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AI-Driven Green Accounting in Saudi Private Firms: The Mediating Role of Data Granularity on ESG Reporting Excellence

Ahmed Salman Almahuzi[1]

Abstract

This study examined the impact of artificial intelligence (AI)-supported green accounting on the environmental, social, and governance (ESG) reporting excellence of Saudi private companies and considered how data granularity mediated that impact. In view of the heightened importance of sustainability reporting under Saudi Vision 2030, the study investigated the impacts of AI solutions—which include the automation and transparency of environmental reporting, predictive analytics of environmental costs, and resource allocation—on the quality of ESG reporting. A quantitative research design was adopted to collect data through a structured questionnaire from Saudi Arabian firms in the private sector. The measurement and structural models were analyzed by partial least squares structural equation modeling in SmartPLS. The results show that using AI in the development of green accounting positively and significantly affects all elements of ESG reporting. Additionally, data granularity plays a mediating role of a slight margin; that is, accurate, comprehensive, and properly organized data are an important factor in AI applications' success in improving accounting practice for quality ESG reporting. The findings also point to the fact that merely adopting technology can do the trick, proper data management and accuracy are components that enhance the outcomes of ESG reporting. The conducted research makes a theoretical contribution by introducing AI-based green accounting concepts and data accuracy into the literature on ESG reporting, and it may inform the practical applications of managers and policymakers aiming to enhance Saudi private companies' sustainability reporting practices.

Keywords: *AI-driven green accounting; ESG reporting excellence; data granularity; sustainability reporting; Saudi private firms; PLS-SEM; Vision 2030.*

Introduction

Green accounting using artificial intelligence (AI) incorporates AI technologies to enhance reporting on sustainability and environmental impact monitoring and aids companies in making sustainable decisions. Generative AI tools such as ChatGPT can automate and enhance the quality of sustainability reporting but may also raise concerns about possible greenwashing, suggesting the importance of caution and regulation in sustainability accounting (De Villiers et al., 2024). The use of AI in green accounting enables analyzing and visualizing data in real time, automating financial and nonfinancial reporting, and facilitating the achievement of the Sustainable Development Goals (SDGs) associated with economic growth, innovation, and sound institutions (Kulkov et al., 2024; Peng et al., 2023). Green AI aims to minimize the carbon footprint of AI models themselves (i.e., by making them energy efficient during training and inference) to make AI applications for accounting processes environmentally sustainable (Bolón-

[1] Accounting Department, College of Business Administration, University of Hafr Al Batin, Al Jamiah, Hafr Al Batin 39524, Eastern Province, Saudi Arabia, ahmedsal9041@gmail.com

Canedo et al., 2024; Verdecchia et al., 2023). AI also has a beneficial impact on green marketing and financial performance through better competitive benefits due to sustainable practices (Al-Ahmed et al., 2025) and the use of blockchain with AI positively affects green finance investment transparency and accountability (Li et al., 2025). In general, AI-related green accounting can be viewed as an amalgamation of cutting-edge technologies that ensures environmental sustainability by adopting better measurement, reporting, and decision-making systems.

Data granularity—the extent of data detail or fineness in a dataset—greatly influences data analysis, modelling, and forecasting. Chain ladder model studies in actuarial science indicate that a model's increasing granularity (i.e., being based on smaller time units) tends to increase the number of data points and make each data point more volatile; this may influence the variance of loss reserve forecasts, and some evidence indicates that the most efficient forecasting is at the highest granularity so as to maximize the variance (Taylor, 2025). The granularity of data in biomedical research, especially cancer studies, can differ widely among types of molecular, imaging, behavioral, and clinical data, and AI interoperability demands solutions that can combine data at different levels of granularity (Cirillo et al., 2021). Multi-granularity methods in machine learning and data mining are designed to overcome problems such as a class imbalance or noisy dataset by processing local data structures at various granularities to enhance the accuracy of a classification policy (Dai et al., 2022). Time series prediction and clustering may also be used with granular computing methods based on the transformation of raw data into coarser or adaptive granules to reduce the dimensions and implement more effective pattern building (H. Chen et al., 2025; Jia et al., 2025; Yin, 2023). Altogether, data granularity is a field of managing the balance between detail and noise and computing efficiency to achieve the best analytical results in various fields.

