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The Impact of Digital Technology on Environmental Quality: An Empirical Evidence from Indonesia

Fitri Kartiasih[1*], Hanifah Putri Rosanti[2], Sabrina Do Miswa[3], Arif Rahman Hakim[4]
[1]DIV Statistics Study Program, Politeknik Statistika STIS, Indonesia
[2]BPS-Statistics of North Kolaka Regency, Indonesia
[3]BPS-Statistics of Balikpapan City, Indonesia
[4]The Postgraduate School, Universitas Airlangga, Indonesia
E-mail: [1]fkartiasih@stis.ac.id, [2]hanifah.putri@bps.go.id, [3]sabrina.domiswa@bps.go.id, [4]arif.rahman@pasca.unair.ac.id
[*]**Corresponding author**

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ABSTRACT

Research Originality: This research investigates how digital technologies influence environmental quality in Indonesia.

Research Objectives: This study examines the impact of digital technologies and socioeconomic variables on environmental quality in Indonesia.

Research Methods: This study employs the System-Generalized Method of Moments (GMM) approach and analyzes data from 2013 to 2023. Key variables include digital technology, gross regional domestic product (GRDP), foreign direct investment (FDI), and mean years of schooling.

Empirical Results: Computer ownership negatively impacts environmental quality due to higher energy consumption and e-waste. In contrast, GRDP improves environmental quality as wealthier regions invest in green infrastructure and stricter policies. FDI has a harmful effect, supporting the 'pollution haven' hypothesis of resource exploitation and unsustainable practices. Education fosters environmental awareness, though its influence is still limited.

Implications: Digital technologies can enhance environmental quality, requiring strategic planning and continuous innovation by central and local governments.

Keywords:
digital technology; environmental quality; sustainable development

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INTRODUCTION

The issue of environmental sustainability and conservation has garnered global attention (Adebayo & Kirikkaleli, 2021; Nathaniel et al., 2021). Environmental challenges persist in many countries, primarily driven by economic activities (Majeed & Luni, 2019). Since the 1972 Stockholm Conference, concerns about the environmental impact of human activities and their link to economic growth have been widely acknowledged (Shi et al., 2019). The Brundtland Report, published by the World Commission on Environment and Development (WCED) in 1987, introduced and popularized the concept of "sustainable development," which has since served as a fundamental framework for developing more practical sustainability strategies. Today, sustainable development emphasizes environmental protection for future generations and the advancement of social and economic well-being. Many nations are actively working to address the challenges posed by environmental degradation while striving for sustainable economic growth (Ali et al., 2019).

Development in Indonesia brings both positive and negative impacts, often conflicting with the principles of sustainable development (Maryunani, 2018). Economic growth is a positive outcome, while environmental degradation is a significant downside. Natural resources are crucial to a country's economic prosperity (Pribadi & Kartiasih, 2020). However, the environmental carrying capacity is often overlooked when pursuing rapid economic expansion. Consequently, such growth tends to yield short-term benefits while causing significant long-term environmental harm. Sustainable economic progress depends on the efficient, effective, and responsible utilization of natural resources (Saleh et al., 2020). Given Indonesia's abundant natural resources, its economy heavily relies on exploitation. However, unsustainable practices in mining, agriculture, industrialization, and deforestation contribute to environmental destruction (Danish et al., 2019; Miswa & Kartiasih, 2025). In 2024, Indonesia ranked 164th out of 180 countries on the Environmental Performance Index (EPI), with a score of 28.2, indicating poor environmental quality (Block et al., 2024). This ranking highlights Indonesia's significant challenge in balancing economic development with environmental sustainability.

The rapid advancement of information and communication technology (ICT) is driving a global shift towards digitalization in economic activities (Kartiasih et al., 2023, 2023a, 2023b). Technologies like the internet, big data, cloud computing, and artificial intelligence are being developed, implemented, and integrated into various sectors, giving rise to a new economic model known as the digital economy (Zhu et al., 2022). The digital economy leverages ICT to enhance productivity and optimize economic structures (Wang et al., 2022).

