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Research Paper

DIGITAL TRANSFORMATION IMPACT ON ENVIRONMENTAL AND ECONOMIC PERFORMANCE: THE MODERATING ROLE OF TECHNOLOGICAL TURBULENCE

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ABSTRACT

This study explores the link between digital transformation and sustainable performance, emphasizing economic and environmental outcomes while considering the moderating effect of technological turbulence. Data from 81 respondents reveal that digital transformation improves economic performance through dynamic capabilities like resource adaptation, process innovation, and agility. It also enhances environmental performance by promoting energy efficiency, waste reduction, and green innovations. However, advanced stages of digital transformation may face diminishing returns due to organizational inertia and the high resource demands of digital technologies. Technological turbulence amplifies both the opportunities and challenges, requiring companies in volatile environments to focus on adaptability and strategic alignment. The study highlights the importance of a phased, context-sensitive approach to digital transformation to avoid resource overuse and environmental harm. These findings offer practical insights for optimizing digital strategies to achieve long-term economic and environmental sustainability. Future research should address limitations such as sample size and context, while exploring additional moderating factors across diverse industries.

Keywords: Digital Transformation, Economic Performance, Environmental Performance, Technological Turbulence, Sustainability

JEL code: M41, Q56

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INTRODUCTION

Economic globalization has driven companies worldwide to continuously create, innovate, and upgrade technologies to leverage digital transformation in achieving their goals and ensuring performance. In order for businesses to thrive in their current environment, business development urges them to enhance corporate performance (Gultom & Wati, 2022). A company's performance is always a reflection of how well it manages its operations (Yanto et al., 2023). In an increasingly interconnected world, businesses are compelled to embrace digital transformation as a survival strategy, adapting to changing market demands, consumer expectations, and competitive pressures. Digital transformation has become the new norm and is widely regarded as a significant influence on business operations (Li, 2022). By embedding technology into organizational processes, businesses can not only optimize internal efficiencies but also respond proactively to external challenges, including environmental uncertainties and technological disruptions. Digital transformation supposedly enables firms to enhance process efficiency and optimize resource management (Pagani & Pardo, 2017), hence promoting sustainable performance in both economic and environmental dimensions (ElMassah & Mohieldin, 2020). It integrates technology into the core operations of companies, enabling them to revolutionize processes and adapt flexibly to environmental uncertainties. Moreover, it fosters innovation by encouraging organizations to rethink traditional business models and adopt forward-thinking strategies.

Consequently, digital transformation is an essential trend for manufacturing firms, particularly as the digitalization of the value chain profoundly influences operations (Albukhitan, 2020). The interconnected nature of modern supply chains means that even minor technological advancements can lead to significant improvements in overall efficiency, productivity, and customer satisfaction (Wen et al., 2021). Therefore, this study aims to explore how leadership capabilities can enhance company performance through digital transformation, ensuring organizations can fully harness the potential of digital tools and platforms while mitigating associated risks (Hirsch-Kreinsen, 2016).

Previous studies suggest that digital transformation can assist firms in achieving market agility (Li, 2022), resulting in business model shifts (Pagani & Pardo, 2017) that increase competitive advantage and consequently, improve firm performance (Ch'ng et al., 2021). Market agility, characterized by a firm's ability to respond swiftly to market changes and customer needs, has become a vital determinant of success in the digital age. Digital transformation empowers manufacturing firms to minimize expenses, enhance productivity, refine product development, accelerate time-to-market, and bolster customer orientation throughout various components of the value chain (Nguyen & Thanh Hoai, 2022). Furthermore, digital transformation drives rapid technological advances (Dubey et al., 2020), enabling the application of production data to predict and prevent waste-related problems before they occur (Kohtamäki et al., 2020). Through advanced analytics, companies can optimize resource allocation, enhance operational visibility, and anticipate future trends, thereby maintaining a competitive edge.

Additionally, it enhances the environmental performance of manufacturing companies (Qiu et al., 2020) compelling them to balance revenue growth with environmental concerns. As part of their operations, businesses are also involved in a number of lawsuits pertaining to social, economic, and environmental issues (Anita & Fatmasari, 2024). Digital tools such as Internet on Things, big data analytics, and cloud computing allow firms to monitor and manage their environmental footprint more effectively, reducing energy consumption, emissions, and waste. Thus, manufacturing companies must rethink strategies to leverage digital transformation in addressing environmental challenges (Zhou et al., 2019). Adopting a proactive approach to sustainability not only benefits the environment but also strengthens stakeholder trust and enhances brand reputation, further reinforcing the value of digital transformation.