Excellence in environmental, social, and governance (ESG) reporting demands reporting disclosures regarding ESG considerations in a high-quality, credible, and comparable manner to inform stakeholders and promote sustainable corporate performance. Studies reveal that the number and quality of ESG reports have grown in certain areas, including Sweden, whereas real ESG performance stagnated, which is why it should be more result oriented than reporting indicators (Arvidsson & Dumay, 2022). ESGRP must be interdisciplinary, with conventional accounting systems adjusted to reflect all the wider effects of sustainability beyond a company-centric perspective so as to enable transparency and alignment with the SDGs (Chopra et al., 2024; Yadav et al., 2025). It has been empirically indicated that strong ESG disclosure positively impacts corporate economic, environmental, and social sustainability performance in terms of increasing stakeholder trust and competitive advantage (Alsayegh et al., 2020; Shaikh, 2022). Nevertheless, problems caused by inconsistent ESG rating systems and the difficulty of aligning international sustainability criteria may undermine the validity and compatibility of ESG reporting (Adams & Abhayawansa, 2022; Berg et al., 2022). In general, excellent ESG reporting requires comprehensive frameworks that enhance the accuracy of the data used, standardize measures, and prioritize practical sustainability results rather than the quantity of disclosed information (Bogdan et al., 2023; Tettamanzi et al., 2022).

The concerns associated with ESG reporting and data granularity in Saudi private companies include a lack of clarity in the definition of ESG, resource differences, and sectoral factors, which make implementing and assessing ESG reports more complex (Alhoussari, 2025). A fluctuating regulatory landscape—for example, the Saudi Capital Market Authority's ESG Disclosure Guidelines—aims to enhance the level of transparency, yet companies may struggle to harmonize data collection and reporting procedures to satisfy the guidelines' requirements (Alhoussari,

2025; Chopra et al., 2024). Data granularity problems exist because traditional systems of accounting are not fully designed to record specific environmental and social impacts, limiting the accuracy and comparability of ESG disclosures (Chopra et al., 2024). Also, small businesses and SMEs in Saudi Arabia usually lack the awareness and resources to adopt extensive ESG reporting, which negatively affects their sustainability reports and quality of disclosure (Shalhoob & Hussainey, 2022). Even more sophisticated data optimization approaches, such as machine learning models on multiyear data, are promising and may be used to enhance the quality of data but still require being combined with green finance measures related to the Saudi environment (Alahmadi, 2024). In general, for Saudi private companies to achieve better ESG reporting practices, it is essential to establish more legal frameworks, increase interdisciplinary knowledge, standardize measurements, and provide dedicated assistance to smaller businesses to help them overcome such difficulties (Alhoussari, 2025; Chopra et al., 2024; Shalhoob & Hussainey, 2022).
Despite the increasing regulatory focus on ESG reporting in Saudi Arabia, private companies still face challenges in achieving consistent, high-quality ESG disclosures. These challenges arise from the ambiguity in defining ESG, industry-specific measurement issues, and differences in organizational resources, particularly within evolving frameworks such as the Saudi Capital Market Authority's ESG Disclosure Guidelines (Alhoussari, 2025; Chopra et al., 2024). Data granularity remains a major obstacle, as traditional accounting systems are not well designed to capture detailed environmental and social performance indicators, which limits the comparability and reliability of ESG reporting. These challenges are more pronounced in small and medium-sized enterprises due to limited technical capacity, financial resources, and awareness of ESG practices (Shalhoob & Hussainey, 2022). Although AI-based data analytics and machine learning have the potential to enhance data accuracy and improve green accounting and ESG reporting systems, empirical research on their integration in the Saudi private sector remains limited (Alahmadi, 2024). Therefore, it is necessary to investigate the technological and structural barriers to AI-driven green accounting as well as the role of data granularity in improving ESG reporting in the Saudi private sector context.
The present research is theoretical and practical in nature. Theoretically, it contributes to the literature on green accounting and ESG reporting by analyzing AI-controlled green accounting and proposing data granularity as an intermediary variable, which can help to explain how the potentials of digitized accounting can be transformed into ESG reporting quality. Empirically, it offers uncommon firm-level data on Saudi private companies, a setting that is rapidly being digitalized and has been subject to sustainability revamping in the context of Vision 2030 but which has been largely underrepresented in earlier ESG and AI studies. In practice, the results provide managers and policymakers with specific information for taking action by encouraging investment in AI-driven accounting technologies and strong data governance to increase the level of ESG disclosure, reporting, and environmental responsibility.

