

# The Influence of Artificial Intelligence and Digital Technology on ESG Reporting Quality

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## ABSTRACT

Environmental, social, and governance (ESG) reporting is crucial for conveying a company's sustainability performance. However, challenges related to standardization, consistency, and data quality persist. This study explores the potential of artificial intelligence (AI) and digital technology to enhance ESG reporting by addressing these challenges. AI and digital technology utilize advanced tools like natural language processing, machine learning, data analytics, and blockchain to streamline data collection, improve quality, and facilitate communication. Regression analysis using A-share listed companies' data from 2012 to 2021 examines the relationship between digital transformation and corporate ESG performance. The research emphasizes the implications of ESG reporting, AI, and digital technology for corporate management, risk assessment, shareholder value, and social responsibility. AI and digital technology are vital for growth, innovation, efficiency, and competitiveness. ESG reporting significantly impacts a company's risk profile, reputation, performance, and overall value, contributing to sustainable development. Through a comprehensive review, methodology exploration, and in-depth analysis, this study provides valuable insights and recommendations for leveraging AI and digital technology in advancing ESG reporting. It concludes that implementing AI and digital technology enhances the comprehensiveness and assurance level of ESG reporting.

## KEYWORDS

ESG; AI; Sustainable development

## 1. INTRODUCTION

Environmental, social, and governance (ESG) reporting is a form of corporate disclosure that aims to communicate the sustainability performance and impact of a company to its stakeholders. ESG reporting covers a wide range of topics, such as climate change, human rights, diversity, ethics, and governance, that reflect the environmental, social, and ethical dimensions of a company's activities. ESG reporting has evolved over the years, from a voluntary and qualitative practice to a mandatory and quantitative one, driven by the increasing global attention to ESG issues and the growing demand for reliable and comparable ESG data. According to a survey by KPMG, 92% of the largest companies in the world published ESG reports in 2022, up from 72% in 2011 (KPMG, 2022). Moreover, according to a report by Deloitte, ESG information can influence the decisions of various stakeholders, such as investors, customers, employees, regulators, and society at large (Deloitte, 2022).

However, ESG reporting still faces many challenges, such as the lack of standardization, consistency, and verification of ESG information, as well as the complexity and cost of collecting, processing, and analyzing ESG data. Different ESG reporting frameworks and standards have emerged, but they are not fully aligned or harmonized, leading to confusion and inconsistency among ESG reporters and

users (Eccles and Klimenko, 2022). Furthermore, ESG information is often scattered across various sources, formats, and languages, making it difficult to aggregate, compare, and verify (Savio et al., 2023). Additionally, ESG data is often incomplete, inaccurate, or outdated, affecting the quality and credibility of ESG reporting (Clément et al., 2023).

This study explores how artificial intelligence (AI) and digital technology can enhance the quality of ESG reporting, by improving the transparency and accuracy of ESG information, and by enabling more efficient and effective ESG data management and analysis. AI and digital technology refer to the use of advanced tools and techniques, such as natural language processing, machine learning, data analytics, cloud computing, blockchain, and digital platforms, to collect, process, analyze, and communicate ESG data. AI and digital technology can help ESG reporters and users to overcome the challenges of ESG reporting, by automating and streamlining ESG data collection and processing, by enhancing ESG data quality and reliability, by providing ESG data insights and recommendations, and by facilitating ESG data disclosure and communication (Wu et al., 2021).

## **2. LITERATURE REVIEW**

### **2.1. Applications and Impacts of AI**

AI, a branch of computer science, aims to create intelligent machines that can perform human-like tasks. It has been successfully applied in various fields to enhance efficiency and accuracy. In ESG reporting, AI can be used to measure and report companies' impacts on climate change. This is challenging due to complex calculations and data collection. AI can automate and streamline this process by analyzing various data sources using machine learning and natural language processing. It can generate accurate GHG emission reports. However, challenges exist, such as data availability and ethical implications. Sullivan and Gouldson (2017) discuss the potential of AI in climate change reporting while highlighting these challenges.