Over the past decade, the rise of digital technology has provided new impetus for economic growth (Li et al., 2020). Amidst the global environmental crisis, digital technology presents opportunities for more effective solutions to environmental challenges (Broo et al., 2021). Recognizing its significance, the United Nations General Assembly (UNGA) identified digital technology as a crucial factor in achieving the Sustainable Development Goals (SDGs) for 2016–2030 (Yang et al., 2022). The digital economy is viewed as a means to address economic development challenges, particularly externalities

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associated with economic activities. Traditional products and services are increasingly being replaced by digital alternatives, such as e-banking, e-commerce, e-books, online education, and virtual meetings (Ahmed & Le, 2021). These shifts contribute to reduced resource consumption and energy use through dematerialization and decreased travel (Ahmed & Le, 2021). However, efforts to expand digital technology have also led to a surge in infrastructure demands and higher energy consumption, ultimately potentially increasing CO_2 emissions more than mitigating them (Zhou et al., 2019). Several studies, including those by Wang et al. (2022), Zhu et al. (2022), Li et al. (2021), and Sultana et al. (2022), have analyzed the impact of digital technology on environmental quality, particularly CO_2 emissions while considering geographical factors.

The debate on the environmental impact of digital technologies is divided between their potential to promote sustainability and their unintended negative consequences. On the positive side, digitalization enhances energy efficiency through smart grids, AI-driven management, and real-time monitoring, reducing waste and emissions (Zhang et al., 2021). It also supports sustainable production via Industry 4.0 technologies, optimizing resource use and promoting circular economy practices (Geissdoerfer et al., 2017). Additionally, digital tools enable environmental monitoring through satellite imaging and big data analytics, aiding conservation and disaster management (Wang et al., 2022; Rolnick et al., 2019). Furthermore, digitalization contributes to decarbonization by facilitating remote work and e-commerce, reducing transportation-related emissions (Hook et al., 2020).

However, digital technologies also pose environmental risks. The rapid growth of electronic devices has led to rising e-waste, with inadequate recycling infrastructure exacerbating pollution (Baldé et al., 2020). The high energy demand of data centers and blockchain technology significantly contributes to carbon emissions, especially in regions reliant on fossil fuels (Jones, 2018). Furthermore, the extraction of rare earth metals for digital infrastructure causes deforestation and water contamination (Ali et al., 2017). Lastly, the rebound effect, where efficiency gains lead to increased consumption, offsets environmental benefits, as evidenced by greater energy use, digital consumerism, and rising waste generation (Santarius et al., 2018; Wiedmann & Lenzen, 2018). Thus, while digitalization presents opportunities for sustainability, its ecological footprint must be carefully managed.

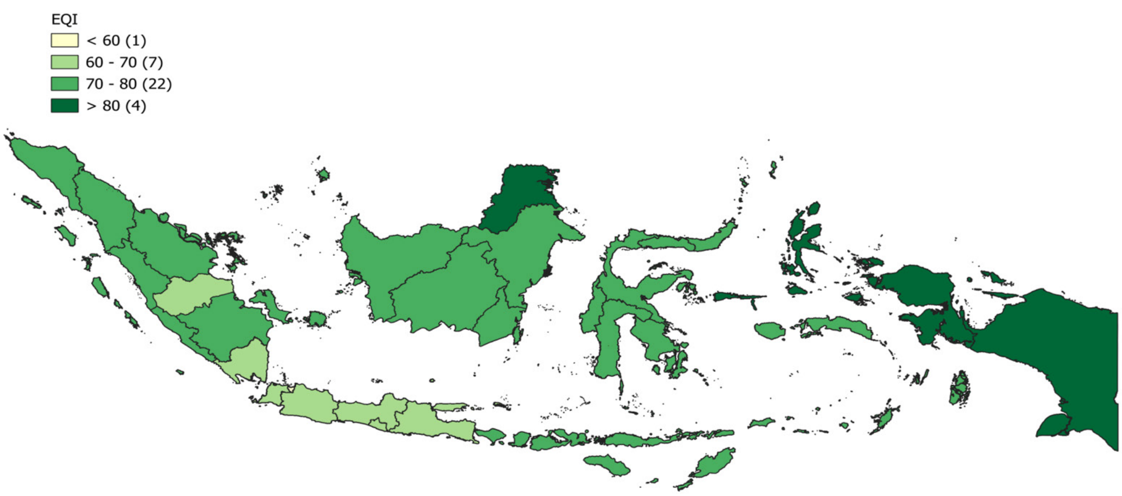
Numerous studies have examined the impact of digital technology on environmental quality in China (Huang et al., 2023; Li et al., 2021; Yang et al., 2022; Zhang et al., 2023; Zhao et al., 2023). However, such studies for the Indonesian region are still limited. Research linking digital technology to environmental quality in Indonesia is scarce. There could be unforeseen detrimental effects of digital technologies on sustainable development (Li et al., 2020). There is still a lack of research on the impact of digital technology on environmental performance and sustainability. Therefore, this study aims to analyze the impact of digital technologies and socio-economic variables on environmental quality. Even though digital technology in Indonesia has great potential to continue to grow so that it can have an impact on environmental conditions in the future, this study utilizes an empirical approach to strengthen the argument and represent one of the actively developing countries in the Asian region, using Indonesia as a case study.