Literature Review

In the case of privately held companies, green accounting is the combination of environmental factors and conventional accounting systems (Zik-Rullahi & Jide, 2023). It entails identifying, measuring, and reporting environmental costs and advantages to business operations (Sudarminto & Harto, 2023). Instead of focusing on financial records of traditional revenues and expenses, green accounting embraces environmental effects, such pollution, resource depletion, and waste management. Firms that adopt this strategy can achieve profitability and environmental responsibility as well as sustainable business practices (Shaheen et al., 2024). Private companies increasingly use green accounting because of emerging regulatory developments, stakeholder demands, and global sustainability practices (Faieq & Cek, 2024), and investors and consumers have become more aware of environmental performance, especially in ESG models (Meiden & Silaban, 2023). Green accounting also helps firms increase transparency, enhance corporate reputation, and make informed strategic decisions by considering environmental cost analysis, ultimately enhancing long-term competitiveness and strength (Marota, 2024).

Green accounting is characterized primarily by defining direct and indirect environmental costs, reporting environmental liabilities, lifecycle costing, and assessing investment in clean technologies (Stasiskiene, 2022). It also entails sustainability reporting, whereby companies offer environmental performance indicators in addition to financial ones. By incorporating these aspects, companies can consider the actual cost of production and determine the impact of environmental initiatives on organizational performance on a global scale (Khan & Gupta, 2024). Although green accounting has advantages, several problems arise in applying it in the private sector. In some cases, such as indirect or long-term effects, environmental impacts cannot be accurately measured (Rahman & Islam, 2023), and the lack of standardized reporting structures can result in inconsistencies in disclosure practices (Dye et al., 2021). High startup costs and a lack of the specialized knowledge required for implementation may also prevent small firms in Saudi Arabia from implementing comprehensive green accounting systems (Khan & Gupta, 2025). Studies indicate, however, that firms practicing green accounting realize long-term financial benefits and can lower their operational costs by minimizing energy use and reducing waste and environmental risk (Rakhmawati, 2025). Furthermore, transparent environmental reporting is attractive to socially responsible investors and increases stakeholder trust. Thus, green accounting offers a positive impact on financial stability and sustainability along with promoting environmental sustainability (Ahmad et al., 2025).

AI-driven green accounting may be defined as the application of AI technologies—including machine learning, predictive analytics, and automation—to improve the measurement, analysis, and reporting of environmental costs and effects in a private firm (Tariq & Rahim, 2024). In contrast to conventional green accounting, wherein manual data collection and periodic reporting are the norm, AI-based systems will be able to handle real-time environmental information on a cross-functional basis, enabling companies to more quickly and precisely account for energy consumption, emissions, waste streams, and resource consumption, eventually underpinning more precise and dynamic environmental accounting (Mayegun & Nwanevu, 2025).

The integration of AI into green accounting has become more important for private firms that are under regulatory pressure and require sustainable performance among stakeholders (Bin-Nashwan & Li, 2025). AI allows companies to track adherence to environmental standards and predict regulatory risks in advance, before they become reality (Walsh, 2022). Also, their stakeholders, including investors, clients, and ESG rating agencies, increasingly attach greater importance to verified, transparent, and real-time environmental information (Saxena et al., 2022). Using AI, companies can increase credibility, minimize risk exposure, and be more strategic in their environmental investments and sustainability ambitions. AI-driven green accounting uses several fundamental technologies. Machine learning algorithms find trends in environmental performance data, forecast future developments, and categorize sources of inefficiency (Uddin et al., 2024). Natural language processing has the potential to automatic the process of extracting environmental data from documents, contracts, and reports (Bommarito II et al., 2021). Also, AIs can track sustainability measurements in real time using dashboards and data visualization tools. Collectively, these functionalities support predictive planning,

