovation have ushered in digitalisation, creating a new paradigm. Economic growth and digitalisation are interdependent, with the digital economy profoundly shaping urban spatial planning-even outweighing general urbanisation's influence (Zhu & Chen, 2022). Furthermore, digitalisation-the development of new technological applications-demands a skilled workforce, including in regional economies (Huaping & Binhua, 2022).

The digital economy's success enhances total factor productivity (TFP) (Pan et al., 2022). This stems from its role as an innovation catalyst, driving broad-based and sustainable TFP growth. Inter-regional digital integration also accelerates TFP quality advancements, underscoring the need for robust, interconnected infrastructure. The digital economy's rapid expansion offers opportunities and challenges, necessitating effective government support (Spence, 2021). Additionally, economic digitalisation shapes entrepreneurship by integrating innovation and environmental sustainability (Ni, 2022; Yang et al., 2022).

This study analyses digitalisation and technological advancements using secondary data from Statistics Indonesia across 32 provinces (2017–2023). The digitalisation variable is divided into three components of the Information and Communication Technology Development Index (IP-TIK): the access and infrastructure sub-index (SIAI), reflecting ICT readiness; the usage sub-index (SIP), measuring ICT utilisation intensity; and the skills sub-index (SIK), assessing ICT competencies. Economic growth serves as the dependent variable, with independent variables including physical capital stock growth, labour growth, and digitalisation growth. To our knowledge, no prior Indonesian study has concurrently employed the ICT index and its sub-indices to construct digitalisation data. This approach offers unique insights and contributes original findings to Indonesia's digitalisation economics research. The simultaneous use of these sub-indices also aims to enrich existing literature on ICT's economic impacts.

The research also analyses digitalisation's influence on economic growth in Indonesia using panel data from 32 provinces (2017–2023). It provides two key contributions: policy recommendations and academic advancements. For policy, three proposals are outlined. First, increased investment in physical capital stock by governments and stakeholders is critical. Second, enhancing human capital quality should be prioritised to drive economic progress. Third, improving ICT readiness—via expanded digital access and infrastructure—is recommended to bolster nationwide growth.

Academically, the study enriches the literature on digitalisation's relationship with economic growth in Indonesia. By systematically analyzing digitalization's effects across 32 provinces, it provides a robust empirical basis for understanding how digital technologies shape Indonesia's economic landscape.

METHODS

Data and Measurement

This study uses a secondary database from Statistics Indonesia (Badan Pusat Statistik/BPS). The methodology draws on Solomon and van Klyton (2020) who applied a Cobb-Douglas production model with ICT capital proxied by indicators such as broadband availability or computers per worker. In contrast, this study disaggregates the digitalisation variable into three components of the Information and Communication Technology Development Index (IP-TIK): the access and infrastructure sub-index (SIAI), reflecting ICT readiness; the usage sub-index (SIP), measuring ICT utilisation intensity; and the skills sub-index (SIK), assessing ICT competencies. Digitalisation data are aggregated at the provincial level to align with variable availability, as Statistics Indonesia records these metrics at this administrative scale. The sample comprises a panel dataset of 32 Indonesian provinces (2017–2023), determined by data accessibility from Statistics Indonesia. Table 1 summarises the variables, including descriptions and sources.

Table 1. Description of Variables

No	Variable	Description	Source	Country
1	Economic Growth (ln GRDP)	Gross Regional Domestic Product (GRDP) is measured at constant prices and expressed in millions of rupiahs	Statistics Indonesia (BPS)	Indonesia
2	Labour (ln L)	Data on the labour force	Statistics Indonesia (BPS)	Indonesia
3	Physical Capital Stock (ln GFCF)	Gross Fixed Capital Formation (GFCF) is measured at constant prices and expressed in millions of rupiahs.	Statistics Indonesia (BPS)	Indonesia
4	Technological Progress/ Digitalization	Three types of data represent digitalization		

a)	Readiness (ln SIAI)	The access and infrastructure sub-index reflect ICT readiness, comprising five indicators: fixed telephone subscribers per 100 population, cellular telephone subscribers per 100 population, international internet bandwidth (bit/s) per user, the proportion of households with computers, and the proportion of households with internet access.	Statistics Indonesia (BPS)	Indonesia
b)	Usage (ln SIP)	Measures ICT utilisation intensity, including three indicators: percentage of individuals using the internet, fixed broadband subscribers per 100 population, and active mobile broadband subscribers per 100 population.	Statistics Indonesia (BPS)	Indonesia
c)	Skills (ln SIK)	Assesses ICT competencies through three proxy indicators: average years of schooling, secondary Gross Enrolment Ratio (GER), and tertiary GER.	Statistics Indonesia (BPS)	Indonesia