This study differs from previous digital technology and environmental quality research in two key aspects. First, we apply the Generalized Method of Moments (GMM) estimation technique to analyze the impact of digital technology on environmental quality. Earlier studies have taken different approaches, including a systematic literature review (Aniqoh, 2020; Charfeddine & Umlai, 2023), a spatial regression model (Zhu et al., 2022), and static panel data analysis (Li et al., 2021). GMM is a robust method that addresses endogeneity through instrumentation (simultaneity) and considers time-invariant omitted variables. Furthermore, it mitigates over-identification issues and accounts for cross-sectional dependencies (Baltagi, 2008). Second, we incorporate three key indicators of digital technology: the percentage of internet users, mobile phone penetration, and computer ownership. The study's results demonstrate that these digital technology indicators have distinct effects on environmental quality. In contrast, prior research, such as Wang et al. (2022) and Zhu et al. (2022), primarily relied on digital economy indexes.

METHODS

This study covers 34 provinces in Indonesia from 2013 to 2023, as seen in Figure 1. Most Indonesians still live below poverty (Tohari et al., 2019). There are many areas with high poverty rates, especially in eastern Indonesia, which includes Papua, West Papua, Maluku, East Nusa Tenggara, West Nusa Tenggara, Central Sulawesi, West Sulawesi, as well as two areas in western Indonesia, namely South Sumatra, and Aceh. Meanwhile, areas with moderate poverty rates are mostly located in western Indonesia, including North Sumatra, Jambi, Riau, Lampung, North Kalimantan, West Java, Central Java, Yogyakarta, East Java, and three areas in eastern Indonesia, namely Southeast Sulawesi, North Sulawesi, and South Sulawesi. Similarly, areas with low poverty rates are mostly located in western Indonesia. The geographical condition, high diversity, population size, and many other factors pose significant challenges in alleviating poverty in Indonesia (Nugroho et al., 2021).

Figure 1. Environmental quality index in Indonesia, 2023



Source: The Ministry of Environment and Forestry, processed.

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The key dependent variable in this study is the Environmental Quality Index (EQI), which serves as a composite measure of environmental conditions. The EQI ranges from 0 to 100 and is derived from four sub-indices: the water quality index, air quality index, land quality index, and seawater quality index. The data on EQI is collected from the Ministry of Environment and Forestry.

The independent variable of interest, digital technology (DT), is represented by three key indicators: internet users, mobile phone penetration, and computer ownership. Control variables include Gross Regional Domestic Product (GRDP), Foreign Direct Investment (FDI), and Mean Years of Schooling (MYS). GRDP is measured in billions of rupiah at constant 2010 prices, while FDI is expressed in millions of USD. MYS reflects the average years of schooling among the population. These control variables are obtained from BPS-Statistics Indonesia. Since GRDP is frequently linked to environmental quality in existing literature, a natural logarithm transformation is applied to improve the accuracy of the estimates and address heteroscedasticity issues (Nosheen et al., 2020). The transformation also helps normalize the data distribution, making it more symmetrical.

FDI is included in the model as it can positively and negatively affect environmental quality. While it can stimulate economic growth through capital infusion, managerial expertise, and technology transfer, it may also lead to environmental degradation if directed toward highly polluting industries (Bekun et al., 2024). The environmental impact of FDI is influenced by the source country's policies rather than the host country's regulations (Adeel-Farooq et al., 2021). Education, represented by MYS, is another critical factor. Studies suggest that higher education levels can lead to better environmental awareness and reduced carbon emissions Zafar et al. (2020). However, in many developing countries, environmental sustainability is not emphasized in the education system, limiting its impact on environmental protection (Zhang et al., 2022).