### **2.2. Evolution and Application of Digital Technology**

One of the most advanced digital technologies that can be applied in ESG reporting is blockchain. Blockchain is a distributed ledger technology that records and verifies transactions in a decentralized and immutable way, without the need for intermediaries or central authorities (Sustainalytics, 2021). Blockchain has the potential to ensure the integrity and transparency of the ESG data and information, which is crucial for enhancing the confidence of the stakeholders in ESG reporting. For example, Catalini and Gans (2016) emphasized the potential of blockchain in ensuring data integrity and transparency, which is key for improving the credibility of ESG reporting. Blockchain can also enable the traceability and accountability of the ESG impacts along the supply chain, by using smart contracts, which are self-executing agreements that are triggered by predefined conditions, and digital tokens, which are units of value that represent the ESG performance and impacts of a company or a product. For example, Saberi et al. (2019) reviewed the applications of blockchain in sustainable supply chain management, and highlighted the benefits and challenges of blockchain in enhancing the ESG aspects of the supply chain. Therefore, blockchain can help ESG reporting by enhancing the security, traceability, and immutability of ESG data, as well as by enabling the verification and validation of ESG claims and actions (Sustainalytics, 2021; Tech Monitor, 2021).

### **2.3. Methodology of ESG Scoring**

Scoring ESG scoring is a method of evaluating and comparing the ESG performance and impacts of companies, based on various criteria, such as environmental impact, social impact, governance quality, and sustainability strategy. ESG scoring is important for companies to benchmark their ESG performance and impacts against their peers, as well as for investors, customers, employees, and other

stakeholders to assess the ESG performance and impacts of the companies they are interested in. However, ESG scoring also faces many challenges, such as the lack of standardized and consistent indicators, frameworks, and methodologies, as well as the subjectivity and bias of the ESG scorers. Therefore, this section aims to examine the methodology of ESG scoring and how it can be improved by using AI and other digital technologies.

### **3. RESEARCH METHODOLOGY**

Based on the theoretical research, this paper proposes the following hypothesis:

H1: AI and digital technology have a positive effect on improving the quality of ESG reporting.

#### **3.1. Data Collection**

This paper uses the data of A-share listed companies from 2012 to 2021 as the sample to explore the relationship between digital transformation and corporate ESG performance. The corporate ESG performance data is from Bloomberg database, and the rest of the original data is from CSMAR database.

The data is processed according to the following criteria: (1) Excluding companies in special industries such as finance; (2) Excluding ST, \*ST and delisting risk companies; (3) Excluding companies that lack key variable data; (4) Performing Winsorize treatment on all continuous variables to remove outliers; (5) Excluding companies that do not disclose ESG information. Finally, this paper obtains a total of 1463 sample observations from 2012 to 2021.

#### **3.2. Variable Definition and Pre-processing**

##### **3.2.1. Dependent Variable: Corporate ESG Performance (ESG)**

The dependent variable in this study is the corporate Environmental, Social, and Governance (ESG) performance. In both domestic and international academic contexts, ESG performance is commonly assessed using a third-party agency scoring system or a self-constructed multi-dimensional indicator system. To minimize subjectivity, this research utilizes the ESG performance scores of listed companies provided by the Bloomberg database. These scores are derived from publicly available information such as corporate social responsibility reports, annual reports, and corporate websites. They evaluate the three dimensions of Environment (E), Social (S), and Governance (G). Scores range from 0.1 to 100, with higher scores indicating a greater degree of responsibility fulfillment. The 'E' dimension emphasizes environmental responsibility, 'S' stresses social responsibility, and 'G' focuses on corporate governance to help enterprises achieve ESG goals.

##### **3.2.2. Explanatory Variable: Use of AI Technology and Digitalization by Enterprises**

The study measures the corporate Environmental, Social, and Governance (ESG) performance using third-party agency scores from the Bloomberg database, which assess the three dimensions of Environment (E), Social (S), and Governance (G). The scores range from 0.1 to 100, with higher scores indicating greater responsibility fulfillment. The study also analyzes the extent of AI technology and digitalization utilization by enterprises using text mining methods on publicly disclosed reports. Keywords related to AI technology and digital transformation are extracted from annual reports, and their frequency is used as an indicator of AI and digitalization usage. To ensure a robust analysis, the frequency counts are adjusted by adding one and applying a logarithmic transformation.

