The Impact of Digitalization on Economic Growth in Indonesia: An Analysis Spline Approach

Syaiful
Universitas Borobudur; Jakarta, Indonesia
E-Mail: syaiful@borobudur.ac.id

Samin Saputra
Universitas Borobudur; Jakarta, Indonesia
E-Mail: cicih_ratnasih@borobudur.ac.id

Yolanda
Universitas Borobudur; Jakarta, Indonesia
E-Mail: yolanda@borobudur.ac.id

Submitted:
OCTOBER 2025

Accepted:
DECEMBER 2025

ABSTRACT

Digitalization is currently developing very rapidly, and various studies have shown that it contributes to increased economic growth in various countries. In Indonesia, the development of digitalization is a crucial factor in driving economic growth between provinces with varying levels of technology adoption. Therefore, this study aims to explore the influence of digitalization on economic growth in Indonesia and identify the contribution of each digitalization indicator to economic growth in each province based on digitalization clusters. This study uses one dependent variable, namely economic growth, which is proxied by GRDP per capita, and five independent variables as digitalization indicators: digital access, digital use, digital capability, digital finance, and digital inequality. The analysis method used is a spline approach to capture differences in influence between provincial clusters. The research results show that the digital capability indicator contributed the most to the increase in GRDP per capita in provinces with the "Very High" cluster, followed by Digital Finance. Thus, digitalization has been shown to significantly influence economic growth in Indonesia. Improving infrastructure and adopting digital technologies, as well as reducing the digital divide, are crucial for driving inclusive and sustainable economic growth across all provinces.

***Keywords**: Digitalization, Economic Growth, Indonesia, Spline Approach.*

ABSTRAK

Digitalisasi saat ini berkembang sangat pesat dan berbagai penelitian menunjukkan bahwa digitalisasi berkontribusi terhadap peningkatan pertumbuhan ekonomi di berbagai negara. Di Indonesia, perkembangan digitalisasi menjadi faktor penting dalam mendorong pertumbuhan ekonomi antarprovinsi yang memiliki tingkat adopsi teknologi berbeda-beda. Oleh karena itu, penelitian ini bertujuan untuk mengeksplorasi pengaruh digitalisasi terhadap pertumbuhan ekonomi di Indonesia serta mengidentifikasi besarnya kontribusi masing-masing indikator digitalisasi terhadap pertumbuhan ekonomi di setiap provinsi berdasarkan klaster digitalisasi. Penelitian ini menggunakan satu variabel dependen, yaitu pertumbuhan ekonomi, yang diproksikan dengan PDRB per kapita, serta lima variabel independen sebagai indikator digitalisasi, yaitu akses digital, penggunaan digital, kapabilitas digital, keuangan digital, dan ketimpangan digital. Metode analisis yang digunakan adalah pendekatan spline untuk menangkap perbedaan pengaruh antar klaster provinsi. Hasil penelitian menunjukkan bahwa indikator Kapabilitas Digital memberikan kontribusi terbesar terhadap peningkatan PDRB per kapita di provinsi dengan klaster "Sangat Tinggi", diikuti oleh keuangan digital. Dengan demikian, digitalisasi terbukti berpengaruh signifikan terhadap pertumbuhan ekonomi di Indonesia. Kesimpulannya, peningkatan infrastruktur dan adopsi teknologi digital serta pengurangan kesenjangan digital

JIAKES
Jurnal Ilmiah Akuntansi Kesatuan
Vol. 13 No. 6, 2025
pp. 2263-2278
IBI Kesatuan
ISSN 2337 – 7852
E-ISSN 2721 – 3048
DOI: 10.37641/jiakes.v13i6.4647

sangat penting untuk mendorong pertumbuhan ekonomi yang inklusif dan berkelanjutan di seluruh provinsi.

***Kata kunci**: Digitalisasi, Pertumbuhan Ekonomi, Indonesia, Pendekatan Spline.*

INTRODUCTION

The world has entered the Fourth Industrial Revolution, marked by rapid digitalization and the widespread use of the Internet of Things (IoT). These changes have fundamentally transformed business processes across the entire production value chain, from production to after-sales services (Rojko, 2017; Parida et al., 2019; Efendi et al., 2025). Internet-driven digital transformation has also led to the growth of the digital economy, expanding access to services and reshaping views on economic growth and competitiveness (Watanabe et al., 2018). As a result, digitalization has attracted strong interest from scholars and policymakers due to its long-term economic effects and social implications (Heimerl & Raza, 2018). However, its effectiveness in improving economic growth and productivity remains an important issue for further study (Ahmad & Schreyer, 2016; Wang et al., 2022; Song et al., 2022).

The digital era has brought numerous technological advancements that enhance public activities and services. One of the most notable developments is digitalization, which involves converting printed, audio, and video media into digital formats. Digitalization has the potential to improve living standards, reduce unemployment, and serve as a key driver of economic and social activities in both developed and developing countries. Digital technologies contribute to economic growth through digital trade and online commerce, increased flexibility in banking operations, and improved communication systems, ultimately enhancing productivity and economic performance (Habibi & Zabardast, 2020).

Advances in digital technology also help reduce transaction costs across economic activities and enhance workers' skills and capabilities, thereby supporting economic growth, particularly in developing countries (Nguyen, 2023). Over the past decade, digitalization has accelerated globally, enabling the creation of new products and improving access to goods and services in developing regions (Asma et al., 2024). As a new phase of technological and economic development, the digital revolution has transformed daily life, created new economic opportunities, and emerged amid rising global tensions. The digital economy plays a central role in this transformation by stimulating business and entrepreneurial activities, strengthening competitiveness across industries, and providing new pathways for international market participation and integration into global electronic value chains (Limna et al., 2022). Despite its many benefits, the digital revolution has also generated negative effects that may adversely affect overall well-being (Tarafdar et al., 2015).

Indonesia, as one of the rapidly developing countries in the ASEAN and Asian regions, reflects these digital transformation dynamics. Digitalization has become a key catalyst in shaping Indonesia's economic landscape in the current digital era. Supported by advances in information and communication technology, Indonesia's business and industrial sectors have experienced substantial changes in production processes, global market engagement, and innovation. Digitalization has also created new opportunities for economic actors, ranging from large corporations to small and medium-sized enterprises, to improve efficiency, expand market reach, and enhance competitiveness (Gultom et al., 2024).