However, digital transformation also exposes companies to new risks, such as data security breaches, cyberattacks, and e-waste (Mikalef et al., 2020). As businesses become increasingly reliant on digital systems, the need for robust cybersecurity measures and effective data governance frameworks has grown. Consequently, some studies argue that digital transformation does not always help companies achieve sustainable performance (Lokuge et al., 2019). These challenges underscore the importance of a strategic, well-planned approach to digital transformation, where potential risks are anticipated and mitigated effectively. Considering the inconsistencies between research and practice, scholars and practitioners continue to prioritize gaining a better understanding of the connection between digital transformation and sustainable performance.

Existing studies, such as (Dubey et al., 2020; Li, 2022), mainly investigate the linear relationship between digital transformation and sustainable performance. These studies argue that oversimplification may explain the paradoxical relationship between digital transformation and performance outcomes. The beneficial effects of digital transformation on long-term performance are specifically mediated by improved organizational capacities, especially dynamic capabilities (Mikalef et al., 2020). Dynamic capabilities, which refer to a firm's ability to integrate, build, and reconfigure resources to address rapidly changing environments, are essential for realizing the full benefits of digital transformation. Moreover, digital transformation necessitates changes in existing resources and routines within the company. These changes often require significant investments in training, infrastructure, and cultural shifts, which can be challenging for organizations to implement. Since resources and routines are often interdependent, organizational inertia can hinder the effectiveness of digital transformation (Raguseo & Vitari, 2018). Resistance to change, whether due to cultural, structural, or financial factors, remains a critical barrier that companies must overcome to unlock the transformative potential of digital technologies.

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Stakeholder Theory

According to (Danso et al., 2020), a stakeholder is any individual or group affected by the goals of a company. This definition underscores the interconnected nature of businesses and their broader social and economic ecosystems. In the business sector, stakeholders are essential to managing the business environment of a firm (Karina et al., 2023). Decisions made by stakeholders, the capital market's trust and efficiency, and the appropriate distribution of scarce economic resources are all greatly affected by accounting quality (Dimitropoulos, 2020 in Wati & Malik, 2021). Employees, clients, suppliers, local communities, shareholders, and even regulatory agencies are examples of stakeholders. Each of these groups is vital in determining the strategic direction and operational results of a business. Corporate Social Responsibility (CSR) considers both external and internal stakeholders who either influence the company or are influenced by it. Companies often face pressure from external parties to mitigate negative impacts and enhance positive outcomes (Stahl et al., 2020). These pressures can stem from environmental concerns, social justice movements, or economic inequalities, all of which compel businesses to act responsibly and transparently in their operations. By addressing stakeholder expectations, organizations can build trust, foster loyalty, and ultimately achieve sustainable growth.

Fundamentally, stakeholder theory is based on the premise that businesses must manage their relationships with stakeholders to achieve long-term success. Stakeholder engagement helps reduce conflicts, create synergies, and drive innovation (Casalegno et al., 2023 in Wati et al., 2024). This entails being aware of and mindful of the frequently competing interests of many stakeholder groups. For example, employees may stress job security and fair compensation, shareholders may prioritize financial returns, and buyers may favor ethical sourcing and product quality. The ability to navigate these competing demands is a hallmark of effective corporate governance and strategic management.

(Deegan & Blomquist, 2006) assert that stakeholder theory emphasizes the importance of reporting specific types of information to attract and retain particular stakeholder groups. Transparent reporting practices enable companies to demonstrate accountability, thereby reinforcing stakeholder confidence and engagement. For instance, disclosing information about a company's social performance is essential for engaging and maintaining the interest of influential individuals or groups involved in its social activities. This could include publishing sustainability reports, outlining efforts to reduce carbon emissions, or detailing initiatives aimed at improving community welfare. Such disclosures not only enhance a company's reputation but also provide stakeholders with the information they need to make informed decisions about their relationship with the organization.