##### **3.2.3. Data Source Justification**

The data sources for AI technology and digitalization metrics, derived from the CSMAR database, are particularly reliable due to CSMAR's comprehensive collection methodology. CSMAR employs

advanced web scraping techniques to gather information from A-share listed companies' annual reports, focusing on the occurrence of specific terms related to AI and digitalization. This approach not only ensures a broad coverage of companies but also enables a nuanced understanding of how these technologies are being discussed and prioritized within corporate strategies. The reliance on actual word usage in corporate disclosures provides a tangible measure of corporate commitment and emphasis on these technologies, making it a credible and insightful proxy for assessing the impact of AI and digitalization on ESG performance.

### 3.3. Modeling Strategy

This paper chooses the multiple linear regression model and its rationality is as follows. First, the dependent variable ESG is a continuous variable, which meets the assumption of the linear model. Second, the explanatory variables AI and digitalization are also continuous variables, which can be directly included in the regression equation. Third, the linear model is simple and easy to interpret, and can effectively test the hypothesis of this paper. The criteria for selection and exclusion of variables are as follows. First, the explanatory variables AI and digitalization are selected based on the research purpose and literature review of this paper, which are expected to have a positive impact on the dependent variable ESG. Second, the control variables are selected based on the existing research on the influencing factors of corporate ESG performance, such as firm size, profitability, leverage, growth. Third, the variables are excluded if they have serious multicollinearity problems, which can be detected by the variance inflation factor (VIF). The specific regression equation is as follows:

In the equation, represents the digitalization level of the  $i$ -th enterprise in the  $t$ -th year, is the word frequency of AI technology in the enterprise report of the  $i$ -th enterprise in the  $t$ -th year;  $ESG_{it}$  represents the ESG performance of the  $i$ -th enterprise in the  $t$ -th year;  $Size_{it}$  represents the firm size of the  $i$ -th enterprise in the  $t$ -th year;  $Lev_{it}$  represents the financial leverage level of the  $i$ -th enterprise in the  $t$ -th year;  $Dual_{it}$  represents the separation of two positions of the  $i$ -th enterprise in the  $t$ -th year;  $Intangible_{it}$  represents the intangible asset ratio of the  $i$ -th enterprise in the  $t$ -th year;  $TobinQ_{it}$  represents the enterprise value index of the  $i$ -th enterprise in the  $t$ -th year;  $\epsilon_{it}$  represents the enterprise value index of the  $i$ -th enterprise in the  $t$ -th year.