Empirical Model

This study adopts a modified Cobb-Douglas production function, adapted from Solomon & van Klyton's (2020) to incorporate digitalisation's effects. The baseline specification is expressed as:

$$\boldsymbol{Y = A_{it}K_{it}^{\beta 1}L_{it}^{\beta 2}C_{it}^{\beta 3}e_{it}^{\sigma it}} \quad \text{....................... (3.1)}$$

Where $\boldsymbol{Y}$ denotes output; $\boldsymbol{L}$ represents labour; $\boldsymbol{K}$ is physical capital stock; $\boldsymbol{C}$ captures ICT capital; $\boldsymbol{A}$ is a country-specific constant reflecting spatially distinct technological capabilities; $\boldsymbol{\beta}$ is the coefficient of each production input factor, and $\boldsymbol{\sigma}$ is an inter-spatial efficiency parameter. For empirical estimation, the model is log-linearised:

$$\boldsymbol{lnY_{it} = \beta_1 lnK_{it} + \beta_2 lnL_{it} + \beta_3 lnC_{it} + \sigma_{it}} \quad \text{....................... (3.2)}$$

Here: $\boldsymbol{lnY, lnK, lnL, lnC}$ are the log-transformed values of output, physical capital stock, labour, and ICT capital growth, respectively. $\boldsymbol{\beta_1}$, $\boldsymbol{\beta_2}$, and $\boldsymbol{\beta_3}$ represent the elasticities of these inputs. Diverging from constant returns to scale, Solomon & van Klyton (2020) introduce $\boldsymbol{\sigma it}$, a country-specific efficiency parameter embedding the lagged production function $\boldsymbol{(Y_{it-1})}$. This allows convergence analysis across countries, aligning with (Barro (1991) and Bond et al. (2001). Therefore, the hypothesis shows that emerging countries grow faster than developed countries and is conditional to other variables used in the model. Therefore, the hypothesis shows that developing countries grow faster than developed countries and is conditional to other variables used in the model.

$$\boldsymbol{\sigma_{it} = a_1 lnY_{it-1} + e_{it}} \quad \text{............ (3.3)}$$

In equation (3.3), the error term ($\boldsymbol{e_{it}}$) consists of several components: an inter-unit fixed effect, denoted by $\boldsymbol{a_1}$, which captures unobserved variations in output across units; $\boldsymbol{\lambda_t}$, representing a time-specific effect that reflects disembodied technical change as described by Ugur et al. (2016), and $\boldsymbol{u_{it}}$, the idiosyncratic error term accounting for residual stochastic variation.

$$\boldsymbol{e_{it} = a_i + \lambda_t + u_{it}} \quad \text{................ (3.4)}$$

n this study, digitalisation—proxied by Information and Communication Technology (ICT) capital—is measured using indicators from the Information and Communication Technology Development Index (IP-TIK). Building on Spence's (2021) analytical framework, this research integrates equation (3.4) into the dynamic specification outlined in equation (3.5) as follows:

$$\boldsymbol{lnY_{it} = a_1 lnY_{it-1} + \beta_1 lnK_{it} + \beta_2 lnL_{it} + \beta_3 lnC_{it} + a_i + \lambda_t + u_{it}} \quad \text{................ (3.5)}$$

In this study, technological progress—conceptualised as digitalisation—is broken down into three components of the Information and Communication Technology Development Index (IP-TIK): the access and infrastructure sub-index ($\boldsymbol{SIAI_{it}}$), indicating ICT readiness; the usage sub-index ($\boldsymbol{SIP_{it}}$), measuring