This study employs a regression model to analyze the effects of digital technology and socioeconomic factors on environmental quality. The initial static model is formulated as follows:

$$EQI_{it} = \beta_0 + \beta_1 DT_{it} + X'_{it} + \varepsilon_{it} \qquad (1)$$

where EQI_{it} is the Environmental Quality Index for province i at time t, DT_{it} is digital technology indicators, X'_{it} are vector of control variables (GRDP, FDI, and MYS), β_0 and ε_{it} are the constant and the error term, respectively.

Since static models may not fully capture the dynamics of the relationship, the model is extended to a dynamic specification by incorporating the lagged dependent variable as an explanatory variable:

$$EQI_{it} = \beta_0 + \beta_1 EQI(-1) + \beta_2 DT + \beta_3 \ln GRDP + \beta_4 FDI + \beta_5 MYS + \varepsilon_{it} \qquad (2)$$

In this dynamic model, EQI_{it} accounts for persistence in environmental quality over time.

The study employs the Generalized Method of Moments (GMM) estimator to estimate this dynamic panel model, following the framework proposed by Arellano &

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Bond (1991) and later refined by Arellano & Bover (1995) and Roodman (2009). GMM is chosen for three primary reasons: (1). Panel Data Suitability: The study's dataset structure (N = 34, T = 11) aligns with the GMM framework, which is well-suited for handling panel data with more cross-sectional units (N) than periods (T); (2). Endogeneity Control: GMM effectively addresses endogeneity issues by using lagged values as instruments, thereby controlling for simultaneity bias; and (3). Robustness to Unobserved Heterogeneity: The method accounts for omitted variables that do not change over time, ensuring unbiased estimation.

The study employs the "Difference GMM" approach, which transforms regressors by taking first differences to eliminate fixed effects. However, different GMMs have limitations, such as weak instrument bias in small samples. To overcome this, the "System GMM" estimator is also utilized, which incorporates both level and difference equations to improve efficiency (Blundell & Bond, 2023). For reliability, GMM estimates must meet two key diagnostic criteria: (1). Autocorrelation Test: The Arellano-Bond test for AR(1) and AR(2) is conducted to ensure the absence of second-order autocorrelation. The model may suffer from autocorrelation issues if the AR(2) test is significant. (2). Instrument Validity Test: The Hansen J-test is applied to confirm the validity of instrumental variables. A rejection of the null hypothesis indicates potential over-identification problems, questioning the reliability of the instruments. By employing the System-GMM method, this study provides a more robust understanding of the dynamic relationship between digital technology and environmental quality, accounting for both short-term and long-term effects.

RESULTS AND DISCUSSION

Initial insights into the relationship between environmental quality, digital technology, and socioeconomic variables are presented in Tables 1 and 2, which include descriptive statistics and the correlation matrix. The estimation results indicate that the System-GMM approach is more effective than FD-GMM in enhancing parameter estimation accuracy. The findings suggest that environmental quality (EQI) exhibits persistence, while economic growth (GRDP) contributes to its improvement, though emissions and energy consumption challenges remain. Additionally, foreign direct investment (FDI) negatively affects the environment, whereas education and digital technology factors have varying influences on environmental quality.

Table 1. Descriptive statistics

Variables	Obs	Mean	Std. Dev.	Min	Max
EQI	374	68.98	9.87	35.66	99.27
GRDP	374	302425.06	431159.85	18208	2050465
FDI	374	964.64	1431.531	2	8283.7
MYS	374	8.38	0.99	5.74	11.45
Internet	374	38.96	20.66	5.25	86.71
Mobile phone	374	60.18	10.49	26.05	82.47
Computer	374	15.66	5.34	6.08	34.51

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The descriptive statistics in Table 2 summarize data from 374 observations for seven variables. The Environmental Quality Index (EQI) has a mean of 68.98 with a standard deviation of 9.87, indicating moderate variability in environmental quality. Internet usage has a mean of 38.96 with a standard deviation of 20.66, reflecting a relatively high degree of dispersion in access. Mobile phone (MP) and computer ownership have averages of 60.18 and 15.66, respectively, with standard deviations of 10.49 and 5.34, indicating that mobile phone is more evenly distributed than computer ownership. Gross regional domestic product (GRDP) has a mean of 302425.06 with high variability (431159.85). In contrast, mean years of schooling (MYS) have a mean of 8.38 with a standard deviation of 0.99, indicating a reasonably uniform distribution in mean years of schooling. Foreign direct investment (FDI) shows a very high degree of dispersion with a standard deviation of 1431.531 and a wide range from 2 to 8283.7, indicating that foreign investment varies significantly between regions.