This perspective aligns with the findings of (Mitchell et al., 1997), who highlighted that legitimacy, urgency, and power are the core principles underpinning the stakeholder framework. Legitimacy refers to the perceived validity of a stakeholder's claims, urgency pertains to the time sensitivity and criticality of those claims, and power denotes the ability of a stakeholder to influence the company's actions. By recognizing and addressing these attributes, organizations can effectively prioritize stakeholder needs and allocate resources accordingly. For example, a company facing pressure from an environmental advocacy group with significant public support (legitimacy), an immediate demand for action (urgency), and the capacity to mobilize widespread campaigns (power) is likely to respond more promptly compared to less influential stakeholders. Thus, stakeholder theory provides a structured approach to identifying and managing the complex web of relationships that influence business success, ensuring that companies remain responsive, accountable, and resilient in a dynamic global environment.

Hypothesis Development

Digital Transformation and Economic Performance

This study argues that digital transformation has the potential to significantly accelerate economic performance. From this perspective, economic performance improves steadily with each incremental advancement in digital transformation. The ability of a business to integrate, renew, and adapt its resources is essential from the standpoint of dynamic capability, which is fundamentally built upon the company's internal processes (Torelli et al., 2020), which are central to its ongoing ability to respond to changes in the business environment. While digital transformation has the theoretical potential to stimulate existing resources, acquire new ones from external sources, and coordinate and integrate both internal and external resources to enhance dynamic capability (Brunetti et al., 2020), these benefits are only realized when a company successfully updates its existing processes. This process of updating is complex and requires considerable effort, suggesting that establishing dynamic capability is inherently challenging.

During the early stages of digital transformation, companies may face difficulties in quickly updating their processes to align with the requirements of dynamic capability. This may hinder their ability to realize the full potential of digital transformation in driving economic performance. However, it is essential to recognize that a company's dynamic capability, once developed, is often difficult for competitors to replicate. Modifications to one component of a company's processes often require significant adjustments in other components, making the establishment of dynamic capabilities a unique competitive asset (Winter, 2003). As digital transformation deepens over time, companies that successfully build dynamic capability through process updates will be better positioned to adapt to increasing customer and market demands. This enables them to gain sustainable competitive advantages, ultimately resulting in significant improvements in economic performance.

During the initial phases of digital transformation, businesses frequently have difficulties in altering their resources and practices due to organizational inertia. Organizational inertia can arise due to several factors, particularly in established companies with existing structures and processes. One significant source of resistance is the presence of sunk costs, which create a substantial barrier to rapid adaptation. Companies that invest in infrastructure, equipment, and specialist staff may find it difficult to quickly adapt to changes brought about by digital transformation because it is difficult to reallocate these resources in a timely manner (Li et al., 2018). In addition, inertia is often fueled by resource bundling, where resources are tightly integrated across different subunits within the company. When resources are bundled in such a way, resistance to change may emerge, especially if key subunits oppose the transformation. This resistance can significantly hinder the progress of digital transformation.

However, as digital transformation progresses, the negative effects of organizational inertia may gradually diminish. Organizational inertia is typically characterized by strong resistance to initial changes, but as the transformation process unfolds and the organization gains momentum, these resistances can begin to break down. Changes that initially face substantial opposition often lead to cascading transformations, triggering additional adjustments throughout the company (Yi et al., 2016). In this way, the speed and sequence of digital transformation may shift unexpectedly, generating positive feedback loops that enhance overall economic performance (Sujatha et al., 2021). Over time, companies can leverage these transformations to further enhance their dynamic capabilities and improve their economic outcomes.

By combining the perspectives of organizational inertia and dynamic capability, this study proposes that when businesses formally establish dynamic capabilities and overcome the lowest levels of organizational inertia, the impact of digital transformation on economic performance reaches a turning point. At this juncture, the company is in a position to experience a substantial acceleration in economic performance, driven by the full realization of its digital transformation efforts. Based on this reasoning, this study proposes:
Hypothesis 1. Digital transformation fosters economic performance at an accelerating rate.