ICT utilisation intensity; and the skills sub-index (SIK_{it}) reflecting ICT proficiency and capabilities. This tripartite framework allows for a nuanced analysis of the multifaceted dimensions of digitalisation. The formal specification is presented in equation (3.6) below.

$$\boldsymbol{lnGDRP_{it} = a_1 lnGDRP_{it-1} + \beta_1 lnGFCG_{it} + \beta_2 lnLabor_{it} + \beta_3 lnSIAI_{it} + \beta_4 lnSIP_{it} + \beta_5 lnSIK_{it} + a_i + \lambda_t + u_{it}} \quad \text{……} \quad (3.6)$$

This study employs panel data to identify the most appropriate estimation technique by comparing static models—namely, Pooled Least Squares (PLS), the Fixed Effects Model (FEM), and the Random Effects Model (REM)—with dynamic models, specifically the First-Differenced Generalised Method of Moments (FD-GMM) and the System Generalised Method of Moments (SYS-GMM). To determine the most suitable static model between PLS and FEM, the Chow test is applied. The test hypotheses are as follows: the null hypothesis (H_0: $\mu_1 = \mu_2 = \ldots = \mu_{n-1} = 0$) assumes no individual effect differentiation, while the alternative hypothesis (H_1: $\mu_1 \neq \mu_0$) suggests the presence of such differentiation. Since the p-value is below the significance level (Prob > F = 0.0000, $\alpha < 0.05$), the null hypothesis is rejected, indicating statistically significant individual effect differentiation. Consequently, the Fixed Effects Model is deemed superior to both the Random Effects Model and PLS in this context.

This study employs the Hausman test to determine the optimal model specification between the Fixed Effects Model (FEM) and the Random Effects Model (REM). The test hypotheses are as follows: the null hypothesis ($H0$: (μit, Xit) = 0) assumes no correlation between the individual-specific error term and the explanatory variables, while the alternative hypothesis ($H1$: $C(\mu it, Xit) \neq 0$) indicates the presence of such a correlation. The study rejects the null hypothesis if the Prob > Chi2 = 0,0000 with alpha < 0,05, indicating a statistically significant correlation between the individual error term and the explanatory variables. Consequently, the Fixed Effects Model is more appropriate than the Random Effects Model.

Blundell and Bond (1998) show that System GMM (SYS-GMM) estimators are more asymptotically efficient than both First-Differenced GMM (FD-GMM) and non-linear GMM estimators in simple AR (1) models. Bond's (1991) simulations found that the linear GMM estimator suffers from substantial finite-sample bias and lower precision. Subsequent research by S. S. Bond et al. (2001) and Windmeijer (2005), using S. Bond (1991) data, demonstrates that the two-step GMM estimator's standard errors are typically downward-biased in small samples. These robustness checks confirm that the estimates satisfy the Best Linear Unbiased Estimator (BLUE) properties under the Gauss-Markov theorem.

RESULTS AND DISCUSSIONS

Table 2 presents descriptive statistics for key economic indicators across 32 Indonesian provinces from 2017 to 2023. Data for Papua and West Papua are excluded due to incomplete records from administrative reorganization in 2023. Economic growth is measured as the natural logarithm of Gross Regional Domestic Product (GRDP), with a mean of 18.94% (standard deviation: 1.16) and values ranging from 16.96% to 21.44%. Physical capital stock accumulation is quantified using the natural logarithm of Gross Fixed Capital Formation (GFCF), averaging 17.80% (standard deviation: 1.14) and spanning 15.79% to 20.45%. The labour force growth rate shows an annual average of 14.58% (standard deviation: 1.01), fluctuating between 12.71% and 17.00%.

Digitalisation is operationalised through three components of the Information and Communication Technology Development Index (ICT Index). The ICT Readiness (SIAI) sub-index, capturing access and infrastructure, records a mean annual growth of 1.78% (standard deviation: 0.12), ranging from 1.49% to 2.00%. The ICT Usage (SIP) sub-index, reflecting adoption intensity, displays a lower average growth of 1.57% per annum. The ICT Skills (SIK) sub-index, evaluating competencies, reports the highest average growth among ICT components at 1.80% annually

Table 3 presents the results of the correlation analysis, highlighting significant interrelationships among the study's economic variables. A strong positive correlation (r = 0.98) exists between physical capital stock growth (ln GFCF) and economic growth (ln GRDP). Additionally, labour growth (ln L) exhibits a substantial positive association (r = 0.87) with economic growth (ln GRDP), underscoring the strong linkage between capital accumulation, labour expansion, and economic expansion.