automated compliance reporting, and enhanced resource allocation (Zaman et al., 2022).
Although this is a promising concept, privately adopted AI-driven green accounting is a challenge to firms. First, the data infrastructure, AI software, and special talent demand a large initial investment (Babina et al., 2024). Second, issues with data quality, including the disaggregation of sources, variations in format, and the absence of environmental records, may limit AI accuracy (Elouataoui, 2024). Third, managing environmental AI systems and existing accounting systems or enterprise resource planning (ERP) systems is potentially costly in terms of management by necessitating changes in the organization (Mhaskey, 2024). The need to ensure that AI is used ethically and that its data remain private adds complexity.
Green accounting based on AI has the potential to greatly improve both the environment and financial performance. Companies with well-developed AI analytics can detect areas of inefficiency and reap huge cost reductions, such as through better energy efficiency or the reduction of waste, which reduces operation costs as well as carbon footprints (L. Chen et al., 2025; Feng et al., 2026). Moreover, enhanced predictive foresight and transparency enhance sustainability reporting, as companies attract responsible investors and fit the ESG purpose. AI-based environmental accounting promotes sustainability, innovation, and competitive advantage in the long run in a sustainable market (Khan & Gupta, 2025; Yu et al., 2025).
Data granularity in the case of private firms represents the degree of detail in which data are gathered, stored, and analyzed in organizational systems. Highly granular data offer fine levels of information, such as transaction-level data, departmental-level performance measures, and real-time operational data instead of aggregate summaries (Beuselinck et al., 2023). At the level of the individual company, granular data increase the visibility of business processes and enable more accurately monitoring financial, operational, and environmental performance (Dare et al., 2022).
Granular data are important in both strategic and operational decision-making processes. When companies use only aggregated data, crucial trends and inefficiencies may escape notice (Thanasas & Kampiotis, 2024). Detailed information enables managers to identify cost drivers, recognize exceptions, and determine performance at miniscule levels (e.g., product lines, units, or projects). This can better predict and increase data-driven approaches to improve competitiveness and operational effectiveness (Oduleye & Medon, 2021).
Digital technologies have progressed significantly and enhanced private firms' ability to obtain and process granular data. ERP systems, cloud computing, IoT devices, and advanced analytics platforms enable companies to gather real-time, high-resolution data and analyze various functions. AI and machine learning also add value to granular data by finding patterns, predicting tendencies, and informing action (Chinta et al., 2024; Li et al., 2025).
Despite the benefits, granular data are difficult to handle. Large amounts of detailed information require well-built storage facilities and cybersecurity (Parmar, 2025). Additionally, excessive granularity can cause information overload, leaving managers unable to draw meaningful insights without appropriate analytical structures (Kashlot et al., 2026). Data quality, problems with integrating data, and adherence to privacy rules are also very important to private companies (Vadde & Engineer, 2023).
In a well-managed environment, data granularity enhances a firm's transparency, accountability, and performance. Detailed information enables improved cost, risk, and resource management (Kehinde, 2025). In the case of sustainability, granular environmental data—such as energy consumption per unit of production—make possible accurate reporting and meeting environmental improvement targets. Thus, data granularity reinforces financial performance and

long-term organizational resilience (Albert Gomes et al., 2025).

The term ESG reporting excellence in private firms describes the quality of the publication of ESG performance in a transparent, consistent, and strategically aligned way (Arvidsson & Dumay, 2022). The focus is not solely on compliance but also on the accuracy, completeness, comparability, and materiality of reporting practices (Ilori et al., 2023). Excellence in ESG reporting ensures that sustainability data are combined with financial information so that stakeholders can evaluate a firm's ability to manage risks and create value in the long run (Dako et al., 2023). Although ESG reporting has been viewed as the responsibility of publicly listed companies, it is becoming a strategic concern among private businesses. The ownership structure does not imply that investors, lenders, customers, and supply chain partners are not demanding more transparency in sustainability (Yang, 2024). Good ESG reporting promotes credibility, builds stakeholders' confidence, and increases access to funds. It equally makes the work of individual companies competitive in markets where business responsibility is the distinguishing element (Ngwa et al., 2025).

Several dimensions are essential to excellence in ESG reporting. First, environmental disclosure involves proper measurement of emissions, consumption of resources, and climate-related risk factors (Nyakuwanika & Panicker, 2025). Second, social reporting covers labor practices, diversity, community involvement, and human rights. Third, governance reporting includes board structure, ethical practices, internal controls, and risk oversight. Incorporating these dimensions within a consistent reporting system makes possible complete and balanced sustainability reporting (Cardillo & Basso, 2025). Private firms encounter several challenges when trying to achieve the highest level of ESG reporting, including minimal regulatory guidance, the absence of standardized reporting structures specific to private entities, and resource constraints, especially in small and medium-sized enterprises (Conte, 2026). Moreover, gathering quality ESG data between various departments and supply chains may be complicated. To ensure credibility, firms must take the additional measures of data verification and avoiding greenwashing (Hossain et al., 2025).

ESG reporting excellence enhances value creation in the long term through greater transparency, management of risks, and alignment. Companies that have a strong disclosure of ESG have a higher chance of predicting regulatory adjustments, controlling environmental and social risks, and appealing to sustainability-oriented investors (Farag, 2025). With time, high levels of ESG performance induce improvement in reputation, performance efficiency, and resilience, which eventually facilitates financial performance sustainability in privately owned companies (Jin et al., 2025).

