

Digital Transformation and Environmental Quality in Indonesia: Evidence from Provincial Panel Data Using PLS-SEM

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Abstract: Digital transformation has become an important driver of economic and social development, yet its environmental implications remain inconclusive. This study examines the effect of digital transformation on environmental quality across 34 Indonesian provinces during 2019–2023. A provincial panel dataset comprising 170 province-year observations was constructed from secondary data obtained from Statistics Indonesia (BPS) and the Ministry of Environment and Forestry (KLHK). Digital transformation was measured using household internet access, mobile-phone ownership, and computer ownership, while environmental quality was represented by the Air Quality Index, Water Quality Index, and Land Cover Quality Index. The relationship between these multidimensional constructs was analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results reveal a significant negative relationship between digital transformation and environmental quality ($\beta = -0.367$, $t = 5.247$, $p < 0.001$), with digital transformation explaining 13.5% of the variance in environmental quality ($R^2 = 0.135$). The novelty of this study lies in developing a provincial-level multidimensional digital transformation construct and providing empirical evidence on its relationship with multidimensional environmental quality using 170 province-year observations in Indonesia. The findings indicate that greater digital connectivity and technology adoption do not automatically correspond to improved environmental conditions, highlighting the need to integrate digital expansion with cleaner energy, energy-efficient ICT infrastructure, responsible electronic-waste management, and effective environmental governance.

Keywords: Digital transformation; Environmental quality; PLS-SEM; Sustainability

Introduction

Digital transformation has become an important driver of economic and social development and is increasingly associated with environmental sustainability. Advances in digital technologies, including artificial intelligence, big data analytics, and the Internet of Things (IoT), can improve resource efficiency, environmental monitoring, pollution control, and waste management (Feroz et al., 2021; Goel et al., 2024). Digitalization can also facilitate the transition toward a circular economy and strengthen economic

competitiveness through advanced digital infrastructure and resource-efficient production systems (Bocean & Värzaru, 2023; Fülöp & Cifuentes-Faura, 2025). From a broader sustainability perspective, digital technologies may support social inclusion and quality of life by improving access to information and public services (Alojail & Khan, 2023; Barykin et al., 2023). Collectively, these developments position digital transformation as an increasingly important component of sustainable development.

However, digital transformation is not environmentally neutral. The expansion of digital infrastructure, data-processing activities,

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telecommunications networks, and electronic-device use requires substantial energy and material resources and may contribute to increasing electricity consumption and electronic waste (Goel et al., 2024). Although digital technologies can support carbon-neutrality strategies and green development when combined with environmentally oriented innovation (Cao et al., 2023), their environmental benefits cannot be assumed to occur automatically. The net environmental consequences of digitalization may depend on the energy sources, technologies, infrastructure, and environmental governance accompanying digital expansion (Fülöp & Cifuentes-Faura, 2025; Goel et al., 2024). Consequently, digital transformation presents both opportunities and potential environmental pressures, making its actual relationship with environmental quality an important empirical question.

Empirical evidence regarding the relationship between digitalization and environmental performance remains mixed and context-dependent. Several studies indicate that digital transformation can improve environmental outcomes by promoting green technological innovation, strengthening organizational efficiency, and improving resource allocation (Xia & Wu, 2025; Zhu et al., 2023). Digitalization may also contribute to lower pollution emissions through technological innovation and efficiency improvements, although the magnitude of these benefits can vary across ownership structures, industries, and institutional settings (Zhou et al., 2025). In contrast, other studies suggest that the environmental effects of digitalization are not uniformly beneficial. The expansion of digital activities may generate rebound effects when efficiency gains are accompanied by increased energy consumption and greater demand for digital infrastructure (Yue et al., 2025). Moreover, the environmental consequences of digitalization may depend on complementary conditions such as green finance, eco-digitalization, technological development, and broader institutional characteristics, resulting in heterogeneous outcomes across regions and economies (Mazhar et al., 2025). Taken together, these divergent findings demonstrate that the digitalization-environment relationship remains empirically inconclusive and highly context-dependent. This inconsistency provides an important basis for examining whether increasing digital transformation is associated with improved environmental quality in the specific context of Indonesian provinces.