Regarding technological advancement, the Access and Infrastructure Sub-Index (ln SIAI)—a proxy for digitalization—shows a significant positive correlation (r = 0.8051) with the Usage Sub-Index (ln SIP). This suggests that enhanced ICT infrastructure and access are strongly associated with higher ICT utilization.

Table 2. Summary Statistic of Variables

Variable	Unit of measurements	Obs	Mean	Std. dev.	Min	Max
Ln GDRP	Constant 2010 (Million Rupiahs)	224	18,94	1,16	16,96	21,44
Ln GFCF	Constant 2010 (Million Rupiahs)	224	17,80	1,14	15,79	20,45
Ln L	Number of Workers	224	14,65	1,01	12,71	17,00
Ln SIP	Index	224	1,57	0,24	0,81	2,03
Ln SIK	Index	224	1,80	0,08	1,62	2,05
Ln SIAI	Index	224	1,78	0,12	1,49	2,12

Source: Data Processed, 2024

Table 3. Correlation of The Variables

	Ln GDRP	Ln GFCF	Ln L	Ln SIP	Ln SIK	Ln SIAI
Ln GDRP	1					
Ln GFCF	0,9824	1				
Ln L	0,8742	0,8530	1			
Ln SIP	0,3975	0,3675	0,1552	1		
Ln SIK	-0,0766	-0,0335	-0,1885	0,2369	1	
Ln SIAI	0,4818	0,4587	0,2447	0,8051	0,4071	1

Source: Data Processed, 2024

Conversely, weakly negative correlations are observed between the Skills Sub-Index (SIK) and economic variables, including ln GRDP (economic growth), ln GFCF (physical capital stock growth), and ln L (labour growth). The SIK, which measures ICT competencies through proxies such as average years of schooling, secondary Gross Enrolment Ratio (GER), and tertiary GER, exhibits these negative correlations. This suggests that current ICT skill levels fail to support economic growth, implying insufficient digital literacy to effectively utilize technology for development.

For model selection, the Chow test was first employed to compare the Pooled Least Squares (PLS) and Fixed Effects Model (FEM). A p-value (Prob > F) below the 0.05 significance threshold resulted in the rejection of the null hypothesis, confirming FEM's superiority over PLS. Subsequently, the Hausman test was conducted to distinguish between Fixed Effects and Random Effects models. With a p-value (Prob > χ^2) of 0.000—statistically significant at $\alpha = 0.05$—the test reinforced the preference for the Fixed Effects Model (FEM) over the Random Effects Model (REM).

Table 4. Summary of Results

Description	FEM		FD-GMM		SYS-GMM	
	Stat	Prob	Stat	Prob	Stat	Prob
F-statistic	69,15	0,000				
Pesaran	23,10	0,000				
Husman test	73,47	0,000				
Wooldrige test (Autocorrelation)	202,20	0,000				
Modified Wald test (Heteroskedasticity)	1.898,1	0,000				
Sargan			132,41	0,000	184,55	0,000
AR (1)			-3,0375	0,002	-3,4933	0,001
AR (2)			-1,9215	0,055	-0,5145	0,607

Note: This table reports statistical tests assessing classical assumptions, instrument validity (Sargan test), and model consistency (Arellano-Bond test).

Source: Data processed, 2024.

Table 4 presents a summary of results from both static and dynamic panel model estimations. The Fixed Effects Model (FEM) demonstrates an adjusted R^2 of 0.668, indicating that 66.8% of the variation in the dependent variable is explained by the independent variables. The Pooled Least Squares (PLS) estimator proves problematic due to the correlation between regressors and the error term, resulting in biased and inconsistent estimates. The FEM successfully mitigates this endogeneity issue through its incorporation of time-invariant individual-specific fixed effects.