The focus on green accounting in private companies in Saudi Arabia has sharpened in accordance with the national sustainability interests described in Vision 2030. Private companies' accounting systems are slowly adopting environmental cost measurement, especially in the energy, manufacturing, and construction sectors. This involves monitoring energy and waste management expenses and costs relating to carbon. Saudi private companies have been enhancing their transparency and aligning their activities with national environmental regulations and sustainability targets by including environmental consideration in their financial reporting (Abobaker & Gunardi, 2023; Berradia, 2026; Hamoudah, 2025). The use of green accounting in Saudi privately owned companies also reflects increased stakeholder expectations, such as the pressure exerted by regulators, financial institutions, and international investors. Companies are becoming aware of the need to measure environmental risks and liabilities as the Kingdom advances its environmental reforms and climate programs (Shalhoob & Hussainey, 2022).

Nonetheless, certain obstacles exist, including a shortage of standardized structures and a lack of environmental awareness among smaller businesses. Nevertheless, green accounting is becoming an instrument of long-term competitiveness and compliance with regulations in the Saudi private sector (Almeflh & Almofleh, 2025).

Green accounting through AI is becoming more important in Saudi Arabia as the pace of digital transformation programs accelerate among private firms in line with Vision 2030. AI digital tools help businesses gather and study real-time environmental data, such as emissions, energy efficiency, and resource use. AI-driven analytics are used to better estimate costs to the environment and forecast sustainability plans in areas such as oil and gas, utilities, and smart cities. The integration also contributes to providing more correct reports and proactive environmental management (Alshareef, 2025; Mgammal, 2024).

The positive effects of AI-based environmental accounting on Saudi private companies include enhanced compliance monitoring and efficiency. AI systems can identify inefficiencies, predict environmental risk, and automate the process of sustainability reporting, (Mekhlaf, 2024) but this will be costly in terms of investment in digital infrastructure as well as qualified human capital. There are also critical considerations in data governance, cybersecurity, and system integration. These challenges notwithstanding, AI-enhanced green accounting can enhance Saudi companies' capacity to balance financial performance and environmental responsibility (Banks, 2025).

The concept of data granularity has gained significance for Saudi Arabian private companies, especially among the growing number of businesses using sophisticated ERP systems and digital platforms. Extremely detailed operational and financial information allows companies to monitor performance at the scale of a specific project, facility, or product line. Granular data are used in the petrochemical, retail, and logistics industries to allocate costs more precisely, manage risks, and monitor sustainability. Such detail increases the level of managerial control and strategic decision-making (Almushaiqeh et al., 2024; Asiri et al., 2024).

In relation to environmental performance and ESG performance, granular data enable Saudi domestic companies to measure and track emissions per production unit as well as to measure energy intensity and waste mitigation efforts more accurately. Nevertheless, managing large amounts of detailed data requires strong infrastructure, cybersecurity measures, and the ability to integrate the data. In the absence of appropriate analytical tools, excessive data granularity can lead to inefficient work. Thus, smart data governance systems are required to maximize the value of detailed data in the Saudi private sector (Liu et al., 2022).

The importance of ESG reporting excellence is growing, especially in relation to private companies in Saudi Arabia and due to increasing demands for sustainability disclosure in the region and other parts of the world. Although ESG reporting has always been associated with publicly listed companies, a great number of privately owned companies are now voluntarily increasing transparency to enter the investment process and improve credibility in the marketplace. Specific carbon emission, water consumption, and climatic risk disclosures in the environment are of particular concern in Saudi Arabia, which is experiencing a changing regulatory environment (Saudi Exchange, 2021; Saudi Tadawul Group, 2024). The key to attaining ESG reporting excellence in Saudi private companies is incorporating ESG measures in strategic planning and risk management systems. Good governance, nationalization of the workforce, and community are important social and governance aspects in the Saudi context (Basali, 2025). Although the issues of standardization and reporting expenses remain, companies that can provide high-quality ESG disclosures will find it easier to access capital, establish stakeholder confidence, and work toward ensuring the Kingdom is able to achieve its long-term sustainable development goals (Alsulamy, 2025; Hussain et al., 2024).