The correlation matrix is utilized to identify relationships between variables, with matrix elements representing correlation coefficients ranging from -1 to 1. This matrix provides insight into the associations among variables within the dataset. As shown in Table 2, EQI has a negative correlation with GRDP (-0.52), FDI (-0.35), and computer ownership (-0.33). These negative correlations suggest that environmental quality tends to decline as these economic indicators increase. GRDP is strongly positively correlated with FDI (0.71), indicating that regions with higher GRDP tend to attract more foreign investment. MYS has a positive relationship with the Internet (0.57), MP (0.71), and computer ownership (0.44), indicating that higher education levels are associated with better access to technology. Meanwhile, MP and Internet have a high correlation (0.79), indicating that Internet access is closely related to mobile phones. However, computer ownership has low or even negative correlations with other variables, except with MYS (0.44) and MP (0.37), which could indicate that computer ownership is unevenly distributed and less related to key economic indicators.

Table 2. Correlation Matrix

Variables	EQI	GRDP	FDI	MYS	Internet	MP	Computer
EQI	1						
GRDP	-0.52	1					
FDI	-0.35	0.71	1				
MYS	-0.14	0.23	0.19	1			
Internet	0.02	0.28	0.21	0.57	1		
Mobile phone	-0.09	0.28	0.18	0.71	0.79	1	
Computer	-0.33	0.22	0.11	0.44	-0.08	0.37	1

Table 3 presents the estimation results using the First-Difference Generalized Method of Moments (FD-GMM) to analyze the factors affecting the environmental quality index (EQI) with the independent variables internet, mobile phone, and computer. AR(1) is significant in all models, indicating the presence of first-order autocorrelation, which is common in dynamic models. AR(2) is significant in all models, indicating second-order autocorrelation, which means the GMM model cannot be considered valid. The Sargan test value is high but only insignificant in models (1) and (4), indicating that the instruments used are valid in these models. However, in the model (2), the Sargan test is significant, indicating that the instruments in this model may be less valid. The overall model significance test (Wald test) is significant in all models, indicating that the independent variables jointly have a significant effect on the dependent variable (EQI).

In Table 3, columns 2-4, the use of digital technology represented by the internet, mobile phones, and computers has a significant positive effect on environmental quality at a significance level of 5 percent. The internet coefficient is 0.1618, meaning that every 1 percent increase in internet users will increase environmental quality by 0.1618 points, assuming other variables are constant. Mobile phone users have a positive and significant effect on environmental quality in Indonesia at a significance level of 5 percent with a coefficient value of 0.5961, meaning that an increase in mobile phone users by 1 percent will increase EQI by 0.5961 points, assuming other variables are constant.

Table 3. FD-GMM estimation findings

Explanatory variables	Dependent variable: EQI		
	Model 1 (Internet)	Model 2 (MP)	Model 3 (Computer)
EQI (−1)	0.1278** (0.0621)	0.0475 (0.0563)	0.0588 (0.0547)
lnGRDP	0.6466 (2.2014)	-3.0181 (3.4326)	0.9099 (2.3781)
FDI	0.0005 (0.0006)	0.0007 (0.0006)	0.0005 (0.0005)
MYS	-3.8930 (3.1382)	-2.9708* (1.7721)	6.2737*** (1.3153)
Internet	0.1618*** (0.0560)	-	-
MP	-	0.5961*** (0.1362)	-
Computer	-		0.2535** (0.1101)
AR(1)	-3.8695 [0.0001]	-3.4594 [0.0005]	-3.5672 [0.0003]
AR(2)	-3.3529 [0.0004]	-3.0455 [0.0023]	-3.9725 [0.0000]
Sargan	34 [0.8615]	33.4302 [0.0023]	33.8282 [0.8662]
Wald Test	40.1006 [0.0000]	32.4323 [0.0000]	43.2203 [0.0000]

Notes: The value in the brackets are the t statistics and the value in the square brackets are the p-value ***p<0.1, **p<0.5, *p<0.1

These results align with research by Haseeb et al. (2019), which states that using a mobile phone increases energy savings and contributes positively to air quality. A study by Asongu et al. (2019) also found that mobile phones as a communication medium

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can contribute to reducing direct (physical) meetings that require motorized vehicles or transportation so that, in the end, they can reduce CO2 emissions. In addition, research by Wathuge and Sedera (2021) indicates that increased individual awareness of the environmental impact of internet use may contribute to reducing carbon emissions related to online activities.