Digital Transformation and Environmental Performance

According to studies, digital transformation helps businesses gather operational data in real time, which makes predictive maintenance, energy management, and remote monitoring easier. This data-driven approach is pivotal in reducing energy consumption, minimizing carbon emissions, and ultimately enhancing environmental performance (Sujatha et al., 2021); Li, 2022). By leveraging cutting-edge technologies, companies can achieve better operational efficiencies, improve sustainability practices, and gain a competitive edge in terms of their environmental impact. However, this study posits that while the initial stages of digital transformation yield substantial environmental benefits, the beneficial effects on environmental performance may start to fade once digital transformation reaches a certain stage of maturity.

Achieving sustained environmental performance goes beyond merely integrating digital transformation; it requires companies to embed environmental concerns into every facet of their operations. This includes integrating these concerns into their products, services, and processes (Schniederjans & Hales, 2016). For instance, sensors embedded in products can continuously monitor and record relevant data throughout the product's lifecycle, offering critical insights into the state of individual components. This data is invaluable for driving sustainable practices such as reuse, recycling, and remanufacturing (Dinerstein et al., 2019).

Furthermore, utilizing cutting-edge technologies like cloud computing, artificial intelligence (AI), and big data analytics can greatly improve information flow management and encourage the development of eco-friendly practices (Dubey et al., 2020). These technologies support green innovations by providing real-time insights into resource consumption and enabling better decision-making in terms of resource optimization.

Companies are in a good position to use digital technologies to improve their dynamic capacities in the early phases of digital transformation, according to this study. This allows for the creation of green products, services, and processes. These innovations typically lead to a reduction in harmful emissions and a decrease in the consumption of natural resources. For instance, companies can optimize production processes, minimize waste, and ensure that resources are used more efficiently, all of which contribute to environmental sustainability. However, it is crucial to understand that enormous amounts of data are a major driving force behind green technologies based on digital transformation. Large dataset processing and management can be an extremely energy-intensive operation, even while good data management can assist cut down on material waste and energy use. The paradox here lies in the fact that while digital transformation aims to optimize environmental outcomes, the energy consumed in handling, storing, and analyzing vast amounts of data may offset some of these benefits.

The accumulation of data over time may be seen as a critical enabler of continuous improvements in environmental performance. However, this approach is not without its drawbacks. (Johnson, 2015) highlights that only a small fraction—roughly 10%—of the data produced is actively used, while the remaining 90% is discarded into what is often referred to as an "online trash landfill". This surplus of unused data contributes to a significant carbon footprint, as managing this data requires substantial computational resources, storage infrastructure, and energy consumption. Consequently, as companies continue to collect and store more data in the pursuit of green innovations, the environmental cost associated with managing that data may eventually outweigh the environmental benefits that these innovations provide.

Furthermore, the growing scale of digitalization and the increasing reliance on technology has led to concerns about the unintended environmental consequences of excessive data collection and processing. (Rehman et al., 2021) show how higher electricity usage, increased radioactivity from electronic gadgets, and the production of e-waste can all be consequences of excessive digitalization. All of these elements work together to seriously harm the environment. For instance, the rapid pace of technological advancements and the frequent obsolescence of devices contribute to mounting quantities of e-waste, which, if not properly managed, can cause significant harm to ecosystems and human health. Additionally, the energy required to power data centers, servers, and cloud-based infrastructures for data processing and storage further compounds the environmental burden.

Thus, while digital transformation undoubtedly plays a crucial role in driving green innovations and improving environmental performance in the early stages, it is essential to consider the broader environmental implications of large-scale data management and digital infrastructure. The paradoxical nature of this challenge suggests that, as companies continue to embrace digital transformation, they must also innovate in ways that minimize the environmental costs associated with digitalization. This may include adopting more energy-efficient technologies, optimizing data management practices, and developing strategies to minimize e-waste and reduce the carbon footprint of digital operations. Only by addressing these challenges can digital transformation truly fulfill its potential as a driver of long-term environmental sustainability. Based on this reasoning, this study proposes:

Hypothesis 2. Digital transformation exhibits an inverse U-shaped relationship with environmental performance.