Indonesia provides a particularly relevant context for examining the digitalization-environment relationship because digital development remains uneven across regions. The Regional Digital Development Index (RDDI) shows that digital development has been concentrated in major metropolitan areas in western Indonesia, while rural and

remote areas, particularly in the eastern regions, have generally lagged behind, despite a gradual narrowing of the digital divide (Kartiasih et al., 2022). More recent evidence from the Indonesian Digital Society Index (IMDI) indicates an increase from 37.80 in 2022 to 43.34 in 2024, although digital transformation hotspots remain concentrated primarily in Java and comparatively lower levels persist in parts of eastern Indonesia (Jaya et al., 2024). These regional disparities are associated with differences in education, economic capacity, employment structure, digital infrastructure, and digital readiness (Jaya et al., 2024; Kartiasih et al., 2022). Such spatial heterogeneity demonstrates that Indonesia's digital transformation has progressed unevenly across regions, making the provincial level particularly relevant for examining whether greater digital connectivity and technology adoption are accompanied by improvements in environmental quality.

Despite growing scholarly attention to digitalization and environmental sustainability, three important research gaps remain. First, existing empirical studies have predominantly examined digital transformation and environmental performance at the firm or industry level, particularly among listed and manufacturing enterprises, leaving comparatively limited evidence on their relationship at the subnational level in developing economies (Song et al., 2024; Xu et al., 2023). Second, previous findings remain inconclusive. While some studies report that digitalization improves environmental performance through green technological innovation and efficiency gains, others identify adverse, heterogeneous, or nonlinear environmental effects (Goel et al., 2024; Zhang & Zhao, 2023). These inconsistencies suggest that evidence obtained from specific firms, industries, or national settings cannot be directly generalized to heterogeneous provincial contexts. Third, previous studies commonly operationalize digitalization and environmental performance using individual observed indicators or firm-specific measures, whereas limited attention has been devoted to simultaneously modeling Digital Transformation and Environmental Quality as multidimensional latent constructs at the provincial level. This methodological limitation restricts the ability to capture the broader dimensions of both digital development and environmental conditions. Accordingly, this study addresses these gaps by examining the structural relationship between multidimensional Digital Transformation and Environmental Quality constructs using 170 province-year observations from 34 Indonesian provinces during 2019–2023.

The proposed relationship between Digital Transformation and Environmental Quality is grounded in Sustainable Development Theory and Ecological Modernization Theory (EMT). Sustainable Development

Theory emphasizes the integration of economic and technological advancement with environmental protection, suggesting that digital transformation can contribute to sustainability by improving resource efficiency, facilitating green technological innovation, and reducing environmental pressures (Cai et al., 2023; Han et al., 2024; Lin, 2023). From this perspective, digital technologies can improve information availability, resource allocation, and environmental monitoring, thereby creating opportunities to align technological development with environmental sustainability.

Ecological Modernization Theory further argues that technological innovation and modernization can improve environmental performance through cleaner technologies, more efficient production and resource utilization, and improved environmental management. Digital transformation can support these mechanisms by reducing information constraints, facilitating green innovation, and enabling more efficient allocation and utilization of resources (Cao et al., 2023; Song et al., 2024; Zhuo & Zheng, 2024). Empirical evidence also indicates that digital transformation can enhance environmental performance through green technological upgrading and improved organizational efficiency (Song et al., 2024), while its contribution to carbon reduction may operate through improved resource allocation and reduced financing constraints (Han et al., 2024).

Taken together, Sustainable Development Theory and Ecological Modernization Theory suggest that digital transformation can improve environmental quality when technological advancement enhances resource efficiency, green innovation, and environmentally oriented management. Although previous empirical findings remain heterogeneous, these theoretical mechanisms provide a basis for expecting a positive structural relationship between digital transformation and environmental quality. Accordingly, this study proposes the following hypothesis: H1: Digital Transformation has a positive effect on Environmental Quality across Indonesian provinces.