As evidenced in Table 5, all five model specifications confirm that physical capital stock and labour growth maintain statistically significant positive relationships with economic growth within the static panel framework. These results support existing findings regarding the positive impact of capital stock on economic growth (Kahouli & Chaaben, 2022; Osei & Kim, 2020). The observed positive effect of labour growth similarly aligns with conclusions from (Baerlocher et al., 2021; Li & Li, 2022; Solarin, 2020).

The impact of technological advancement on digitalization metrics varies significantly across different dimensions. Growth in ICT usage (ln SIP), ICT skills (ln SIK), and ICT infrastructure (ln SIAI) hows statistically significant effects only within the Pooled Least Squares (PLS) model. While ICT usage and infrastructure display positive coefficients, ICT skills exhibit a negative association. These results align with Mura and Donath (2023), who identified digitalization's positive economic effects, a conclusion reinforced by Lechman and Anacka (2022).

Table 5. Robustness Estimated of Economic Growth with Static and Dynamic Panel Models

Variables	PLS	FEM	REM	FD-GMM	SYS-GMM
Ln GFCF	0,815**	0,419**	0,526**	0,220*	0,291**
	(0,023)	(0,079)	(0,115)	(0,093)	M (0,032)
Ln L	0,181**	0,146	0,452**	0,019	0,026
	(0,025)	(0,090)	(0,117)	(0,075)	(0,064)
Ln SIP	0,170*	0,070	0,049	0,147**	0,171**
	(0,086)	(0,052)	(0,056)	(0,050)	(0,029)
Ln SIK	-0,804**	0,967*	0,441	-0,276	-0,607*
	(0,153)	(0,359)	(0,275)	(0,445)	(0,239)
Ln SIAI	0,694**	0,187*	0,157	-0,373**	-0,577**
	(0,176)	(0,105)	(0,152)	(0,119)	(0,113)
L,ln GDRP				0,673**	0,749**
				(0,133)	(0,067)
constant	1,736**	7,151**	1,806*	2,966**	1,080
	(0,278)	(1,415)	(0,954)	(0,790)	(0,710)
N	224	224	224	160	192
Adj.R^2	0,976	0,834			

Standard errors in parentheses ($^{*}p < 0,10$, $^{**}p < 0,05$, $^{***}p < 0,01$)

Source: Data Processed, 2024.

Furthermore, ICT readiness growth, measured by the access and infrastructure sub-index, significantly boosts economic growth in both the Fixed Effects Model (FEM) and Random Effects Model (REM). A skilled workforce combined with robust ICT policies amplifies these growth effects. Existing research highlights human capital quality as a key complementary factor linking ICT adoption to economic expansion. Investing in human capital is therefore a strategic priority for maximizing ICT-driven economic benefits. Individual users are positioned to drive digitalization across Indonesian provinces, requiring the government to intensify technology use to meet the needs of a tech-savvy population. Expanding mobile phone-based applications to support distance learning and other services could enhance accessibility and efficiency. To achieve this, the government must strengthen digital technology deployment and technical capacity building through robust science, technology, and innovation policies.

These empirical findings corroborate existing literature that demonstrates technology's positive economic externalities (Arvin et al., 2021; Habibi & Zabardast, 2020; Mendonça et al., 2020; Nair et al., 2020; Pradhan et al., 2021; Sawng et al., 2021; Vu et al., 2020). Within the dynamic panel framework, both the First-Differenced Generalized Method of Moments (FD-GMM) and System Generalized Method of Moments (SYS-GMM) estimators reveal statistically significant individual effects for both the lagged economic growth variable and physical capital stock growth. Notably, the SYS-GMM results indicate an inverse relationship between ICT skills development and economic growth. Table 4 presents a comparative evaluation of five panel data specifications, while Table 5 documents robustness checks that collectively establish the Fixed Effects Model (FEM) as the most statistically reliable among both static and dynamic model alternatives.