Rapid technological development and digitalization have driven the growth of Indonesia's digital economy, which is characterized by the expansion of technology-based businesses and digital trade transactions. In 2022, Indonesia's digital economy reached a value of IDR 714.4 trillion, representing a 27.6 percent increase compared to the previous year. Economic growth in Indonesia is increasingly supported by rising internet penetration, greater use of digital devices, and innovation across various economic sectors

(Abdillah, 2024). According to Statistics Indonesia (2023), the government aims for the digital economy to reach IDR 1,700 trillion by 2025. To achieve this target, the government has implemented policies to support digital economy development, including investment in digital infrastructure such as internet networks, data centres, and digital payment systems (Uddin, 2024), as well as regulations that promote digital industry growth and improve public digital literacy (Zhang et al., 2022; Octavianty et al., 2025).

Despite the rapid expansion of the digital economy, most existing studies on the relationship between digitalization and economic growth focus on developed countries and rely on linear analytical approaches. Research in Indonesia and other developing countries has not sufficiently explored the non-linear effects of digitalization, even though the digital economy is dynamic and influenced by complex internal and external factors. Therefore, this study aims to examine the impact of digitalization on Indonesia's economic growth using a spline approach. This method enables the identification of non-linear relationships and critical threshold points across different levels of digitalization, providing a more comprehensive understanding of how digitalization influences economic growth, innovation, and competitiveness in Indonesia.

LITERATURE REVIEW

Empirical Evidence on the Impact of ICT and Digitalization on Economic Growth

Early studies provide mixed evidence regarding the relationship between ICT and economic growth. Several researchers reported negative or insignificant effects of ICT investment on economic performance. Pohjola (2002), for example, analyzed 42 countries during 1985–1999 and found no significant relationship between ICT investment and economic growth. Similarly, Jacobsen (2003) identified a negative association between telecommunications infrastructure and economic growth across 84 countries in the period 1990–1999. In Japan, ICT investment was shown not to contribute directly to economic growth, although it helped reduce energy consumption (Ishida, 2015). Niebel (2018) also highlighted that ICT investment does not provide statistically superior growth benefits for developing and emerging economies compared to developed countries.

In contrast, a growing body of literature supports the positive role of ICT and digitalization in economic development. Ahmed and Ridzuan (2013), using panel data and GLS for ASEAN countries, found that telecommunications investment has a positive long-term effect on GDP. Focusing on Indonesia, Rath and Hermawan (2019) demonstrated that ICT development significantly stimulates economic growth in both the short and long run. Parviainen et al. (2017) further argued that highly digitalized countries enjoy substantially greater economic advantages than those at an early digital stage. Complementary evidence indicates that digitalization reduces unemployment, improves quality of life, enhances public service delivery, and supports better governance, thereby strengthening overall economic performance (Raeskyesa & Lukas, 2019; Habibi & Zabardast, 2020; Aleksandrova et al., 2022).

Application of Spline and MARS Methods in Socioeconomic and Engineering Studies

Spline-based nonparametric regression methods have been widely used in empirical studies, particularly when relationships among variables are nonlinear and difficult to specify using conventional parametric models. This approach is considered effective because it can capture changes in data patterns across different intervals through the use of knot points, resulting in more flexible and accurate models. For example, Alwi et al. (2023) applied spline nonparametric regression to model poverty levels in South Sulawesi. Their study was motivated by the absence of a clear functional relationship between poverty and its determinants. The results showed that a spline model with three optimal knot points provided strong explanatory power, with an R^2 value of 79.75%. These findings demonstrate that spline methods are well-suited to describing complex socioeconomic relationships involving variables such as unemployment, population growth, and literacy.

Beyond socioeconomic research, spline-based approaches have also been applied in engineering and predictive modelling. Naser et al. (2022) used Multivariate Adaptive Regression Splines (MARS) to predict the compressive strength of eco-friendly concrete. Through a five-fold cross-validation process, the optimized MARS model outperformed other machine learning methods, such as Random Forest and Support Vector Machine, in terms of predictive accuracy. The results indicate that spline-based models can provide reliable support for technical decision-making. Overall, previous studies confirm that spline regression offers strong flexibility and robustness in capturing nonlinear patterns across diverse research fields, including economics, social sciences, and engineering.

RESEARCH METHODS

This study employs one dependent variable, namely economic growth in each province of Indonesia. Economic growth is proxied by Gross Regional Domestic Product (GRDP) per capita, which represents regional economic performance. It is measured by the increase in GRDP per capita as an indicator of total income associated with the annual change in real GDP (Jones, 2002). Conceptually, economic growth reflects an increase in production and is defined as the inflation-adjusted rise in the market value of goods and services produced within a certain period (Thaddeus et al., 2020).

In addition, five independent variables are used to represent the level of digitalization in Indonesia, namely digital access, digital usage, digital capability, digital finance, and digital inequality. The study uses secondary cross-sectional data for the year 2023 covering 34 provinces. These indicators capture internet availability and utilization, digital literacy, adoption of digital payment systems, as well as regional competitiveness and the potential of the digital economy. All data are obtained from official and credible institutions, including BPS Indonesia, the Financial Services Authority, Bank Indonesia, and East Ventures, ensuring the reliability of the analysis.

Data analysis is conducted using a spline regression approach, a flexible polynomial method that can effectively adapt to complex data characteristics. This method is chosen for its high flexibility and efficiency in handling various types of variables (Eubank, 1998). Spline construction is based on an optimization framework (Prenter, 2008), and the accuracy of the estimation depends heavily on the selection of knot points that indicate changes in functional patterns across intervals (Eilers & Marx, 2010).

One of the main advantages of spline regression lies in its ability to capture sharp variations in data patterns through the use of knot points, resulting in well-fitted curves. Spline estimators can also generate estimates automatically, allowing the development of models that closely follow the data even when the data exhibit dynamic behavior (Brugnano et al., 2024). Suppose the observed data are $(x_{1i}, x_{2i}, \dots, x_{pi}, y_i)$, where the response variable y_i is related to predictors $(x_{1i}, x_{2i}, \dots, x_{pi})$. The corresponding nonparametric regression model can be expressed as follows (Hardle, 1990):

$$y_i = \sum_{j=1}^{p} f(x_{ji}) + \varepsilon_i \tag{1}$$

With $k_{1j}, k_{2j}, \dots, k_{mj}$denoting knot points that indicate changes in the function over certain intervals, and $q$representing the polynomial degree, the spline regression model can be written as follows (Perperoglou et al., 2019):

$$\begin{aligned} y_i = {} & \beta_{01} + \beta_{11}x_{1i} + \cdots + \beta_{q1}x_{1i}^q + a_{11}(x_{1i} - k_{11})_+^q \dots a_{m1}(x_{1i} - k_{m1})_+^q + \beta_{02} + \\ & \beta_{12}x_{2i} + \cdots + \beta_{q2}x_{2i}^q + a_{12}(x_{2i} - k_{12})_+^q \dots a_{m2}(x_{2i} - k_{m2})_+^q + \beta_{0p} + \\ & \beta_{p1}x_{pi} + \cdots + \beta_{qp}x_{pi}^q + a_{1p}(x_{pi} - k_{1p})_+^q \dots a_{mp}(x_{pi} - k_{mp})_+^q + \varepsilon_i \end{aligned} \tag{2}$$