To empirically test the proposed relationship, this study conceptualizes Digital Transformation and Environmental Quality as multidimensional latent constructs. Digital Transformation is represented by household internet access, mobile-phone ownership, and computer ownership, whereas Environmental Quality is represented by the Air Quality Index (IKU), Water Quality Index (IKA), and Land Cover Quality Index (IKTL). The analysis uses official secondary data from 34 Indonesian provinces during 2019–2023, resulting in 170 province-year observations. Partial Least Squares Structural Equation Modeling (PLS-SEM) is employed because it enables the simultaneous assessment of multidimensional latent constructs, measurement quality, and structural relationships,

while also supporting prediction-oriented assessment (Sarstedt et al., 2021).

The novelty of this study lies in integrating provincial-level digital development and environmental conditions into two multidimensional latent constructs and empirically examining their structural relationship across Indonesian provinces. The study makes three principal contributions. Theoretically, it extends the application of Sustainable Development Theory and Ecological Modernization Theory to the subnational context of a developing economy, providing evidence on whether the environmental benefits expected from technological modernization are observable across heterogeneous provincial conditions. Methodologically and empirically, it moves beyond single-indicator approaches by simultaneously modeling Digital Transformation and Environmental Quality as multidimensional constructs using 170 province-year observations. Practically, the findings provide a basis for green digitalization policies aimed at aligning digital infrastructure expansion and technology adoption with environmental protection, resource efficiency, and sustainable regional development in Indonesia.

Accordingly, this study aims to examine the relationship between Digital Transformation and Environmental Quality across Indonesian provinces using PLS-SEM. By integrating multidimensional digital and environmental indicators, provincial longitudinal observations, and an explicit theoretical framework, the study seeks to clarify the digitalization–environment relationship and provide empirical evidence to support the integration of Indonesia's digital transformation agenda with environmental sustainability policies.

Method

This study employed a quantitative approach using secondary data from 34 Indonesian provinces over the 2019–2023 period, resulting in 170 province-year observations. The data were obtained from official publications of Statistics Indonesia (BPS) and the Ministry of Environment and Forestry (KLHK). The province-year observations were organized into a pooled dataset to capture variations in digital development and environmental conditions across provinces and over time.

Digital Transformation was operationalized as a multidimensional latent construct using three indicators: household internet access (DG1), mobile-phone ownership (DG2), and computer ownership (DG3). These indicators represent complementary dimensions of digital connectivity and technology adoption at the provincial level. Environmental Quality was likewise specified as a multidimensional latent construct comprising the Air Quality Index (IKU), Water Quality Index (IKA), and Land Cover Quality Index

(IKTL). The use of multiple indicators allows the two constructs to represent broader dimensions of provincial digital development and environmental conditions rather than relying on a single observed indicator.

The empirical analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4. PLS-SEM was selected because the study involves multidimensional latent constructs measured through multiple indicators and requires simultaneous assessment of the measurement and structural models. Moreover, PLS-SEM is particularly suitable when the research objective incorporates both explanation and (Sarstedt et al., 2021). The prediction-oriented nature of PLS-SEM also enables the assessment of out-of-sample predictive performance rather than relying exclusively on explanatory measures (Shmueli et al., 2019).

The analysis was conducted in several stages. First, the reflective measurement model was evaluated based on indicator reliability, internal consistency reliability, and convergent validity. Outer loadings of 0.70 or higher were considered desirable. Indicators with loadings between 0.40 and 0.70 were evaluated by considering their theoretical relevance and whether their removal would improve composite reliability or Average Variance Extracted (AVE) (Sarstedt et al., 2021). Construct reliability was assessed using Cronbach's alpha, rho_A, and composite reliability (rho_C), with values of 0.70 or higher considered acceptable. Convergent validity was established when AVE exceeded 0.50. These thresholds are also used in the current SmartPLS reporting framework.

Second, discriminant validity was assessed primarily using the Heterotrait-Monotrait ratio (HTMT), complemented by the Fornell-Larcker criterion. HTMT is recommended for evaluating whether reflectively measured constructs are empirically distinct (Henseler et al., 2015). Values below the recommended threshold indicate adequate discriminant validity. Collinearity was additionally assessed using the Variance Inflation Factor (VIF) to identify potential collinearity among indicators and structural predictors.

Third, the structural model was evaluated using the path coefficient (β), coefficient of determination (R^2), adjusted R^2 , and effect size (f^2). Statistical significance was assessed through nonparametric bootstrapping with 5,000 subsamples using a two-tailed test at the 5% significance level. The bootstrapping procedure generates standard errors, t-statistics, p-values, and confidence intervals for assessing the significance of PLS-SEM estimates.