Materials and Methods

Research Design

This study adopted a quantitative research design using a structured survey to investigate the impact of AI-driven green accounting practices on ESG reporting excellence among Saudi private companies. The design was selected to enable the gathering of quantifiable data and to investigate both direct and indirect interrelations among the study constructs as well as the possibility of mediation by data granularity. This method can be statistically tested in SmartPLS through partial least squares structural equation modeling (PLS-SEM), a particularly appropriate model for examining multiple constructs and mediating factors. The research design ensured that the study captured the insights of employees in relevant departments, such as accounting, sustainability, data analytics, IT, and corporate governance, whose services are directly or indirectly engaged in green accounting and ESG reporting processes made possible by AI. The range of organization sizes, industries, and employee positions increases the findings' generalizability to the broader Saudi private sector while offering solid evidence on the importance of AI practices in enhancing transparency, resource distribution, and the overall quality of ESG reporting.

Population and Sample

The research population included employees of Saudi Arabian private companies whose roles were directly or indirectly related to environmental accounting, data analytics, financial reporting, sustainability management, or ESG disclosure regulations. The target respondents comprised employees working in corporate governance or reporting departments, information technology and data management units, sustainability and compliance departments, and accounting and finance departments. They were selected because they were directly involved in the development of ESG-related disclosures and the implementation of AI-based green accounting processes in private sector organizations. The study conducted with a sample of 372 respondents. The sample size was statistically adequate to support multivariate analysis, specifically structural modeling and mediation testing, with acceptable statistical power. The participants included executive or general managers, department managers, accountants or financial analysts, sustainability or ESG officers, IT or data analytics specialists, and administrative staff, ensuring that they had the knowledge and experience to evaluate AI-driven green accounting practices and ESG reporting quality. The data were statistically analyzed to examine the direct and mediating relationships proposed in the research model.

Sample Characteristics

Table 1 presents the demographic characteristics of the study's respondents.

Table 1. Demographic profile of the respondents (N = 372).

Variable	Category	Frequency	Percentage (%)
Gender	Male	230	61.8
	Female	142	38.2
Age	Below 30 years	95	25.5
	30–39 years	149	40.1
	40–49 years	88	23.7
	50 years and above	40	10.8
Job title	Executive/general manager	38	10.2
	Department manager	74	19.9
	Accountant/financial analyst	107	28.8
	Sustainability/ESG officer	42	11.3
	IT/data specialist	60	16.1
	Administrative staff	51	13.7
Educational level	Diploma	50	13.4
	Bachelor’s degree	210	56.5
	Master’s degree	91	24.5
	Doctoral degree	21	5.6
Years of experience	Less than 5 years	72	19.4
	5–9 years	119	32.0
	10–14 years	106	28.5
	15 years and above	75	20.2

Table 1 shows that the majority of respondents (61.8%) were male, whereas females were less strongly represented at 38.2%. Those 30–39 years old were the sample’s dominant age group at 40.1%, whereas those 50 years and above constituted the smallest group at 10.8%. In terms of job titles, the most common was accountants/financial analysts at 28.8%; the lowest percentage (10.2%) was among executives/general managers. Regarding education, most respondents held a bachelor’s degree (56.5%), and those with a doctorate had the smallest percentage (5.6%). Lastly, with reference to years of experience, the largest group included those with a moderate 5–9 years of experience (32.0%); those with less than 5 years’ experience made up the smallest group at 19.4%.

Validity and Reliability

Expert validation (content validity). After the questionnaire was developed and its measurement items constructed, a panel of experts evaluated the instrument’s effectiveness in measuring the study objectives. This process aimed to ensure the relevance of each item to its corresponding dimension, the statements’ clarity and linguistic accuracy, and the suitability of the items for achieving the intended objectives of each construct. The experts were also invited to provide recommendations for improving the instrument through deletion, addition, rewording, or other modifications they deemed appropriate. Such procedures are commonly used to establish content validity and ensure that the measurement items adequately represent the constructs under investigation (DeVellis & Thorpe, 2021; Hair et al., 2019). After receiving the reviewed versions and considering the experts’ suggestions, the researcher revised the questionnaire accordingly. Items were eliminated or reworded when more than 80% of the experts agreed on the modification. The questionnaire in its final form comprised 38 items distributed across three primary axes, thereby ensuring face and content validity of the measurement instrument (Boateng et al., 2018).

Construct validity of the instrument (questionnaire). Instrument validity indicates how well a questionnaire assesses what it is meant to measure (Hair et al., 2019). This study examined the tool's construct validity as described next.