Knot points play a crucial role in nonparametric spline regression because changes in data behavior may occur in specific intervals. The selection of the best spline estimator is determined using the Generalized Cross Validation (GCV) criterion, where the optimal model is identified based on the minimum GCV value. The GCV function is defined as follows (Zhang & Goh, 2013):

$$GCV(k_1, k_2, \dots, k_j) = \frac{MSE(k_1, k_2, \dots, k_j)}{[n^{-1}\text{Trace}(I - A(k_1, k_2, \dots, k_j))]^2} \quad (3)$$

The research procedure begins with descriptive statistical analysis, followed by economic growth modeling based on digitalization indicators, determining optimal node points using the smallest GCV value, spline estimation regression, as well as significance testing, R^2 calculation, and visualization of results in regional maps.

RESULTS

This section presents the empirical findings of the impact of digitalization indicators on economic growth across Indonesian provinces, measured by GRDP per capita in 2023. The analysis begins with descriptive statistics and spatial distribution to provide an overview of regional disparities, followed by correlation analysis to examine bivariate relationships among variables. Subsequently, the optimal spline regression model is identified using the Generalized Cross Validation (GCV) criterion, and parameter significance tests are conducted to determine the influence of each digitalization indicator. The results reveal non-linear patterns in the relationships, allowing for the identification of provincial clusters based on varying levels of digitalization and their corresponding contributions to economic growth potential.

Table 1. Descriptive Statistic

Variable	Mean	Variance	Std. Dev	Skewness	Kurtosis	Minimum	Maximum
GDPRC	47209.08824	1283063463	35819.87	2.715062	8.2622601	13513	192133
DAI	86.3332	89.39443	9.45486	-3.99178	20.295146	38.17	98.08
DUI	67.1644	108.4042	10.41173	-1.16162	4.1546507	29.87	86.71
DCI	70.0647	4.13992	2.03468	-0.91219	0.7306377	64.2	72.8
DFI	22.6082	251.60823	15.8565	0.799138	-0.145803	1.86	59.46
DII	41.2176	83.48573	9.13705	2.007569	5.3150566	28.9	75.6

Table 1 shows the differences in characteristics between provinces in Indonesia. Per capita GRDP (GDPRC) exhibits high variation and a right-skewed distribution, indicating unequal economic growth across regions. Digital Access (DAI) and Digital Usage (DUI) have high average values, indicating relatively good internet access and utilization, although some provinces still have low levels. Digital Capability (DCI) is relatively even with small variations between provinces. Meanwhile, Digital Finance (DFI) and Digital Inequality (DII) exhibit large variations, indicating gaps in the adoption of digital financial services and digital economic competitiveness between provinces.

The results of the regional distribution analysis for each of the variables used by province in Indonesia are shown in Figure 2. From the distribution of the indicators of economic growth and the digitalization indicators used, it can be seen that the more intense the colour produced in the region depicted, the higher the value of the indicators in the region.