Technological Turbulence as a Moderator of the Digital Transformation–Performance Relationship

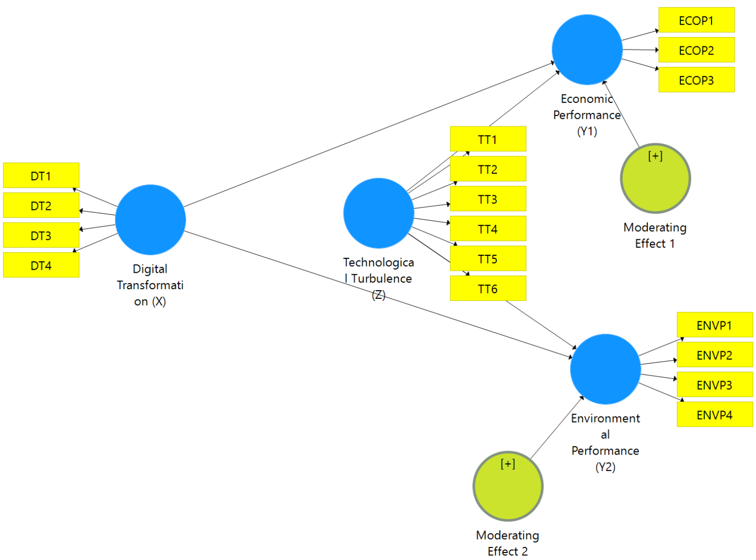
The success of digital transformation (DT) projects frequently depends on both external environmental factors and internal capabilities in quickly changing business contexts. Technological turbulence, or the rate and unpredictability of technological development within an industry, is one such crucial contextual aspect (Li, 2022). The ability to manage these dynamics becomes essential as businesses deal with disruptive technology, quicker innovation cycles, and changing customer expectations. Although technological instability creates uncertainty, it also gives agile firms the chance to use digital tools to gain a competitive edge.

According to earlier studies, companies with sophisticated digital skills may be better able to adapt to change in highly volatile technological environments by updating business models, rearranging processes, and speeding up decision-making (Dubey et al., 2020). Through increased innovation, client response, and operational efficiency, these businesses can generate superior financial results. Proactive environmental management, such real-time energy monitoring or predictive maintenance, may be made possible by digital transformation under high turbulence, which could result in better environmental outcomes (Schniederjans & Hales, 2016). On the other hand, businesses might not feel as much pressure to change in technologically stable environments, and the advantages of digital initiatives would not be as noticeable.

Therefore, the relationship between digital transformation and firm performance may be strengthened by technological turbulence acting as a moderating variable. Digital initiatives are likely to have a greater impact on economic and environmental performance results for businesses operating in more variable environments.

Hypothesis 3. The positive impacts of digital transformation are more pronounced when technological turbulence is high.

Research Model



Source: (Processed Research Data, 2024)

RESEARCH METHODOLOGY

Data and Sample

A total of eighty-one respondents participated in this study by completing a structured questionnaire that was distributed through Google Forms, ensuring easy access and convenience for participants. The sample group consisted of individuals aged between 20 and

50 years, representing a broad and diverse demographic. The group was relatively evenly distributed in terms of gender, with 55% identifying as men and 45% as women. This balanced gender representation added to the diversity of perspectives, enriching the insights gained from the study and contributing to a more comprehensive understanding of the research topic.

The questionnaire itself was meticulously designed to address key variables that were central to the study's objectives. It comprised a total of 17 questions, which were thoughtfully organized into four main sections, each tailored to explore a distinct area of interest. The areas assessed included technological turbulence, economic performance, environmental performance, and digital transformation. These topics were carefully selected to align with the study's aims and to provide a holistic view of the issues under investigation.

To ensure consistency and reliability in data collection, a 5-point Likert scale was utilized for each question. This scale ranged from "strongly disagree" to "strongly agree". Allowing respondents to express varying degrees of agreement or disagreement with the statements provided. The use of a Likert scale enabled the collection of nuanced and detailed responses, capturing the complexities of the participants' attitudes and perceptions. This structured approach to questionnaire design not only facilitated the gathering of relevant data but also ensured that the responses could be systematically analyzed to yield meaningful insights into the research topic.

The first section, which focused on technological turbulence, contained six questions aimed at gauging the respondents' perceptions of the rate and intensity of technological changes in their industries. Technological turbulence refers to the rapid and sometimes unpredictable nature of technological advancements and disruptions that organizations must navigate. The second section, dedicated to economic performance, included three questions that explored respondents' views on how digital transformation impacts organizational economic outcomes, such as profitability, efficiency, and growth.