Table 6. Robustness Estimated of Ordinary Least Square (OLS) with Provincial Dummies

Ln GDRP	Coef.	St. Err	t-value	p-value	[95% Conf	Interval]	Sig
Ln GFCF	0,419	0,026	16,11	0,000	0,368	0,471	***
Ln L	0,146	0,083	1,76	0,080	-0,017	0,309	*
Ln SIP	0,070	0,041	1,72	0,087	-0,010	0,151	*
Ln SIK	0,967	0,289	3,34	0,001	0,397	1,538	***
Ln SIAI	0,187	0,119	1,57	0,118	-0,048	0,421	
Province: base Aceh	.	.	.	.	.	.	
Bali	0,066	0,038	1,71	0,089	-0,010	0,141	*
Banten	0,669	0,088	7,58	0,000	0,495	0,843	***
Bengkulu	-0,568	0,078	-7,31	0,000	-0,721	-0,414	***
Yogyakarta	-0,252	0,054	-4,70	0,000	-0,357	-0,146	***
Jakarta	1,247	0,088	14,20	0,000	1,073	1,420	***
Gorontalo	-0,523	0,129	-4,07	0,000	-0,776	-0,269	***
Jambi	0,395	0,054	7,32	0,000	0,288	0,501	***
West Java	1,326	0,198	6,69	0,000	0,935	1,717	***
Central Java	1,067	0,184	5,81	0,000	0,705	1,429	***
East Java	1,331	0,193	6,90	0,000	0,951	1,712	***
West Kalimantan	0,259	0,071	3,64	0,000	0,119	0,400	***
South Kalimantan	0,333	0,066	5,02	0,000	0,202	0,464	***
Central Kalimantan	-0,012	0,073	-0,16	0,874	-0,155	0,132	
East Kalimantan	0,838	0,050	16,64	0,000	0,738	0,937	***
North Kalimantan	-0,085	0,168	-0,51	0,614	-0,416	0,246	
Bangka Belitung Islands	0,035	0,128	0,27	0,784	-0,217	0,288	
Riau Islands	0,227	0,085	2,66	0,008	0,059	0,394	***
Lampung	0,442	0,081	5,47	0,000	0,282	0,601	***
Maluku	-0,691	0,099	-6,96	0,000	-0,887	-0,495	***
North Maluku	-0,747	0,118	-6,33	0,000	-0,979	-0,514	***
West Nusa Tenggara	-0,068	0,046	-1,46	0,147	-0,159	0,024	
East Nusa Tenggara	-0,362	0,050	-7,24	0,000	-0,461	-0,264	***
Riau	0,814	0,049	16,78	0,000	0,718	0,910	***
West Sulawesi	-0,396	0,117	-3,40	0,001	-0,626	-0,166	***
South Sulawesi	0,436	0,061	7,14	0,000	0,315	0,556	***
Central Sulawesi	0,051	0,046	1,10	0,274	-0,041	0,142	
Southeast Sulawesi	-0,172	0,056	-3,07	0,002	-0,282	-0,061	***
North Sulawesi	-0,117	0,069	-1,69	0,093	-0,253	0,020	*
West Sumatera	0,197	0,026	7,56	0,000	0,146	0,248	***
South Sumatera	0,558	0,078	7,16	0,000	0,404	0,711	***
North Sumatera	0,737	0,098	7,48	0,000	0,542	0,931	***
constant	6,931	1,288	5,38	0,000	4,390	9,473	***

Mean dependent var	18,936	SD dependent var	1,158
R-squared	0,999	Number of obs	224
F-test	5700,795	Prob > F	0.000
Akaike crit. (AIC)	-793,904	Bayesian crit. (BIC)	-667,673

**** p<0,01, ** p<0,05, * p<0,10*

Source: Data Processed, 2024

This study investigates the heterogeneous effects of independent variables on economic growth across Indonesia's 32 provinces. As detailed in Table 6, employing Aceh as the reference province, the analysis uncovers statistically significant spatial variation in provincial contributions to national economic growth. Twenty-seven provinces demonstrate measurable impacts, while five provinces exhibit no statistically significant influence.

The provinces with significant effects include Bali, Banten, Bengkulu, Yogyakarta, DKI Jakarta, Gorontalo, Jambi, West Java, Central Java, East Java, West Kalimantan, South Kalimantan, East Kalimantan, Bangka Belitung Islands, Riau Islands, Lampung, Maluku, North Maluku, East Nusa Tenggara, Riau, West Sulawesi, South Sulawesi, Southeast Sulawesi, North Sulawesi, West Sumatra, South Sumatra, and North Sumatra.