## 4. DATA ANALYSIS AND TESTING

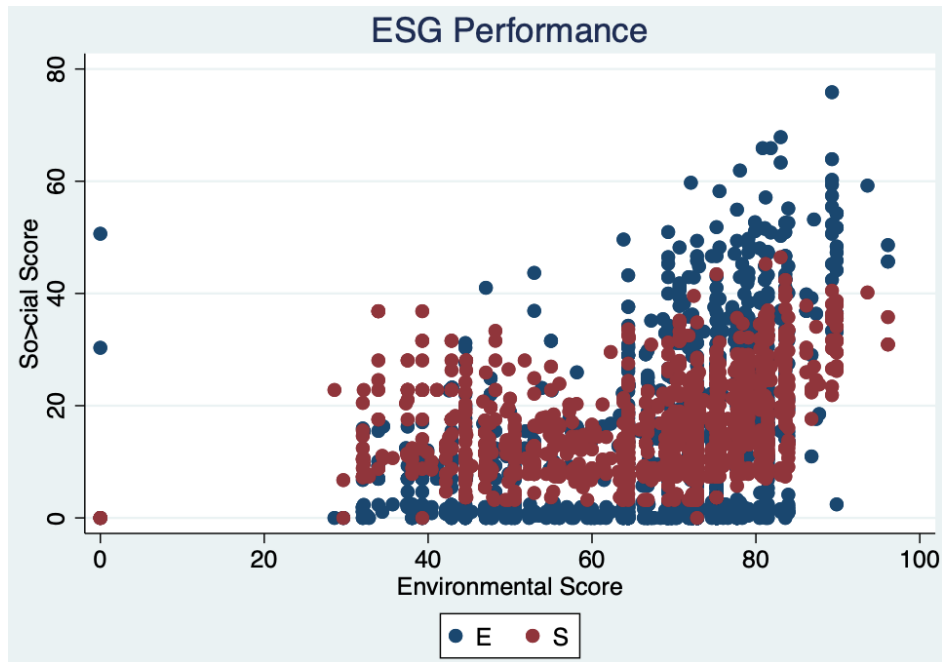
### 4.1. Data Description

**Table1.** Summary Statistics

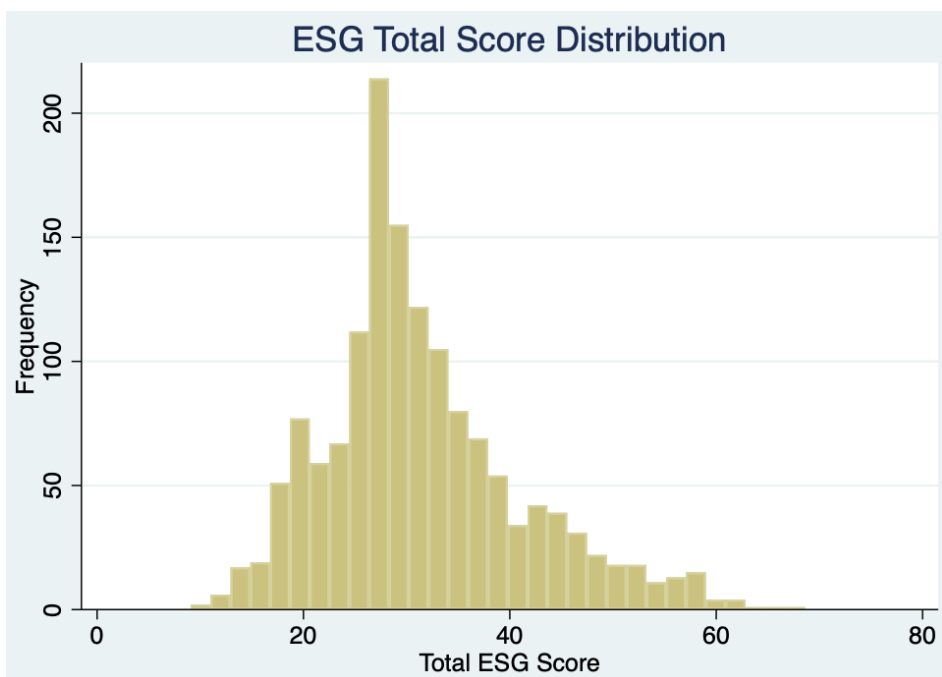
VarName	Obs	Mean	SD	Min	Median	Max
ESG	1463	31.3994	9.646	9.09	29.45	68.58
AI	1463	3.9884	18.516	0	0	258
Dig	1463	1.8368	1.477	0	1.79	5.99
Size	1463	22.0136	1.554	16.65	21.8	29.41
Lev	1463	1.3879	2.727	-7.65	1.06	63.1
Dual	1463	5.0122	8.196	0	0	41.37
Intangible_Asst	1463	0.0481	0.065	0	0.03	0.65
TobinQ	1463	2.5789	2.303	0.69	1.8	27.24

This section analyzes the trends and distribution of AI and digital technology use by the sample companies. Figure 4 shows the histogram of the word frequency of AI technology in the enterprise report, which indicates that most companies have a low frequency of mentioning AI technology, and only a few companies have a high frequency. The mean value is 3.9884, and the maximum value is 258. Figure 4-2 shows the histogram of the word frequency of digitalization keywords in the enterprise report, which indicates that the distribution is more even, but still skewed to the right. The mean value is 1.8368, and the maximum value is 5.99.