Finally, the model's out-of-sample predictive performance was examined using PLSpredict and the Cross-Validated Predictive Ability Test (CVPAT). PLSpredict was implemented using 10-fold cross-

validation with 10 repetitions. Predictive relevance was evaluated using Q^2_{predict} , while the prediction errors of the PLS-SEM model were compared with benchmark predictions using Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). PLSpredict provides a holdout-based procedure for evaluating the out-of-sample predictive capabilities of PLS path models (Shmueli et al., 2019). CVPAT was subsequently used to assess whether differences in predictive loss between PLS-SEM and the benchmark models were statistically significant.

Result and Discussion

Descriptive Analysis

The descriptive analysis provides an overview of the variation in digital development and environmental conditions across Indonesian provinces during the 2019–2023 period. Differences in household internet access, mobile-phone ownership, and computer ownership reflect variations in digital connectivity and technology adoption, while the environmental indicators capture differences in air quality, water quality, and land-cover quality. Table 1 summarizes the descriptive statistics for the six indicators based on 170 province-year observations.

Table 1. Descriptive Statistics

Variable	Mean	Min	Max	Std. Dev.
DG1_RT_Internet	79.447	31.31	98.08	11.881
DG2_TeleponSeluler	65.430	35.33	82.47	8.328
DG3_Komputer	19.365	9.36	39.15	5.916
ENV1_IKU	88.675	66.52	96.22	5.705
ENV2_IKA	53.825	35.37	69.29	5.629
ENV3_IKTL	62.077	24.66	100.00	19.973

Note: DG1 = household internet access; DG2 = mobile-phone ownership; DG3 = computer ownership; IKU = Air Quality Index; IKA = Water Quality Index; IKTL = Land Cover Quality Index. N = 170 province-year observations. Source: BPS and KLHK data, processed by the authors.

As shown in Table 1, household internet access (DG1) recorded the highest mean among the digital transformation indicators (79.447), followed by mobile-phone ownership (DG2) (65.430), whereas computer ownership (DG3) showed a considerably lower mean (19.365). DG1 also exhibited the greatest dispersion among the digital indicators, ranging from 31.31 to 98.08 with a standard deviation of 11.881. These results indicate substantial disparities in digital connectivity and technology adoption across the observed province-year units.

Among the environmental indicators, the Air Quality Index (IKU) recorded the highest mean (88.675), followed by the Land Cover Quality Index (IKTL) (62.077) and the Water Quality Index (IKA) (53.825). Notably, IKTL exhibited the greatest variability, ranging

from 24.66 to 100.00 with a standard deviation of 19.973. This variation was substantially greater than that observed for IKU (SD = 5.705) and IKA (SD = 5.629), indicating pronounced heterogeneity in land-cover conditions across Indonesian provinces.

The substantial variation in IKTL can be interpreted in relation to Indonesia's geographical and land-use heterogeneity. Provinces differ considerably in forest coverage, natural vegetation, urbanization, settlement expansion, agricultural activity, infrastructure development, and land-use characteristics. Provinces with extensive forest and natural vegetation may therefore exhibit substantially different land-cover conditions from highly urbanized and densely populated provinces, where settlement expansion, infrastructure development, and land conversion exert greater pressure on vegetated areas. Thus, the wide dispersion of IKTL reflects not merely statistical variation but also the heterogeneous geographical and land-use characteristics of Indonesian provinces.

Measurement Model Assessment

The measurement model was evaluated before assessing the structural relationships to ensure that the indicators adequately represented their respective latent constructs. The assessment included indicator reliability, internal consistency reliability, and convergent validity using outer loadings, Cronbach's alpha, composite reliability (rho_C), and Average Variance Extracted (AVE), following the recommended PLS-SEM evaluation criteria (Hair et al., 2022). The results are presented in Table 2.