The absence of statistically significant effects in the remaining provinces may indicate suboptimal leveraging of information and communication technology (ICT) for productivity enhancement. This could arise from the allocation of ICT resources toward non-productive activities, such as leisure, digital self-expression, or applications yielding limited economic value. These findings highlight the role of sociocultural determinants in shaping technology adoption patterns and necessitate deeper inquiry into regional disparities in ICT implementation and utilisation behaviours.

Telecommunications infrastructure—including internet and mobile telephony—represents a crucial indicator of technological advancement. Using the Fixed Effects Model (FEM) estimator, this study demonstrates that internet penetration significantly enhances economic growth, though only in provinces with established ICT infrastructure. These findings highlight the importance of widespread ICT access as a fundamental requirement for realizing the economic benefits of internet connectivity.

The synergistic relationship between fixed-line telephones, mobile phones, computers, and internet access (core components of the infrastructure sub-index) warrants special attention. Mobile subscriptions often enable internet access, supporting diverse applications beyond voice communication—such as video conferencing, academic research, virtual meetings, and distance education. The results indicate that household access to these technologies collectively contributes to economic growth, suggesting smartphone adoption may further stimulate development. Future studies should examine the distinct economic impacts of internet-enabled mobile users. Additionally, both physical capital stock growth and labour expansion show statistically significant positive correlations with economic growth

Technological progress, particularly through digital transformation, is expected to deliver significant benefits by driving economic development – a cornerstone of national prosperity. Solomon and van Klyton (2020) conceptualise technology's impact across three dimensions (individual, organisational, and governmental), demonstrating that strategic alignment with growth initiatives produces substantially positive outcomes. Crucially, the synergistic combination of skilled labour and supportive policy frameworks amplifies the advantages of Information and Communication Technology (ICT), underscoring human capital investment as a pivotal factor in policy formulation.

From a policy perspective, two key interventions emerge as essential. First, promoting productive mobile technology applications requires particular emphasis in provinces with underdeveloped digital infrastructure. Second, the effective nationwide implementation of digital infrastructure programmes – notably those administered by the Telecommunication and Information Accessibility Agency under the Ministry of Communications and Informatics – demands sustained prioritisation.

CONCLUSION

This study examines the influence of information and communication technology (ICT) advancement and digital transformation on economic growth in Indonesia. The analysis demonstrates that ICT readiness—operationalised as access to infrastructure—can stimulate economic growth, though with notable regional variation across provinces. Telecommunications infrastructure, particularly internet connectivity and mobile telephony, emerges as a critical determinant of technological progress. The Fixed Effects Model (FEM) estimation reveals that internet penetration contributes positively to economic growth, but only in provinces with established ICT infrastructure.

These findings highlight the imperative of improving ICT accessibility to fully realise the internet's economic potential. Additionally, the study confirms the consistent positive impact of physical capital accumulation and labour force expansion on economic performance.

The role of digitalisation as a catalyst for economic growth has gained widespread recognition in both developed and developing contexts. Comparative research, including studies of European Union economies (Mura & Donath, 2023), establishes digitalisation's positive economic effects. Parallel findings from investigations in low-income and lower-middle-income settings Lechman & Anacka (2022) further substantiate this relationship.

This research makes dual contributions to policy and scholarship. From a policy perspective, three key recommendations emerge: increased investment in physical capital stock by both public and private actors; enhancement of human capital quality; and improvement of ICT readiness through expanded digital infrastructure. The latter objective necessitates strengthening the operational capacity of Indonesia's Telecommunication and Information Accessibility Agency (BAKTI) under the Ministry of Communications and Informatics. Academically, the study advances understanding through its comprehensive analysis of digitalisation's economic impact across all 32 Indonesian provinces, with particular attention to inter-provincial heterogeneity—a novel contribution to the extant literature.

The study's limitations primarily concern its reliance on a constrained temporal dataset and aggregate-level digitalisation proxies. Subsequent research would benefit from extended timeframes and more granular data, such as village-level indicators from Indonesia's Village Potential Statistics (PODES). Furthermore, detailed investigation into ICT application patterns, especially their orientation toward productive economic activities, would yield more targeted policy insights

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