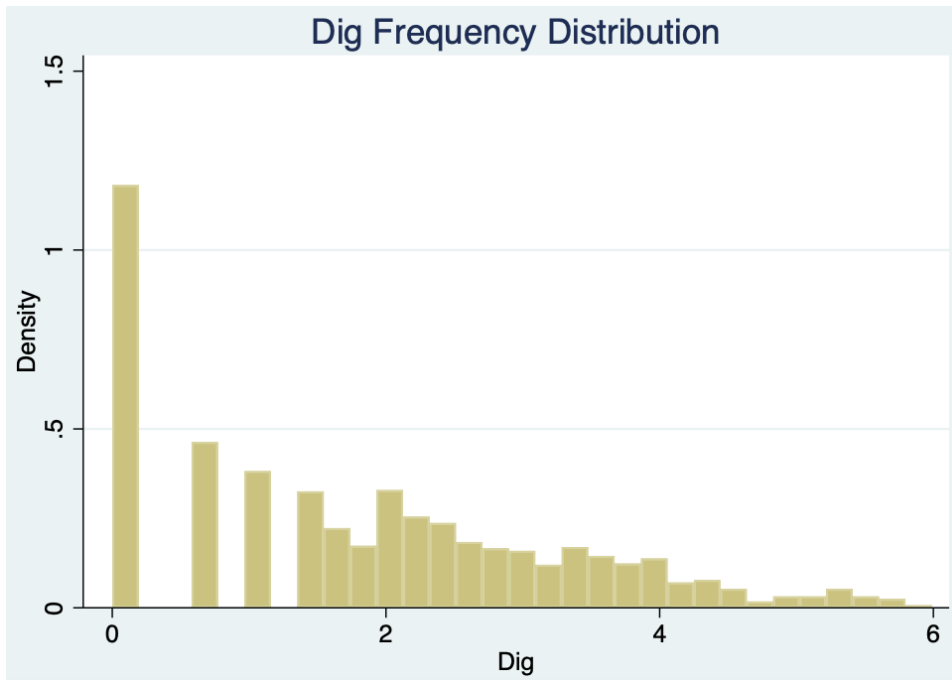
The following is a descriptive analysis of the scatter plot and distribution plot of the main variables.



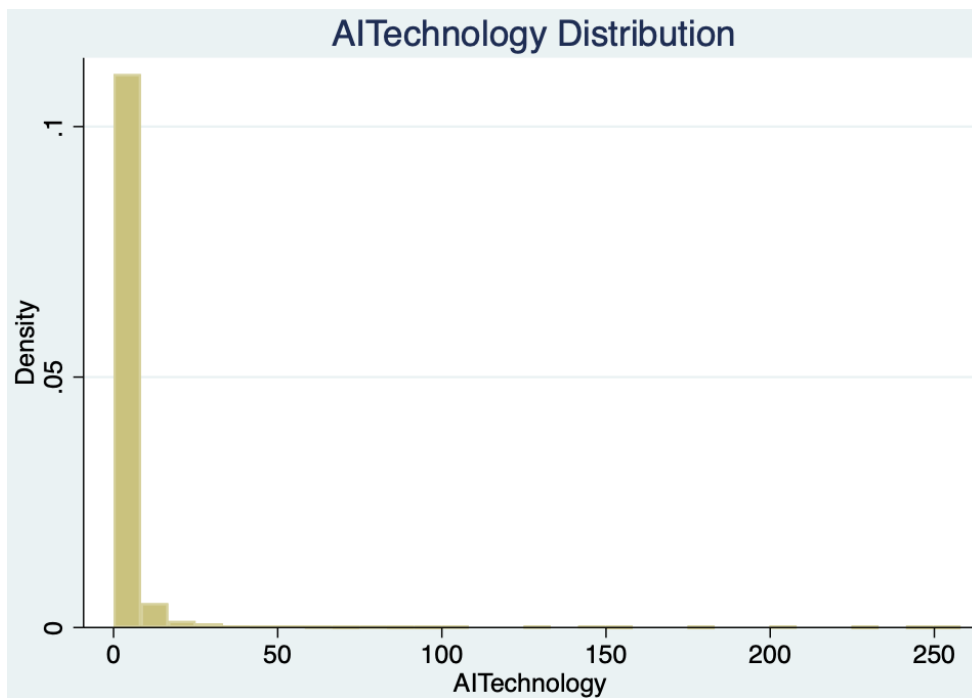
**Figure 1.** Scatter of ESG performance