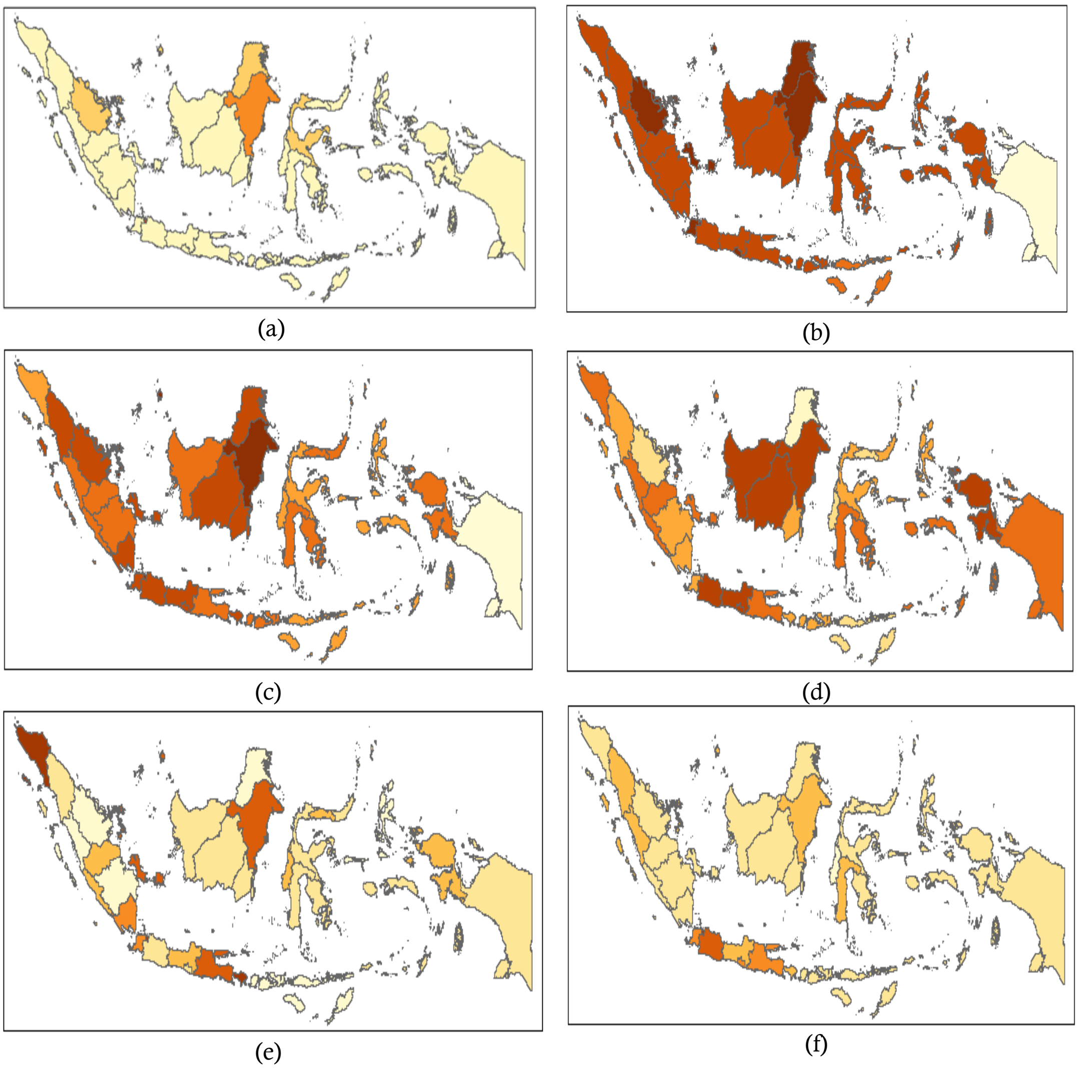

Figure 2. Spatial Distribution Map, (a) Economic Growth Variables, (b) Digital Access Indicator, (c) Digital Usage Indicator, (d) Digital Capability Indicator, (e) Digital Finance Indicator, (f) Digital Inequality Indicator

Following the descriptive analysis, a correlation test was performed to examine the relationships among the variables. Correlation analysis is commonly employed to measure and identify the degree of association between two or more variables, allowing researchers to determine the strength of these relationships.

From the correlation results illustrated in Figure 3, it is evident that each variable shows a perfect correlation with itself along the diagonal. Furthermore, the analysis reveals a strong positive relationship between economic growth and all digitalization indicators included in this study, except for the digital capability indicator.

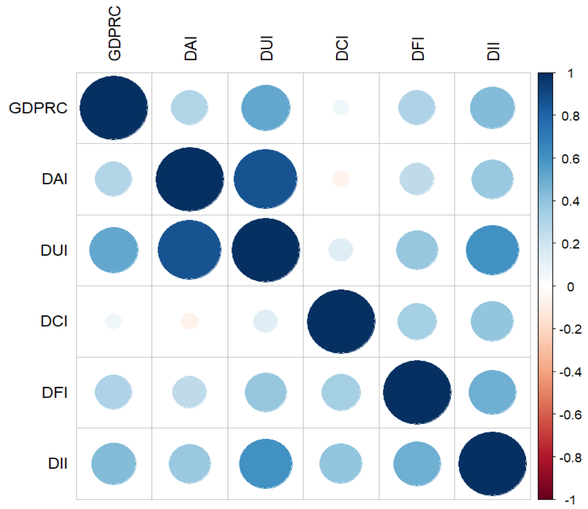

Figure 3. Correlation Plot

Figure 3 shows the correlation matrix between economic growth (GDPRC) and digitalization indicators. In general, all variables have a positive correlation. GDPRC is positively correlated with DAI, DUI, DFI, and DII, while its relationship with DCI is relatively weak. The strongest correlation is seen between DAI and DUI, indicating that better internet access leads to higher internet usage rates. Furthermore, DUI also has a fairly strong relationship with DII, reflecting the link between digital usage and digital economic competitiveness across regions.

Table 2. GCV Value Generated by Each Knot Point

No	Knot Point	GCV Value Generated
1	Knot Point 1	268388070
2	Knot Point 2	185872974
3	Knot Point 3	131621479

Table 2 indicates that the lowest GCV value is obtained at knot point 3, with a value of 131,621,479. Accordingly, the economic growth model based on digitalization indicators will use knot point 3, as presented in the following model Equation.

$$\begin{aligned}\hat{y} = 7168.859 &+ 69864.848DAI_1 + 114797.154(DAI_2 + 45.979) + 21991.377(DAI_3 + 58.096)\\ &+ 70814.392(DAI_4 + 92.022) + 27304.005DUI_1 + 97948.998(DUI_2 + 36.83)\\ &+ 9098.051(DUI_3 + 48.43) + 79752.894(DUI_4 + 80.91) + 82876.117DCI_1\\ &+ 25727.451(DCI_2 + 65.253) + 28503.659(DCI_3 + 67.008)\\ &+ 314281.827(DCI_4 + 71.922) + 99267.348DFI_1\\ &+ 113952.915(DFI_2 + 8.913) + 7426.18(DFI_3 + 20.668)\\ &+ 22579.706(DFI_4 + 53.582) + 58878.076DII_1 + 83795.038(DII_2 + 34.618)\\ &+ 19317.036(DII_3 + 44.148) + 45160.97(DII_4 + 70.834)\end{aligned}$$

Table 3. Simultaneous Parameter Test

<table>
<tr><th>Source of Variance</th><th>df</th><th>SS</th><th>MS</th><th>F</th><th>P-Value</th></tr>
<tr><td>Regresssion</td><td>20</td><td>25988301068</td><td>1299415053</td><td rowspan="3">3.032998</td><td rowspan="3">0.0489052</td></tr>
<tr><td>Error</td><td>13</td><td>16352793215</td><td rowspan="2">1257907170</td></tr>
<tr><td>Total</td><td>33</td><td>42341094282</td></tr>
</table>

Based on Table 3, the statistical test yields a p-value of 0.0489052. When compared with the chosen significance level, the decision is to reject the null hypothesis. This indicates that at least one variable significantly influences the constructed model. As a result, individual parameter testing is required to identify which specific variables have a significant effect. The outcomes of the individual tests are presented in Table 4.

Table 4. Individual Test

Variable	Parameter	Estimator	P-Value	Note
Constant	β_0	7167.859	0.0389705	Significant
DAI	β_1	69864.848	0.0089494	Significant
	β_2	114797.154	0.07200023	Not Significant
	β_3	21991.377	0.0197812	Significant
	β_4	70814.392	0.5817898	Not Significant
DUI	β_5	27304.005	0.0147016	Significant
	β_6	97948.998	0.0656112	Not Significant
	β_7	9098.051	0.6212975	Not Significant
	β_8	79752.894	0.0098623	Significant
DCI	β_9	82876.117	0.7492769	Not Significant
	β_{10}	25727.451	0.8044908	Not Significant
	β_{11}	28503.659	0.7614235	Not Significant
	β_{12}	314281.827	0.0032051	Significant
DFI	β_{13}	99267.348	0.7957309	Not Significant
	β_{14}	113952.915	0.0445693	Significant
	β_{15}	7426.18	0.64488	Not Significant
	β_{16}	22579.706	0.0523396	Not Significant
DII	β_{17}	58878.076	0.0362809	Significant
	β_{18}	83795.038	0.7559008	Not Significant
	β_{19}	19317.036	0.0190505	Significant
	β_{20}	45160.97	0.0214163	Significant