Table 4 presents the estimation results using System-GMM, which is more efficient than FD-GMM as it considers additional moments to improve parameter estimates. The results show that EQI in the previous period had a significant positive effect in all models, indicating a persistent effect on environmental quality, where previous conditions strongly influenced current conditions. This result aligns with the research of Zhang et al. (2020), which found that environmental quality has a strong, persistent effect in developing countries. GRDP also has a significant positive impact in all models, indicating that regions with higher income tend to have better environmental quality, possibly due to the allocation of funds for green infrastructure and better environmental policies. While an increase in the quality of life, marked by an increase in GRDP, will increase the demand for goods and services, requiring producers to expand production activities, this can lead to an increase in resource consumption and pollution (Ilham, 2021). The economy in Indonesia still relies on energy sources that are not environmentally friendly, so economic growth will still be accompanied by an increase in CO2 emissions (Sasana & Aminata, 2019). The study by Wang et al. (2019) also demonstrates that economic growth frequently leads to environmental degradation in countries with high fossil energy dependence.

Table 4. System-GMM estimation findings

Explanatory variables	Dependent variable: EQI		
	Model 4 (Internet)	Model 5 (MP)	Model 6 (Computer)
EQI (−1)	0.0828*** (0.0352)	0.7965*** (0.0382)	0.8004*** (0.0349)
lnGRDP	0.5852*** (0.0352)	0.6609*** (0.1635)	0.6461*** (0.1544)
FDI	-0.0006*** (0.0002)	-0.0007*** (0.0002)	-0.0007*** (0.0002)
MYS	0.2194 (0.3432)	0.3045 (0.4435)	0.5372* (0.2908)
Internet	0.0076 (0.0086)	-	-
MP	-	0.0072 (0.3363)	-
Computer	-	-	-0.0993* (0.0569)
AR(1)	-3.7452 [0.0001]	-3.9436 [0.0000]	-4.5853 [0.0000]
AR(2)	-2.4040 [0.0162]	-2.4137 [0.0158]	-2.4262 [0.0152]
Sargan	33.7194 [0.9940]	33.7246 [0.9939]	33.7205 [0.994]
Wald Test	172567.8 [0.0000]	98424.49 [0.0000]	151082.5 [0.0000]

Notes: The value in the brackets are the t statistics and the value in the square brackets are the p-value ***p<0.1, **p<0.5, *p<0.1

Our findings indicate a negative and significant impact of foreign direct investment (FDI) across all models, suggesting that increased foreign investment may lead to a decline in environmental quality. This study supports the 'pollution haven' hypothesis, which posits that foreign investment can lead to the exploitation of natural resources or adopting more lenient environmental policies in the host country. FDI contributes to higher environmental emissions in developing nations by facilitating industrial migration from developed countries, with stricter pollution controls, to regions with weaker regulations (Gill et al., 2018). Countries with less stringent environmental policies become attractive destinations for foreign investors seeking to lower pollution-related costs and maximize economic gains (Fang et al., 2018). Consequently, foreign investment tends to exacerbate pollution in the recipient nation.

Furthermore, mean years of schooling (MYS) are statistically significant only in model (3), exhibiting a positive effect ($p<0.1$). Higher education levels may contribute to greater environmental awareness and adoption of sustainable practices. As education improves, environmental quality tends to follow suit. The interaction between humans and the environment plays a crucial role in sustainable development, particularly in efforts to achieve clean and affordable energy (Scharlemann et al., 2020). This finding aligns with the study by Koçak & Çelik (2022), which indicates that human development, as measured by the human development index, reduces PM 2.5 levels, ultimately benefiting environmental quality. This result is also supported by the research of Liu et al. (2021), which found that an increase in education correlates with broader adoption of green policies.

The impact of digital technologies yielded mixed results. Internet and mobile phone usage were insignificant, differing from previous FD-GMM findings, suggesting that their influence on environmental quality (EQI) may be indirect. However, computer use exhibited a negative effect in model (4), potentially indicating that increased computer usage contributes to higher energy consumption or e-waste, negatively affecting the environment. Diagnostic tests confirm the model's validity, as there is no evidence of second-order autocorrelation (AR(2) is insignificant), and the Sargan test supports the instrument's validity. Additionally, the Wald test was significant ($p<0.01$), verifying that the independent variables collectively impact EQI.