The third section of the questionnaire focused on environmental performance, with four questions designed to assess the respondents' perceptions of how digital transformation influences environmental sustainability, resource efficiency, and the reduction of waste and emissions. The final section, related to digital transformation, included four questions that specifically aimed to understand respondents' experiences with and attitudes toward the ongoing digitalization processes in their organizations, particularly in terms of technological adoption, change management, and innovation.

The data collected from these responses provided a valuable dataset that was used for analyzing the impact of technological turbulence on both economic and environmental performance. By investigating how rapid technological changes affect organizational outcomes in these two areas, the study sought to provide insights into the broader implications of digital transformation in a rapidly evolving technological landscape. This approach allowed for a deeper understanding of the dynamic relationship between technology, business performance, and sustainability, offering actionable insights for organizations navigating the challenges of digital transformation in today's highly competitive and fast-paced business environment.

RESULTS AND DISCUSSION

Matrix of Path Coefficients Among Variables and Moderating Effects

	Moderating Effect 1	Moderating Effect 2	X	Y1	Y2	Z
Moderating Effect 1				0.186		
Moderating Effect 2					-0.497	
X				0.417	0.795	
Y1						
Y2						
Z				0.598	0.298	

Source: (Processed Research Data, 2024)

Based on the table above, the correlation relationships between the research variables are evident, with the correlation values indicating varying strengths of association. Moderating Effect 1 exhibits a low to moderate positive correlation with other variables, specifically 0.186 with Moderating Effect 2, 0.417 with X, 0.598 with Y2, and 0.298 with Z. In contrast, Moderating Effect 2 demonstrates a moderate negative correlation with X (-0.497), but no correlation data is available for its relationships with other variables. Variable X shows a strong positive correlation with Y1 (0.795), while Y2 has a moderate positive relationship with Moderating Effect 1 (0.598). However, the correlations between certain other variable pairs are not presented in the table. Overall, the results suggest weak to moderate relationships among most research variables, with the exception of the strong association between X and Y1. These findings provide a foundation for further analysis of the moderating roles and inter-variable relationships within the research model.

Measurement Model Evaluation: Cronbach's Alpha, rho_A, Composite Reliability, and Average Variance Extracted (AVE)

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
Moderating Effect 1	0.759	1.000	0.605	0.429
Moderating Effect 2	0.759	1.000	0.729	0.418
X	0.858	0.862	0.904	0.701
Y1	0.875	0.884	0.924	0.802
Y2	0.814	0.842	0.883	0.660
Z	0.335	0.926	0.243	0.613

Source: (Processed Research Data, 2024)

The table above presents the results of reliability and validity tests for several variables, including Moderating Effect 1, Moderating Effect 2, X, Y1, Y2, and Z. Based on the Cronbach's Alpha and rho_A values, most variables exhibit good reliability, with values exceeding 0.7, except for variable Z, which has a Cronbach's Alpha value of 0.335, indicating very low reliability. Regarding Composite Reliability, most variables also meet the acceptable threshold of 0.7, except for Moderating Effect 1 (0.605) and Z (0.243), which fall below the required level. Furthermore, the Average Variance Extracted (AVE) values show that variables X (0.701), Y1 (0.802), Y2 (0.660), and Z (0.613) satisfy the criteria for convergent validity (AVE > 0.5), whereas Moderating Effect 1 (0.429) and Moderating Effect 2 (0.418) do not meet this standard. Overall, these findings indicate that while the reliability and validity of most variables are adequate, improvements are necessary, particularly for Moderating Effect 1, Moderating Effect 2, and Z, to enhance the robustness of the research model.

The square roots of the Average Variance Extracted (AVE) for each construct are as follows: Moderating Effect 1 (√0.429 = 0.655), Moderating Effect 2 (√0.418 = 0.647), X (√0.701 = 0.837), Y1 (√0.802 = 0.895), Y2 (√0.660 = 0.812), and Z (√0.613 = 0.783). Among these, construct Y1 exhibits the highest square root of AVE (0.895), followed by constructs X (0.837) and Y2 (0.812), indicating a strong empirical capacity for discriminant validity. Conversely, the relatively lower values observed for Moderating Effect 1 and Moderating Effect 2 (0.655 and 0.647, respectively) may raise concerns regarding discriminant validity, particularly if the inter-construct correlations exceed these thresholds.