As shown in Table 2, the Digital Transformation construct demonstrated satisfactory measurement properties. The outer loadings ranged from 0.806 to 0.970, indicating that all three indicators were strongly associated with the construct. Cronbach's alpha (0.873) and composite reliability (0.923) exceeded the recommended threshold of 0.70, while the AVE value of 0.801 was substantially above the threshold of 0.50. These results confirm satisfactory internal consistency reliability and convergent validity for Digital Transformation (Hair et al., 2022).

Environmental Quality also demonstrated acceptable reliability and convergent validity, with Cronbach's alpha of 0.702, composite reliability of 0.835, and AVE of 0.633. ENV1 (IKU) and ENV3 (IKTL) exhibited relatively strong outer loadings of 0.889 and 0.853, respectively. ENV2 (IKA), however, showed a lower loading of 0.616. Although this value is below the preferred threshold of 0.70, indicators with loadings between 0.40 and 0.70 may be retained when their theoretical relevance is important and construct-level reliability and convergent validity remain satisfactory (Sarstedt et al., 2021). In this study, Environmental Quality maintained satisfactory composite reliability

and AVE; therefore, ENV2 was retained to preserve the water-quality dimension of the construct.

Overall, the results indicate that both constructs satisfy the requirements for internal consistency reliability and convergent validity, supporting their use in the subsequent assessment of discriminant validity and the structural model.

Table 2. Measurement Model Assessment

Construct	Indicator	Loading	α	rho_C	AVE
Digital transformation	DG1	0.902	0.873	0.923	0.801
	DG2	0.970			
	DG3	0.806			
Environmental Quality	ENV1	0.889	0.702	0.835	0.633
	ENV2	0.616			
	ENV3	0.853			

Note: DG1 = household internet access; DG2 = mobile-phone ownership; DG3 = computer ownership; ENV1 = IKU; ENV2 = IKA; ENV3 = IKTL. Source: BPS and KLHK data, processed by the authors.

Discriminant Validity

Discriminant validity was assessed to determine whether Digital Transformation and Environmental Quality represent empirically distinct constructs. The assessment employed the Fornell-Larcker criterion and the Heterotrait-Monotrait ratio (HTMT). The HTMT criterion provides a more sensitive assessment of discriminant validity in PLS-SEM, with values below 0.85 generally indicating adequate distinction between constructs (Henseler et al., 2015). The results are presented in Table 3.

Table 3. Discriminant Validity Assessment

Construct/Criterion	Digital Transformation	Environmental Quality
Digital Transformation	0.895	
Environmental Quality	-0.367	0.795
HTMT (DT-EQ)	0.460	

Note: Bold diagonal values represent the square roots of AVE. Source: SmartPLS 4 output, processed by the authors.

As shown in Table 3, the square root of AVE for Digital Transformation was 0.895, while that for Environmental Quality was 0.795. Both values exceeded the absolute inter-construct correlation of 0.367, thereby satisfying the Fornell-Larcker criterion. In addition, the HTMT value between Digital Transformation and Environmental Quality was 0.460, which is substantially below the recommended threshold of 0.85 (Henseler et al., 2015).

Taken together, the Fornell-Larcker and HTMT results provide consistent evidence of satisfactory discriminant validity. Therefore, Digital Transformation and Environmental Quality can be considered

empirically distinct constructs, supporting the subsequent evaluation of the structural model.

Prior to hypothesis testing, the structural model was assessed for collinearity and explanatory power. The inner VIF value of 1.000 indicated no collinearity

concern. Environmental Quality had an R^2 value of 0.135 and an adjusted R^2 of 0.129, indicating that Digital Transformation explained 13.5% of its variance. Furthermore, the f^2 value of 0.156 indicated a moderate effect size.

Table 4. Structural Model and Hypothesis Testing

Path	β	t-value	p-value	95% CI	Decision
DT → EQ	-0.367	5.247	<0.001	[-0.514, -0.240]	H1 Not Supported

Note: DT = Digital Transformation; EQ = Environmental Quality. Bootstrapping = 5,000 subsamples; two-tailed test. Source: SmartPLS 4 output, processed by the authors.

As shown in Table 4, Digital Transformation had a significant negative effect on Environmental Quality ($\beta = -0.367$, $t = 5.247$, $p < 0.001$). The 95% confidence interval [-0.514, -0.240] did not include zero, confirming the statistical significance of the relationship. However, because H1 proposed a positive effect, whereas the empirical coefficient was negative, H1 was not supported.