Table 4 shows that not all digitalization indicator parameters have a significant effect on economic growth. The constant is significant, indicating the existence of a baseline value for economic growth. For DAI, only β_1 and β_3 are significant, indicating that the influence of digital access on economic growth is uneven across segments. For DUI, β_5 and β_8 are significant, indicating that internet usage at a certain level contributes significantly to economic growth. For DCI, only β_{12} is significant, indicating that increasing digital capability at a high level has a significant impact on economic growth. For DFI, only β_{14} is significant, while for DII, β_{17}, β_{19}, and β_{20} are significant, confirming that different levels of digital inequality significantly affect economic growth. The final step of this analysis is to calculate the coefficient of determination, which indicates how well the model explains variations in economic growth based on the digitalization indicators used.

$$R^2 = \frac{SS_{Regresi}}{SS_{Total}} x100\% = \frac{25988301068}{42341094282} x100\% = 61.38\%$$

From these calculations, the coefficient of determination is found to be 61.38 percent. This indicates that the digitalization indicators used in the model account for 61.38 percent of the variation in Indonesia's economic growth, while the remaining percentage is influenced by other factors not examined in this study. After completing the analysis using the Spline method and confirming that the residual assumptions were satisfied, the findings indicate that the digitalization indicators employed have a significant impact on economic growth in Indonesia. The next step is to examine the potential for improving economic growth in each Indonesian province based on the digitalization indicators used. If the digital usage, digital capability, digital finance and digital inequality indicators are held constant, the influence of the digital access indicator on Indonesia's potential economic growth can be described as follows:

$$\hat{y} = 69864.848 DAI_1 + 114797.154(DAI_2 + 45.979) + 21991.377(DAI_3 + 58.096) + 70814.392(DAI_4 + 92.022)$$

$$\hat{y} = \begin{cases} 69864.848; DAI_1 < 45.979 \\ 184662.002; 45.979 \leq DAI_2 > 58.096 \\ 206653.379; 58.096 \leq DAI_3 > 92.022 \\ 277467.771; DAI_4 > 92.022 \end{cases}$$

Based on the model equation, three regional clusters are identified according to the Spline breakpoints, showing how the Digital Access Indicator influences Indonesia's economic growth. These regional groupings are illustrated in Figure 4.

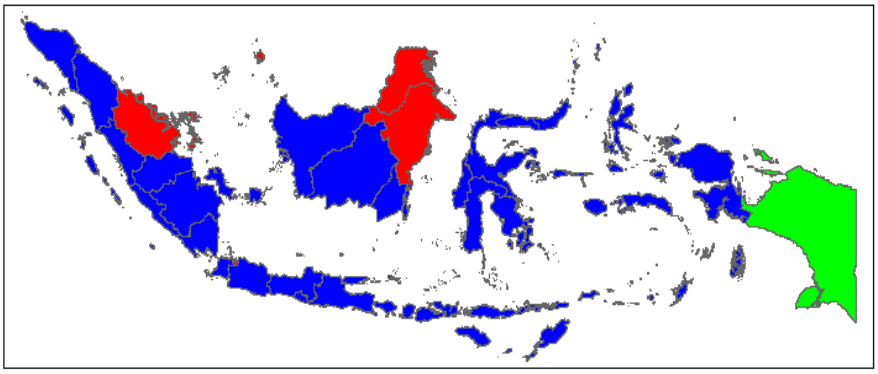

Figure 4. Provincial Clusters in Indonesia based on Digital Access Indicator

Figure 4 shows that provinces with a DAI Indicator below 45.979 fall into the low category, where their potential GDP per capita increase is estimated at 69,864.848 thousand rupiah. Provinces with a Digital Access Indicator ranging from 59.096 to 92.022 are classified as high, with a projected rise in GDP per capita of 206,653.379 thousand rupiah. Meanwhile, provinces whose Digital Access Indicator exceeds 92.022 belong to the very high category, showing a potential GDP per capita increase of 277,467.771 thousand rupiah. If the digital access, digital capability, digital finance and digital inequality indicators are held constant, the influence of the digital usage indicator on Indonesia's potential economic growth is as follows:

$$\hat{y} = 27304.005DUI_1 + 97948.998(DUI_2 + 36.83) + 9098.051(DUI_3 + 48.43) + 79752.894(DUI_4 + 80.91)$$

$$\hat{y} = \begin{cases} 27304.005; DUI_1 < 36.83 \\ 125253.003; 36.83 \leq DUI_2 > 48.43 \\ 134351.054; 48.43 \leq DUI_3 > 80.91 \\ 214103.948; DUI_4 > 80.91 \end{cases}$$

Based on the model equation, three regional clusters emerge from the Spline breakpoints for the DUI, each reflecting its influence on Indonesia's economic growth. These clusters are illustrated in Figure 5.

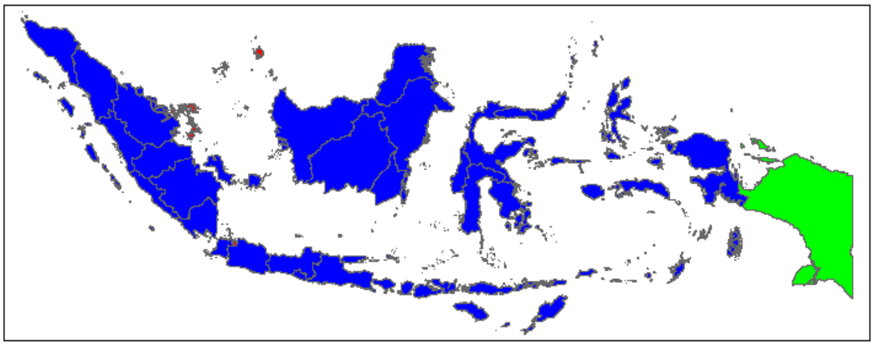

Figure 5. Provincial Clusters in Indonesia based on Digital Usage Indicator

Figure 5 shows that provinces with a DUI <36.83 are in the low category, with a potential increase in GRDP per capita of 27,304,005 thousand rupiah. Provinces with a value of 48.43–80.91 are in the high category, with the potential to increase GRDP per capita by 134,351,054 thousand rupiah. Meanwhile, provinces with a Digital Usage Indicator >80.91 are in the very high category, with a potential increase in GRDP per capita of 214,103,948 thousand rupiah. If the digital access, digital usage, digital finance and digital inequality indicators are considered constant, the effect of digital capability indicator on the potential for economic growth in Indonesia is as follows.

$$\hat{y} = 82876.117DCI_1 + 25727.451(DCI_2 + 65.253) + 28503.659(DCI_3 + 67.008) + 314281.827(DCI_4 + 71.922)$$

$$\hat{y} = \begin{cases} 82876.117; DCI_1 < 65.253 \\ 109603.568; 65.253 \le DCI_2 > 67.008 \\ 137107.227; 67.008 \le DCI_3 > 71.922 \\ 451389.54;\ DCI_4 > 71.922 \end{cases}$$

Based on the model equation, four regional clusters are identified from the Spline breakpoints for the Digital Capability Indicator, each showing its influence on Indonesia's economic growth. These clusters are presented in Figure 6.