Internal consistency of the axes. This study assessed internal consistency by calculating Pearson's correlation coefficient between each item score and the total score of the axis to which the item belongs. This procedure verified that each item was consistent with the overall score of its axis and contributed meaningfully to measuring the intended construct. Tables 2, 3, and 4 present the Pearson correlation coefficients between each item and the total score of its corresponding axis.

Table 2. Pearson correlation coefficients between each item and the total score of its corresponding axis in the first axis (AI-Driven Green Accounting).

Statement No.	Correlation Coefficient	Statement No.	Correlation Coefficient	Statement No.	Correlation Coefficient
First dimension: Automation & Transparency in Environmental Reporting					
1	.933**	2	.855**	3	.884**
4	.850**	5	.701**		
Second dimension: Predictive Analytics of Environmental Costs					
6	.872**	7	.720**	8	.820**
9	.898**	10	.917**		
Third dimension: Resource Allocation					
11	.840**	12	.870**	13	.797**
14	.865**	15	.836**		

Table 2 shows that the correlation coefficients between the items and the total score of the dimension to which each item belongs within the first axis, AI-Driven Green Accounting, were all statistically significant at a level of .01. All correlation coefficient values were statistically significant, ranging from .701–.933 in the first dimension (Automation & Transparency in Environmental Reporting), from .720–.917 in the second dimension (Predictive Analytics of Environmental Costs), and from .797–.870 in the third dimension (Resource Allocation), indicating a high degree of internal consistency for the items of the first axis in the questionnaire.

Table 3. Pearson correlation coefficients between each item and the total score of its corresponding dimension in the second axis (ESG Reporting Excellence).

Statement No.	Correlation Coefficient	Statement No.	Correlation Coefficient	Statement No.	Correlation Coefficient
First Dimension: Environmental					
16	.878**	17	.888**	18	.839**
19	.816**	20	.762**		
Second Dimension: Social					
21	.846**	22	.837**	23	.798**
24	.782**	25	.892**		
Third Dimension: Governance					
26	.828**	27	.853**	28	.840**
29	.910**	30	.870**		

Table 3 shows that the correlation coefficients between the items and the total score of the dimension to which each item belongs within the second axis, ESG Reporting Excellence, were all statistically significant at the level of .01. All correlation coefficient values were statistically significant, ranging from .762–.888 in the first dimension (Environmental), from .782–.892 in the second dimension (Social), and from .828–.910 in the third dimension (Governance), which indicates a high degree of internal consistency for the items of the second axis.

Table 4. Pearson correlation coefficients between each item and the total score of its corresponding dimension in the third axis (Data Granularity).

Statement No.	Correlation Coefficient	Statement No.	Correlation Coefficient	Statement No.	Correlation Coefficient
		Data Granularity			
31	.856**	32	.852**	33	.902**
34	.747**	35	.865**	36	.801**
37	.745**	38	.845**		

Table 4 shows that the correlation coefficients between the items and the total score of the axis to which each item belongs within the third axis, Data Granularity, were all statistically significant at the level of .01. All the correlation coefficient values were statistically significant, ranging from .745–.902, which indicates a high degree of internal consistency for the items of the third axis.

Reliability of the instrument (questionnaire). The reliability of an instrument means that the responses would be approximately the same if the questionnaire were administered repeatedly to the same individuals at different points in time. The reliability of the instrument (questionnaire) was examined as described next.

Reliability of the first axis: AI-Driven Green Accounting. Cronbach's alpha was calculated to measure the reliability of the dimensions of the first axis: AI-Driven Green Accounting; the results are presented in Table 5

Table 5. Cronbach's alpha reliability coefficients for the dimensions of the first axis (AI-Driven Green Accounting).

Dimensions	Items	Cronbach's Alpha
Automation & Transparency in Environmental Reporting	5	.893
Predictive Analytics of Environmental Costs	5	.899
Resource Allocation	5	.894

The results in Table 5 indicate that that Cronbach's alpha coefficients for the dimensions of the first axis (AI-Driven Green Accounting) were high, reaching .893 for the dimension Automation & Transparency in Environmental Reporting, .899 for Predictive Analytics of Environmental Costs, and .894 for Resource Allocation, indicating a high level of reliability for the dimensions of the first axis.

Table 6. Cronbach's alpha reliability coefficients for the dimensions of the second axis (ESG Reporting Excellence).

Dimensions	Items	Cronbach's Alpha
Environmental	5	.890
Social	5	.888
Governance	5	.909

The results in Table 6 indicate that the Cronbach's alpha coefficients for the dimensions of the second axis (ESG Reporting Excellence) were high, reaching .890 for the Environmental dimension, .888 for Social, and .909 for Governance, indicating a high level of reliability for these dimensions.