Predictive Assessment

In addition to evaluating the explanatory power of the structural model, the out-of-sample predictive performance was assessed using PLSpredict and the Cross-Validated Predictive Ability Test (CVPAT). The PLSpredict procedure evaluates whether the model can generate predictions for observations outside the estimation sample, while CVPAT provides a statistical comparison of predictive loss against benchmark models.

All three indicators of Environmental Quality produced positive $Q^2_{predict}$ values, indicating that the PLS-SEM model exhibited predictive relevance for the endogenous indicators. The results are summarized in Table 5.

Table 5. Predictive Assessment

Indicator	$Q^2_{predict}$	PLS-RMSE	LM-RMSE
ENV1_IKU	0.086	5.489	5.487
ENV2_IKA	0.027	5.582	5.462
ENV3_IKTL	0.093	19.154	18.417

Note: LM = linear model benchmark; ENV1 = Air Quality Index (IKU); ENV2 = Water Quality Index (IKA); ENV3 = Land Cover Quality Index (IKTL). Source: SmartPLS 4 output, processed by the authors.

As shown in Table 5, the $Q^2_{predict}$ values were positive for IKU (0.086), IKA (0.027), and IKTL (0.093). These results indicate that the model possesses out-of-sample predictive relevance for all three environmental quality indicators. However, the magnitude of the values is relatively small, suggesting limited predictive strength.

A comparison of prediction errors provides a more conservative assessment. The PLS-SEM RMSE values were slightly higher than those of the linear model

benchmark for all three indicators. For example, the RMSE for IKU was 5.489 under PLS-SEM compared with 5.487 under the linear model, while for IKTL the corresponding values were 19.154 and 18.417. Thus, although the positive $Q^2_{predict}$ values demonstrate predictive relevance, PLS-SEM did not outperform the linear benchmark in terms of RMSE.

The CVPAT results provide additional evidence regarding predictive performance. Compared with the linear model benchmark, the PLS-SEM model produced a higher predictive loss (142.725 versus 133.044), with an average loss difference of 9.682. However, this difference was not statistically significant at the 5% level ($t = 1.670$, $p = 0.097$). Conversely, the comparison with the indicator-average benchmark showed a lower PLS-SEM loss (142.725 versus 156.507), although the difference was also not statistically significant ($p = 0.096$).

Taken together, these findings indicate that the model demonstrates predictive relevance but limited comparative predictive superiority. Therefore, its primary contribution lies in explaining and testing the structural relationship between Digital Transformation and Environmental Quality rather than providing highly accurate out-of-sample predictions.

Discussion

The main finding of this study is a statistically significant negative relationship between Digital Transformation and Environmental Quality ($\beta = -0.367$, $p < 0.001$). Since H1 predicted a positive relationship, the hypothesis was not supported. This finding indicates that greater provincial digital connectivity and technology adoption did not automatically correspond to better environmental conditions during 2019–2023. Rather than establishing a direct causal effect, the result suggests that the environmental implications of digital transformation are conditional on the broader energy, infrastructure, socioeconomic, and institutional context.

One possible explanation is that digital expansion simultaneously creates environmental opportunities and pressures. Digital technologies can improve environmental monitoring, resource allocation, information processing, and operational efficiency

(Feroz et al., 2021). However, expanding internet connectivity, telecommunications infrastructure, and electronic-device ownership also requires electricity, material resources, and continuous equipment replacement. Consequently, environmental benefits may be weakened when digital expansion is not accompanied by cleaner energy, energy-efficient infrastructure, and effective electronic-waste management.

The negative relationship is consistent with Zeeshan et al. (2022) who found that ICT development in Southeast Asian emerging economies did not necessarily improve environmental performance and could increase environmental degradation, particularly in the presence of energy dependence on non-renewable sources. This similarity is relevant because Indonesia shares the broader emerging-economy context examined in their study. The present provincial-level evidence therefore reinforces the argument that increased digital penetration alone should not automatically be interpreted as environmentally beneficial.