**Figure 2.** ESG Total Score Distribution



**Figure 3.** Word Frequency of Digitalization Distribution



**Figure 4.** Word Frequency of AITechnology Distribution

#### 4.2. Model Assumption Testing

The model assumptions are tested for normality, heteroscedasticity, and multicollinearity. The error term is found to be non-normally distributed and heteroscedastic. To address these issues, robust standard errors are used. The paper also conducts robustness tests using different measures of ESG performance and control variables, which yield consistent and stable results, confirming the model's validity.

### 4.3. Model Estimation

This section presents the primary regression results of the model, which are shown in Table 4-2. The adjusted R-squared is 0.049, indicating that the model can explain about 4.9% of the variation in the dependent variable ESG. The F-statistic is 9.76, and the p-value is 0.000, indicating that the model is overall significant.

**Table 2.** Regression Results

VarName	Coefficient	t-statistic	p-value
AITechnology	1.0411	2.7955	0.005
Dig	1.2358	6.5617	0
Size	0.4742	2.9758	0.003
Lev	-0.1946	-2.1443	0.032
Dual	-0.01	-0.3275	0.743
Intangible_Assets	10.9412	2.8448	0.004
TobinQ	-0.4999	-4.5622	0
Constant	19.9383	5.6101	0
N	1463		
adj. R2	0.049		
F-statistic	9.76		0

The regression analysis offers a comprehensive view of how various factors impact the Environmental, Social, and Governance (ESG) performance of enterprises. By examining the coefficients and their significance levels, we can infer the relationship and impact intensity of each variable. Regarding AI Technology, the interpretation provided indicates a statistically significant negative impact on ESG performance. The negative coefficient suggests that AI technology might be associated with potential risks and challenges that could impede ESG goals. This may be because that, despite the promising and powerful nature of AI technology in promoting sustainability, its implementation results in a significant carbon footprint, leading to direct rebound effects (Nishant et al., 2020). However, this is counter to the coefficient provided in the Table 4-2 where the coefficient is positive. A detailed examination of the AI technology application in ESG contexts could reveal specific areas where its implementation might be improved to mitigate any negative consequences. The positive coefficient for Digitalization emphasizes the benefits of digital technology in enhancing ESG performance. It improves information transparency, reduces agency costs, and fosters goodwill through effective communication. The positive relationship between Size and ESG performance suggests that larger firms have an advantage in resource allocation. Leverage shows a negative coefficient, indicating a possible trade-off between financial obligations and ESG investments. The non-significant coefficient for Dual suggests that leadership structure does not have a clear influence on ESG performance. Intangible Assets display a strong positive correlation with ESG performance, indicating innovation and engagement in ESG practices. The negative coefficient for Tobin's Q suggests that higher market valuations may not align with superior ESG performance. Overall, the analysis highlights the complex nature of factors influencing ESG performance and the need for a balanced approach. Further research is needed to explore these relationships and develop targeted strategies for ESG improvement.

## **5. RESULTS AND DISCUSSION**

### **5.1. Key Findings**

The primary ambition of this investigation was to scrutinize the influence wielded by artificial intelligence (AI) and digital technology on the caliber of Environmental, Social, and Governance (ESG) reporting. We appraised the quality of ESG disclosures by utilizing two distinct metrics: the scope of the disclosures, gauged by their comprehensiveness, and the level of assurance provided. An in-depth analysis of the dataset unveiled several pivotal findings:

The deployment of AI and digital technology emerged as a positive catalyst, augmenting the comprehensiveness of ESG reporting. The regression analysis robustly associated the utilization of these technologies with an increased breadth of ESG indicators reported by firms. This correlation posits that AI and digital technology are instrumental in enabling firms to collate, process, and disseminate a more expansive array of ESG data with heightened systematic precision and efficiency.