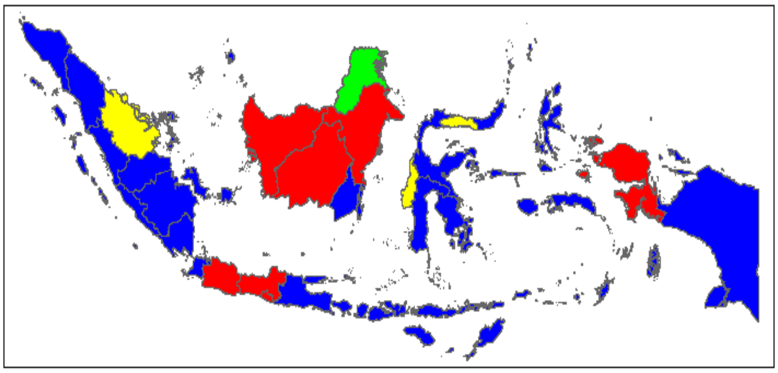

Figure 6. Provincial Clusters in Indonesia based on Digital Capability Indicator

Figure 6 shows that provinces with a DUI below 65.253 fall into the low category, with a potential GDP per capita increase of 82,876.117 thousand rupiah. Those with an indicator value between 65.253 and 67.008 are classified as medium, showing a potential rise of 109,603.658 thousand rupiah. Provinces scoring between 67.008 and 71.922 are placed in the high category, with an estimated GDP per capita increase of 137,107.227 thousand rupiah. Meanwhile, provinces with a Digital Capability Indicator above 71.992 belong to the very high category, exhibiting a potential GDP per capita increase of 451,389.54 thousand rupiah. If the digital access, digital usage, digital capability and digital inequality indicators are held constant, the influence of the digital finance indicator on Indonesia's potential economic growth is as follows:

$$\hat{y} = 99267.348DFI_1 + 113952.915(DFI_2 + 8.913) + 7426.18(DFI_3 + 20.668) + 22579.706(DFI_4 + 53.582)$$

$$\hat{y} = \begin{cases} 99267.348; DFI_1 < 8.913 \\ 213220.263; 8.913 \leq DFI_2 > 20.668 \\ 220646.443; 20.668 \leq DFI_3 > 53.582 \\ 243226.149;\ DFI_4 > 53.582 \end{cases}$$

Based on the model equation, four regional clusters emerge from the Spline breakpoints for the Digital Finance Indicator, each reflecting its impact on Indonesia's economic growth. These clusters are illustrated in Figure 7.

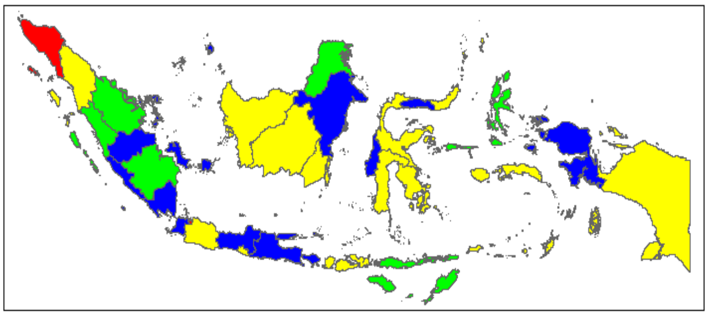

Figure 7. Provincial Clusters in Indonesia based on Digital Finance Indicator

Figure 7 shows that provinces with a Digital Finance Indicator below 8.913 fall into the low category, with a potential GDP per capita increase of 99,267.348 thousand rupiah. Those with indicator values between 8.913 and 20.668 belong to the medium category, with an estimated increase of 213,220.268 thousand rupiah. Provinces scoring between 20.668 and 53.582 are classified as high, showing a potential GDP per capita rise of 220,646.443 thousand rupiah. Meanwhile, provinces with a Digital Finance Indicator above 53.582 are in the very high category, with a projected increase of 243,226.149 thousand rupiah. If the digital access, digital usage, digital capability and digital finance indicators are held constant, the influence of the digital inequality indicator on Indonesia's potential economic growth is as follows.

$$\hat{y} = 58878.076DII_1 + 83795.038(DII_2 + 34.618) + 19317.036(DII_3 + 44.148) + 45160.97(DII_4 + 70.834)$$

$$\hat{y} = \begin{cases} 58878.076; DII_1 < 34.618 \\ 142673.114; 34.618 \leq DII_2 > 44.148 \\ 335850.15; 44.148 \leq DII_3 > 70.834 \\ 381011.12;\ DII_4 > 70.834 \end{cases}$$

Based on the estimated model, four regional clusters were identified from the Digital Finance Indicator, each exerting a distinct influence on Indonesia's economic growth according to the resulting spline segmentation. These regional groupings are illustrated in Figure 8.