Furthermore, although construct Z demonstrates an acceptable Average Variance Extracted (AVE) of 0.613, it exhibits notably low reliability, thereby casting doubt on its discriminant validity. To ensure a more robust assessment of discriminant validity, additional analyses—such as the Heterotrait-Monotrait Ratio (HTMT) method—are recommended. An HTMT value below 0.85 would indicate that the constructs are indeed empirically distinct (Henseler et al., 2015). While a definitive conclusion cannot yet be drawn due to the unavailability of inter-construct correlation data, preliminary findings suggest that particular attention should be directed toward Moderating Effect 1, Moderating Effect 2, and construct Z.

Discriminant Validity Assessment

	Moderating Effect 1	Moderating Effect 2	X	Y1	Y2	Z
Moderating Effect 1	0.655					
Moderating Effect 2	0.971	0.647				
X	-0.250	-0.303	0.837			
Y1	0.556	0.513	0.054	0.895		
Y2	-0.370	-0.456	0.774	0.098	0.813	
Z	0.815	0.802	-0.534	0.516	-0.490	0.783

Source: (Processed Research Data, 2024)

The table displays the relationships between different variables, represented as Moderating Effect 1, Moderating Effect 2, X, Y1, Y2, and Z. The values in the table indicate the strength and direction of the correlation between each pair of variables. For example, Moderating Effect 1 and Moderating Effect 2 have a strong positive correlation (0.971), while Moderating Effect 1 and X have a weak negative correlation (-0.250). Analyzing these correlations helps us understand how the variables interact and predict potential outcomes or influences. For instance, a strong positive correlation indicates a direct relationship between the variables, while a negative correlation suggests an inverse relationship.

R-squared and Adjusted R-squared

	R Square	R Square Adjusted
Y1	0.427	0.405
Y2	0.676	0.663

Source: (Processed Research Data, 2024)

The table above presents the R-squared and Adjusted R-squared values for the two models analyzed, namely Y1 and Y2, which illustrate each model's ability to explain the variance in the dependent variable. Model Y1 has an R-squared value of 0.427, indicating that 42.7% of the variance in the dependent variable can be explained by this model, with an Adjusted R-squared value of 0.405. The Adjusted R-squared value accounts for the number of independent variables in the model, providing a more accurate estimate. On the other hand, Model Y2 shows a higher R-squared value of 0.676, meaning that this model explains 67.6% of the variance in the dependent variable, with an Adjusted R-squared value of 0.663. This value remains at a very good level after adjustment. In general, a higher R-squared value indicates better explanatory power of the model. Based on the presented data, Model Y2 demonstrates superior performance in explaining the variance in the dependent variable compared to Model Y1. This suggests that Model Y2 is more suitable for research that requires a more comprehensive explanation of the dependent variable.

Structural Model Assessment – Path Coefficients and Hypothesis Testing

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Moderating Effect 1 -> Y1	0.186	0.235	0.134	1.384	0.167
Moderating Effect 2 -> Y2	-0.497	-0.482	0.119	4.174	0.000
X -> Y1	0.417	0.392	0.104	4.021	0.000
X -> Y2	0.795	0.772	0.079	10.009	0.000
Z -> Y1	0.598	0.556	0.147	4.059	0.000
Z -> Y2	0.298	0.270	0.131	2.276	0.023

Source: (Processed Research Data, 2024)

The table presents the results of the statistical tests for the six variables under examination. The first column lists the name of each variable, such as Moderating Effect 1 → Y1. The second column shows the original value (O), representing the value of the variable in the original sample. The third column displays the sample mean (M), which reflects the average value of the variable in the sample. The fourth column indicates the standard deviation (STDEV), representing the distribution of variable values within the sample. The fifth column presents the T statistic, which is the statistical value used to test the significance of the difference between the original value and the sample mean. The final column shows the P value, which indicates the probability of obtaining a result as extreme as the observed one, assuming there is no difference between the original value and the sample mean.