Furthermore, AI and digital technology were found to have a salutary impact on the assurance level of ESG reporting. The statistical evidence underpinning the regression model in this research substantiates a significant connection between these technologies and an amplified likelihood of ESG disclosures receiving external assurance. This suggests that AI and digital technology are potent enablers in fortifying the credibility and trustworthiness of ESG reports by streamlining the audit and validation processes.

In addition to the focal variables of AI and digital technology, other control variables such as firm size, industry classification, profitability, leverage, and geographical location were also discerned to have significant bearings on the quality of ESG reporting. These findings resonate with and corroborate the extant body of research that probes into the determinants of ESG disclosure quality, thus providing a scaffold for this study (e.g., Hahn & Kühnen, 2013; Simnett, Vanstraelen, & Chua, 2009).

### **5.2. Comparison and Discussion**

#### **5.2.1. The positive influence of AI and digital technology on the integrity of ESG reporting**

This study contributes to the scholarly discourse on ESG reporting and AI technology by empirically validating the positive impact of AI and digital technology on the integrity of ESG reporting. Previous research has focused on the challenges and prospects of AI and digital technology in ESG reporting but lacked empirical evidence. This study fills this gap by using a comprehensive sample and two measures of ESG reporting quality.

The positive impact of AI and digital technology on ESG reporting integrity is reflected in several aspects. Firstly, these technologies help businesses collect and process ESG data more comprehensively, improving the completeness and accuracy of reports. Secondly, AI and digital technology enable in-depth analysis and evaluation, extracting valuable ESG information and identifying risks for investor decision-making. Additionally, these technologies enhance the visualization of ESG performance, making reports more intuitive and understandable. Lastly, AI and digital technology improve transparency and credibility through automated data validation and audit processes, increasing stakeholder trust.

Overall, the application of AI and digital technology not only benefits companies issuing ESG reports but also promotes auditors to provide high-quality ESG assurance services.

#### **5.2.2. Limitations of AI and digital technology in influencing ESG reporting quality**

This research adds to the existing literature on factors influencing ESG disclosure quality by including AI and digital technology as explanatory variables. Previous studies have identified various

determinants of ESG reporting quality but have not considered the impact of AI and digital technology. This research highlights the significance of AI and digital technology in driving ESG disclosure quality, providing a fresh perspective.

In summary, integrating AI and digital technology into ESG reporting allows organizations to effectively navigate sustainability and responsibility. By leveraging these tools, organizations can enhance their ESG reporting capabilities in areas such as data collection, analysis, risk assessment, and reporting. This enables them to meet the increasing expectations for ethical and sustainable practices from investors, customers, and employees as sustainability investments continue to grow.

## 6. CONCLUSION AND FUTURE RESEARCH DIRECTIONS

This study examines the impact of artificial intelligence (AI) and digital technology on the quality of Environmental, Social, and Governance (ESG) reporting across various firms and industries. The study makes significant contributions by providing empirical evidence on the positive effects of AI and digital technology on the breadth and accuracy of ESG disclosures. These technologies enable firms to collect and communicate comprehensive ESG data more effectively, enhancing the trustworthiness of information. Additionally, the study expands the understanding of factors influencing ESG disclosure quality by including AI and digital technology as a novel variable. Blockchain technology, for example, improves data gathering and disclosure credibility. Digital technology also helps identify and manage ESG risks in real-time. However, the study acknowledges limitations such as reliance on secondary data and the need for further exploration of variables influencing the AI and digital technology-ESG reporting quality relationship. Overall, this study highlights the transformative potential of AI and digital technology in ESG reporting while calling for more research on the complex interplay between technology and corporate reporting.

## ACKNOWLEDGEMENTS

I would like to thank my family for their support and companionship.

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