The System-GMM estimation results (Table 4) allow for a comparison of the effects of digital technology. The Internet, mobile phones, and computers on environmental quality represent it. In this dynamic model, the Internet and mobile phones do not significantly impact environmental quality. While the Internet may contribute to increased environmental awareness and energy efficiency, its overall effect depends on how it is utilized (Zhao et al., 2022). Unlike the findings from the FD-GMM estimation, mobile phone usage in the System-GMM model does not show a clear impact on environmental quality, potentially due to more complex long-term effects, such as energy consumption and environmental costs associated with device production offsetting any benefits (Shahbaz et al., 2020). Conversely, an increase in computer ownership or usage is linked to a decline in environmental quality, possibly due to higher electricity consumption, increased e-waste, and carbon emissions from the manufacturing of computer devices (Wang et

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al., 2023). This finding aligns with research by Sinha et al. (2020), which found that the use of digital technology devices, especially computers, correlates with increased electricity consumption and carbon emissions in developing economies. The findings are also consistent with the study by Liu et al. (2021), which highlights that increasing reliance on information technology can increase the carbon footprint, particularly if not supported by adequate renewable energy use.

Moreover, computer usage significantly impacts environmental quality, but negatively. This result suggests that increased computer use is associated with decreased environmental quality. Conversely, internet and mobile phone usage do not exhibit a strong influence in the long run. These results align with research by Sinha et al. (2020), who found that the use of digital technology devices, especially computers, correlates with increased electricity consumption and carbon emissions in developing economies. This finding is also consistent with the study by Liu et al. (2021), which highlights that increasing reliance on information technology can increase the carbon footprint, primarily if not supported by adequate renewable energy use.

The main findings show that economic growth (GRDP) contributes to improved environmental quality, while foreign investment (FDI) has a negative impact, supporting the 'pollution haven' hypothesis (Gill et al., 2018; Fang et al., 2018). Educational factors also play a role in increasing environmental awareness, although the effect is not consistently significant (Koçak & Çelik, 2022; Scharlemann et al., 2020). Conversely, the impact of digital technologies on environmental quality varies, with computer use showing significant negative effects, likely due to increased energy consumption and e-waste (Wang et al., 2023; Sinha et al., 2020; Liu et al., 2021). Meanwhile, Internet and mobile phone use do not have significant direct impacts in the long term, indicating that the environmental benefits of digital technologies depend primarily on their usage patterns (Zhao et al., 2022; Shahbaz et al., 2020). Therefore, policies that encourage the sustainable use of digital technologies and stricter regulation of foreign investment are needed to ensure that economic growth and technological development do not come at the expense of environmental quality.

CONCLUSION

Therefore, by analyzing the impact of digital technology on environmental quality in 34 provinces in Indonesia from 2013 to 2023 using the System-GMM approach, our results indicate that, of the three digital technology indicators analyzed—internet usage, mobile phone (MP) penetration, and computer ownership—only computer ownership has a significant impact on environmental quality (EQI), and this impact is negative. This condition is likely due to higher energy consumption and e-waste. Meanwhile, the internet and mobile phones do not show significant effects in the long run, which could be due to more complex impact mechanisms or suboptimal energy and digital waste management policies. From an economic perspective, GRDP contributes positively to EQI, suggesting that regions with higher incomes tend to have better environmental quality, possibly due to investments in green infrastructure and stricter environmental policies. In contrast, foreign direct investment (FDI) has a negative impact on EQI, supporting the 'pollution haven' hypothesis, which suggests that foreign investment may encourage the exploitation of natural resources and less environmentally friendly industrial practices.

Both central and local governments must develop sustainability-focused digital strategies and actively promote green technology innovation. Internet and mobile phone technologies should be utilized more effectively to raise environmental awareness through digital campaigns, eco-friendly applications, and data-driven emission monitoring systems. Conversely, the negative impacts of computer use can be reduced through policies that encourage energy-efficient devices and strengthen regulations and incentives for effective e-waste management. In addition, the government should ensure that foreign investments meet strict sustainability standards to prevent environmental degradation. Financial support and subsidies for developing green technologies such as smart grids are also indispensable to ensure that digitalization improves environmental quality in the long run. With the right policies, the utilization of digital technology in Indonesia can be optimized as a tool to improve environmental sustainability, not just as a driver of economic growth.

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