Based on the table, we observe that the variable Moderating Effect 1 → Y1 has a P value of 0.167, suggesting insufficient evidence to reject the null hypothesis of no difference between the original value and the sample mean. Conversely, the variables Moderating Effect 2 → Y2, X → Y1, and Z → Y1 each have a P value of 0.000, providing strong evidence to reject the null hypothesis and concluding that there is a significant difference between the original values and the sample means. Additionally, the variable X → Y2 has a P value of 0.000, further supporting the rejection of the null hypothesis. The variable Z → Y2 has a P value of 0.023, which also provides sufficient evidence to reject the null hypothesis at the 0.05 significance level.

In conclusion, the results from the table indicate that most variables show significant differences between the original values and the sample means. This suggests that these variables may have a notable impact on the research findings. However, the variable Moderating Effect 1 → Y1 does not exhibit a significant difference, implying that it may not have a substantial effect on the research outcomes.

CONCLUSION AND SUGGESTION

This research highlights the crucial role of digital transformation in enhancing both economic and environmental performance within organizations. By leveraging digital technologies, companies can significantly strengthen their dynamic capabilities, streamline operational processes, and tackle environmental challenges more effectively. The findings indicate that digital transformation enables organizations to conduct real-time data monitoring, implement predictive maintenance, and foster green innovations, all of which collectively contribute to driving sustainability. Furthermore, the research underscores the transformative potential of digital technologies in addressing complex environmental issues, promoting efficiency, and optimizing resource utilization.

However, the study also reveals the presence of diminishing returns at advanced stages of digital transformation, where excessive data accumulation and heightened energy consumption may begin to outweigh the environmental benefits. This highlights the importance of strategic planning in balancing technological advancements with sustainability objectives. Furthermore, the relationship between digital transformation and performance outcomes is influenced by technological instability, which has a moderating effect in this setting. This interplay underscores the need for adaptive and flexible strategies to ensure that digital initiatives yield optimal results. Overall, the research emphasizes the multifaceted and complex nature of leveraging digital transformation effectively, suggesting that while it offers significant potential for enhancing organizational performance, its implementation must be approached thoughtfully and strategically to overcome inherent challenges.

Despite its valuable contributions, this study faced several limitations that should be acknowledged. First, the reliance on self-reported data collected through questionnaires introduces the possibility of response biases, where participants may inadvertently overestimate or underestimate certain factors. The relatively small sample size of 81 respondents, although informative, limits the statistical power of the analysis and restricts the generalizability of the findings to a broader range of contexts. Furthermore, the study's cross-sectional design limits its capacity to draw conclusions about the causal links between performance outcomes, technological instability, and digital transition.

The research also focused on a specific set of variables and industries, which may have overlooked sector-specific dynamics or other moderating factors that could play a significant role in shaping the results. Another limitation lies in the scope of the study, which primarily explored economic and environmental performance, leaving the social dimensions of sustainability, such as employee well-being and community impact, largely unaddressed. Moreover, the study did not delve deeply into the long-term implications of digital transformation, which leaves room for future investigations to provide a more holistic evaluation of its effects on sustainable development.

To build upon these findings, the limitations described above should be addressed in future studies in order to create a more thorough knowledge of the effects of digital transformation. Employing longitudinal research designs would enable a deeper exploration of causal relationships and allow researchers to examine how organizational capabilities evolve over time in response to digital initiatives. Increasing the sample size and incorporating a wider variety of sectors and geographical areas might improve the findings' generalizability and offer more comprehensive understanding of the phenomena under study. Incorporating qualitative research methods, such as interviews and case studies, could uncover nuanced perspectives on how organizations navigate technological turbulence and implement digital strategies effectively in varying contexts.

Moreover, future studies should examine the social dimensions of sustainability, including aspects such as employee satisfaction, community engagement, and broader societal impacts, to provide a more well-rounded understanding of digital transformation's role in sustainable development. Lastly, additional research is recommended to investigate innovative solutions for mitigating the environmental costs associated with digital transformation. This could include exploring energy-efficient technologies, strategies for managing electronic waste, and other practices that ensure sustainability goals are achieved without unintended negative consequences. Such efforts will be critical in advancing the responsible and effective use of digital transformation as a driver of organizational and societal progress.

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