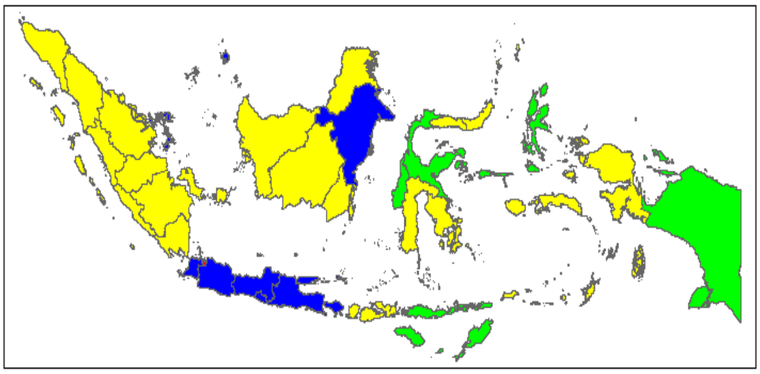

Figure 8. Provincial Clusters in Indonesia based on Digital Inequality Indicator

Figure 8 shows that provinces with a Digital Inequality Indicator below 34.618 are classified in the low category and are projected to experience an increase in GDP per capita of approximately 58,878.076 thousand Rupiah. Provinces with an indicator ranging from 34.618 to 44.148 fall into the medium category, with a potential GDP per capita rise of about 142,647.114 thousand Rupiah. Those with values between 44.148 and 70.834 are considered in the high category and may see an estimated increase of 335,850.15 thousand Rupiah. Meanwhile, provinces with a Digital Inequality Indicator above 70.834 classified as very high are expected to record an increase of around 381,011.12 thousand Rupiah in GDP per capita.

DISCUSSION

The results of this study indicate that digitalization has a significant impact on economic growth in Indonesia. The digital access indicator, which reflects the availability and ease of access to digital technology across provinces, provides the largest contribution to the increase in GRDP per capita in provinces classified as very high. This finding suggests that the development of better digital infrastructure can substantially enhance regional economic capacity. This result is consistent with Parviainen et al. (2017), who argue that countries or regions with higher levels of digitalization gain greater economic benefits compared to those at an early stage of digital development.

The digital usage indicator also shows a positive and significant relationship with increases in GDP per capita. Provinces with higher levels of digital technology usage are able to exploit broader economic opportunities. This finding supports the studies of Ahmed and Ridzuan (2013) and Rath and Hermawan (2019), which demonstrate that the development and utilization of Information and Communication Technology (ICT) contribute positively to economic growth, both in the short and long term, particularly in Indonesia and the ASEAN region.

The digital capability indicator is another important factor in driving economic growth. Provinces with very high levels of digital capability experience substantially larger increases in GRDP per capita compared to other categories. This highlights the importance of improving digital skills and literacy so that technology can be utilized more effectively across various economic sectors. This finding aligns with Habibi and Zabardast (2020) and Han et al. (2022), who show that ICT contributes positively to economic growth regardless of a country's level of development and plays a role in enhancing productivity and human capital quality.

Meanwhile, the digital finance indicator indicates that the use of digital-based financial services also plays a significant role in supporting economic growth, particularly in provinces classified as very high. This suggests that digital financial inclusion and literacy can stimulate economic activity by improving transaction efficiency and access to financial services. This result is consistent with the literature emphasizing the role of digitalization in expanding financial inclusion and strengthening regional economic performance.

The digital inequality indicator provides noteworthy findings. Although digital inequality can constrain economic potential in some provinces, the results show that reducing the digital divide can significantly increase GDP per capita. This underscores the importance of policies aimed at narrowing digital disparities, both through equitable infrastructure development and improved digital literacy in less developed regions. This finding supports Aleksandrova et al. (2022) and Kravtsov et al. (2022), who argue that digitalization can enhance quality of life, governance, and economic performance when accompanied by more equal access.

However, these findings are not entirely consistent with several earlier studies that reported negative or insignificant effects of ICT on economic growth, such as Pohjola (2002), Jacobsen (2003), Ishida (2015), and Niebel (2018). These differences may be attributed to variations in regional context, time periods, and methodological approaches. By employing a nonparametric spline approach, this study is able to capture non-linear relationships between digitalization and economic growth that may not be detected by conventional linear models. Thus, these findings confirm that digitalization, when managed appropriately and inclusively, can serve as a key catalyst for sustainable economic growth, both in Indonesia and in other developing countries.

CONCLUSION

This study concludes that digitalization has a significant impact on economic growth in Indonesia. Based on the spline analysis, digital access, digital usage, digital capability, digital finance, and digital inequality indicators are proven to influence the increase in GRDP per capita across provinces. The main finding shows that provinces with higher levels of digitalization tend to have greater economic growth potential, while provinces with lower levels of digitalization experience more limited growth. This confirms the strategic role of digitalization in strengthening regional economic capacity. The implications of these findings indicate that inclusive and sustainable economic growth is highly dependent on the quality and equitable distribution of digitalization. Improvements in digital infrastructure, wider adoption of digital technology, stronger digital capabilities among the population, and the development of digital financial services are essential factors in supporting regional economic performance. In addition, the results related to digital inequality highlight that gaps in digital access and usage remain a major challenge, as they can slow down economic growth in less developed regions.

Based on these findings, this study recommends the implementation of an integrated and regionally balanced digitalization strategy. Such efforts should focus not only on expanding digital infrastructure but also on increasing digital usage, enhancing digital skills, and reducing digital inequality so that economic benefits can be shared more evenly across regions. For future research, it is recommended to continue using or further developing non-linear approaches such as spline methods, as the relationship between digitalization and economic growth is complex and cannot always be adequately captured by linear models.

REFERENCES

[1] Abdillah, F. (2024). The impact of digital economy on economic growth in Indonesia. *BENEFIT: Journal of Business, Economics, and Finance, 2*(1), 27–35.

[2] Ahmad, N., & Schreyer, P. (2016). Are GDP and productivity up to the challenges of the digital economy? *International Productivity Monitor, 30*, 4–27.

[3] Ahmed, E. M., & Ridzuan, R. (2013). The impact of ICT on East Asian economic growth: Panel estimation approach. *Journal of the Knowledge Economy, 4*(4), 540–555.

[4] Aleksandrova, A., Tryntsevsky, Y., & Polutova, M. (2022). Digitalization and its impact on economic growth. *Brazilian Journal of Political Economy, 42*(2), 424–442.

[5] Alwi, W., Irwan, Ermawati, Nurman, T. A., Hernawati, & Ibnas, R. (2023). Modeling of poverty level in South Sulawesi Province through spline nonparametric regression approach. *Communications in Mathematical Biology and Neuroscience, 2023*(12), 1–18.

[6] Asma, H., Batool, S., & Rehman, B. (2024). Impact of digitalization on economic growth in developing countries: A panel ARDL analysis. *Qlantic: Journal of Social Sciences, 5*(3), 11–23.

[7] Brugnano, L., Giordano, D., Lavernaro, F., & Rubino, G. (2024). An entropy-based approach for a robust least squares spline approximation. *Journal of Computational and Applied Mathematics, 443*(1), 115-133.