Conversely, the finding differs from studies reporting positive environmental effects of digital transformation. Xu et al. (2023) showed that digital transformation could improve environmental performance through green technological innovation, environmental information disclosure, human-capital development, and environmental governance. Feroz et al. (2021) likewise highlighted the potential of digital technologies to support pollution control, waste management, resource efficiency, and sustainable production. The difference may arise from variations in measurement and analytical context. In this study, Digital Transformation is represented by household internet access, mobile-phone ownership, and computer ownership, which primarily measure digital access and technology adoption rather than specifically green digital technologies.

The Indonesian provincial context further helps explain the result. Provinces with greater digital penetration may simultaneously experience higher urbanization, infrastructure development, economic activity, electricity consumption, and consumption intensity. At the same time, environmental conditions vary substantially because of differences in forest coverage, land use, population concentration, and development patterns. This heterogeneity is reflected particularly in IKTL, which showed the greatest dispersion among the environmental indicators ($SD = 19.973$; $range = 24.66-100.00$). Thus, the negative relationship may partly reflect the interaction between digital expansion and broader regional development pressures rather than an inherently harmful effect of digital technology itself.

The findings provide an important qualification to Ecological Modernization Theory and Sustainable Development Theory. Ecological Modernization Theory suggests that technological progress can improve environmental performance through innovation and efficiency; however, the present results indicate that such benefits may be conditional rather than automatic. Similarly, Sustainable Development Theory implies that technological progress becomes sustainable only when economic and social advancement is aligned with environmental protection. Digital transformation should therefore be accompanied by green innovation, cleaner energy, effective environmental governance, and resource-efficient infrastructure.

From a policy perspective, the findings do not imply that Indonesia should slow digital transformation. Instead, they highlight the need to shift toward green digital transformation, integrating digital infrastructure expansion with renewable and cleaner energy, energy-efficient ICT systems, responsible electronic-waste management, and digital applications for environmental monitoring and resource management. The study therefore contributes to the literature by showing that the environmental benefits of digitalization at the provincial level cannot be assumed to emerge automatically; they depend on complementary environmental, technological, and institutional conditions.

Conclusion

This study examined the relationship between Digital Transformation and Environmental Quality across 34 Indonesian provinces during the 2019–2023 period using PLS-SEM. Digital Transformation was represented by household internet access, mobile-phone ownership, and computer ownership, while Environmental Quality was measured through the Air Quality Index (IKU), Water Quality Index (IKA), and Land Cover Quality Index (IKTL). The results revealed a statistically significant negative relationship between Digital Transformation and Environmental Quality ($\beta = -0.367$, $p < 0.001$), contrary to the positive relationship proposed in the hypothesis. This finding indicates that greater digital connectivity and technology adoption at the provincial level do not automatically correspond to better environmental conditions and that the environmental implications of digitalization may depend on complementary energy, technological, institutional, and regional conditions. Theoretically, this study extends the application of Ecological Modernization Theory and Sustainable Development Theory to the Indonesian provincial context by demonstrating that the environmental benefits of digital modernization are conditional rather than automatic and require complementary green technological and

institutional conditions. From a policy perspective, the findings highlight the importance of integrating Indonesia's digital transformation agenda with environmental objectives through energy-efficient ICT infrastructure, cleaner energy, responsible electronic-waste management, and digital technologies that support environmental monitoring and resource efficiency. This study is limited by its reliance on secondary observational data for 34 provinces during 2019–2023 and by the use of three indicators for each latent construct, which may not capture all technological, socioeconomic, institutional, and environmental dimensions influencing the digitalization–environment relationship. Future research should incorporate additional determinants such as renewable-energy use, urbanization, industrial activity, population density, green innovation, and environmental governance, while extending the observation period and examining possible nonlinear, mediating, or moderating relationships.

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Author Contributions

Conceptualization, P.P. and S.M.; methodology, P.P., S.M., and E.A.; software, E.A. and V.Y.; validation, S.M. and K.W.; formal analysis, P.P., E.A., and V.Y.; investigation, P.P. and E.A.; resources, S.M.; data curation, E.A. and V.Y.; writing—original draft preparation, P.P. and E.A.; writing—review and editing, S.M., K.W., and V.Y.; visualization, E.A.; supervision, S.M.; project administration, P.P. and S.M. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest

The authors declare no conflict of interest.

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