[8] Efendi, B., Nasution, D. P., Rusiadi, R., & Pratiwi, D. (2025). The impact human development index and industrial labor on economic growth in North Sumatra Province. *Jurnal Ilmiah Akuntansi Kesatuan, 13*(3), 643–654.

[9] Eilers, P. H. C., & Marx, B. D. (2010). Splines, knots, and penalties. *Wiley Interdisciplinary Reviews: Computational Statistics, 2*(6), 637–653.

[10] Eubank, R. L. (1998). *Spline smoothing and nonparametric regression*. New York, NY: Marcel Dekker.

[11] Gultom, D., Hutabarat, G. S. P., Dirgantara, M., Pratama, R., & Hidayah, A. (2024). Positive impact of digitalization on the Indonesia economy. *Jurnal Konstanta: Ekonomi Pembangunan, 3*(1), 107–116.

[12] Habibi, F., & Zabardast, M. A. (2020). Digitalization, education and economic growth: A comparative analysis of Middle East and OECD countries. *Technology in Society, 63*(3), 360-370.

[13] Han, D., Ding, Y., Shi, Z., & He, Y. (2022). The impact of digital economy on total factor carbon productivity: The threshold effect of technology accumulation. *Environmental Science and Pollution Research, 29*(37), 55691–55706.

[14] Hardle, W. (1990). *Applied nonparametric regression*. New York, NY: Cambridge University Press.

[15] Heimerl, V., & Raza, W. (2018). *Digitalization and development cooperation: An assessment of the debate and its implications for policy*. Vienna: Austrian Foundation for Development Research.

[16] Ishida, H. (2015). The effect of ICT development on economic growth and energy consumption in Japan. *Telematics and Informatics, 32*(1), 79–88.

[17] Jacobsen, K. F. L. (2003). *Telecommunications: A means to economic growth in developing countries?*. Bergen: Chr. Michelsen Institute.

[18] Jones, R. (2002). The necessity of the unconscious. *Journal for the Theory of Social Behavior, 32*(3), 344–365.

[19] Kravtsov, D., Bragaru, T., & Gyrlea, M. (2022). Digitalization and sustainable growth in the quality of life. *ARA Journal of Sciences, 5*(1), 125–131.

[20] Limna, P., Kraiwanit, T., & Siripipatthanakul, S. (2022). The growing trend of digital economy: A review article. *International Journal of Computing Sciences Research, 6*(1), 1–11.

[21] Naser, A., Badr, A., Henedy, S. N., Ostrowski, K. A., & Imran, H. (2022). Application of multivariate adaptive regression splines (MARS) approach in prediction of compressive strength of eco-friendly concrete. *Case Studies in Construction Materials, 17*(1), 12-22.

[22] Nguyen, T. H. (2023). Cooperation between universities and businesses in developing human resources to participate in the digital economy. *Journal of the Knowledge Economy, 15*(2), 5230–5249.

[23] Niebel, T. (2018). ICT and economic growth: Comparing developing, emerging and developed countries. *World Development, 104*(1), 197–211.

[24] Octavianty, E., Ilmiyono, A. F., Tartilla, N., & Andriani, D. D. (2025). Stock price determinants in defensive industries: the role of macroeconomic factors and profit growth in Indonesia's pharmaceutical sector. *Jurnal Ilmiah Akuntansi Kesatuan, 13*(4), 1011–1014.

[25] Parida, V., Sjödin, D., & Reim, W. (2019). Reviewing literature on digitalization, business model innovation, and sustainable industry. *Sustainability, 11*(2), 391–410.

[26] Parviainen, P., Tihinen, M., Kääriäinen, J., & Teppola, S. (2017). Tackling the digitalization challenge: How to benefit from digitalization in practice. *International Journal of Information Systems and Project Management, 5*(1), 63–77.

[27] Perperoglou, A., Sauerbrei, W., & Abrahamowicz, M. (2019). A review of spline function procedures in R. *BMC Medical Research Methodology, 19*(1), 46–60.

[28] Pohjola, M. (2002). The new economy in growth and development. *Oxford Review of Economic Policy, 18*(3), 380–396.

[29] Prenter, P. M. (2008). *Splines and variational methods*. Mineola, NY: Dover Publications.

[30] Raeskyesa, D. G. S., & Lukas, E. N. (2019). Does digitalization increase economic growth? Evidence from ASEAN-8 countries. *Indonesia Economic Journal, 8*(2), 267–278.

[31] Rath, B. N., & Hermawan, D. (2019). Do information and communication technologies foster economic growth in Indonesia? *Bulletin of Monetary Economics and Banking, 22*(1), 103–122.

[32] Rojko, A. (2017). Industry 4.0 concept: Background and overview. *International Journal of Interactive Mobile Technologies, 11*(5), 77–90.

[33] Song, M., Peng, L., Shang, Y., & Zhao, X. (2022). Green technology progress and total factor productivity of resource-based enterprises: A perspective of technical compensation of environmental regulation. *Technological Forecasting and Social Change, 174*(1), 121-136.

[34] Tarafdar, M., Gupta, A., & Turel, O. (2015). Editorial. *Information Systems Journal, 25*(3), 161–170.

[35] Thaddeus, K., Ngong, C., & Manasseh, C. (2020). Digital financial inclusion and economic growth: Evidence from Sub-Saharan Africa (2011–2017). *International Journal of Business and Management, 8*(4), 212–225.

[36] Uddin, M. R. (2024). The role of the digital economy in Bangladesh's economic development. *Sustainable Technology and Entrepreneurship, 3*(1), 100-114.

[37] Wang, J., Wang, W., Ran, Q., Irfan, M., Ren, S., Yang, X., ... & Ahmad, M. (2022). Analysis of the mechanism of the impact of internet development on green economic growth: Evidence from 269 prefecture cities in China. *Environmental Science and Pollution Research, 29*(7), 9990–10004.

[38] Watanabe, C., Moriya, K., Tou, Y., & Neittaanmäki, P. (2018). Consequences of the digital economy: Transformation of the growth concept. *International Journal of Managing Information Technology, 10*(2), 21–39.

[39] Zhang, J., Zhao, W., Cheng, B., Li, A., Wang, Y., Yang, N., & Tian, Y. (2022). The impact of digital economy on economic growth and development strategies in the post-COVID-19 era. *Frontiers in Public Health, 10*, 1–17.

[40] Zhang, W., & Goh, A. T. C. (2013). Multivariate adaptive regression splines for analysis of geotechnical engineering systems. *Computers and Geotechnics, 48*, 82–95.