Table 7. Cronbach's alpha reliability coefficient for the third axis (Data Granularity).

Axis	Items	Cronbach's Alpha
Data Granularity	8	. 931

The results in Table 7 show a Cronbach's alpha coefficient of .931 for the third axis (Data Granularity), reflecting a very high level of reliability for the axis.

Results

Descriptive Statistics

This study used descriptive statistics to summarize and explain the most important aspects of the research variables, calculating means and standard deviations (SDs) to identify the respondents'' perspectives on the research axes and their dimensions. These measurements show the main trends in the data and the answers' distribution. The mean scores express the extent of agreement on each axis and its dimensions, whereas the SDs reveal the differences and distribution of the responses. Tables 8–10 show the results for each axis of the study.

Table 8. Descriptive statistics for the dimensions of the first axis (AI-Driven Green Accounting).

No.	Dimension	Mean	SD	Rank	Response Level
1	Automation & Transparency in Environmental Reporting	3.72	.617	1	High
2	Predictive Analytics of Environmental Costs	3.44	.633	2	High
3	Resource Allocation	3.36	.625	3	Moderate
	Overall	3.51	.603		High

Table 8 shows that the dimensions of the first axis, AI-Driven Green Accounting, yielded an overall mean of 3.51, with an SD of 0.603, indicating a high response level. Automation & Transparency in Environmental Reporting ranked first, with a mean of 3.72 and an SD of 0.617 at a high response level, followed by Predictive Analytics of Environmental Costs with a mean of 3.44 and an SD of 0.633 at a high response level. Resource Allocation ranked third with a mean of 3.36 and an SD of 0.625, indicating a moderate response level. These findings suggest that companies are highly inclined toward the use of AI-based tools to improve transparency and automation of environmental reporting. However, the average of resource allocation is relatively low, meaning that the implementation of AI in the management of environmental resources is at the initial stage of its growth.

Table 9. Descriptive statistics for the dimensions of the second axis (ESG Reporting Excellence).

No.	Dimension	Mean	SD	Rank	Response Level
1	Environmental	3.63	.601	3	High
2	Social	3.81	.603	1	High
3	Governance	3.65	.620	2	High
	Overall	3.69	.589		High

ESG Reporting Excellence reached a mean of 3.69, with an SD of 0.589, indicating a high response level. Social ranked first, with a mean of 3.81 and an SD of 0.603 at a high response level, followed by Governance, with a mean of 3.65 and an SD of 0.620 at a high response level. Environmental ranked third, with a mean of 3.63 and an SD of 0.601, also indicating a high response level. The outcomes suggest that the respondents had a good general commitment to the ESG reporting practice. The fact that the social dimension is rated higher implies that the organizations pay special attention to the social responsibility and stakeholder-related practices in ESG reporting.

Table 10. Descriptive statistics for the third axis (Data Granularity).

Axis	Mean	SD	Response Level
Data Granularity	3.55	.610	High

Table 10 shows that the third axis, Data Granularity, reached an overall mean of 3.55, with an SD of 0.610, indicating a high response level. The findings show that the organizations were very concerned with the level of detail and accuracy in their data, reflecting that it is necessary to have detailed data to make well-grounded decisions and proper analysis.

Measurement Model Assessment

The measurement model was assessed using SmartPLS before hypothesis testing was conducted to ensure that the survey indicators reliably and accurately measured their corresponding constructs. Evaluating the measurement model is essential to confirm the reliability and validity of the study constructs. The assessment was conducted using composite reliability (CR), average variance extracted (AVE), and predictive relevance (Q^2/model fit) following the guidelines of Hair et al. (2022).

1. **Composite reliability**

- Purpose: assess the internal consistency of each construct.
- What it measures: Whether the indicators collectively provide a stable and reliable measurement of the construct.

2. **Average variance extracted**

- Purpose: Evaluate convergent validity.
- What it measures: The proportion of variance in the indicators explained by the construct. A higher AVE indicates that the construct explains a significant amount of variance in its items.

3. **Predictive relevance**

- Purpose: Assess the predictive accuracy of the measurement model.
- What it measures: How well the model can guess how the indicators will respond to each construct. A Q^2 number greater than zero means that the model is good at making predictions.

The results of the measurement model evaluation, including indicator loadings, CR, AVE, and Q^2 values for all constructs, are presented in Tables 11 and 12.

Table 11. Composite reliability and convergent validity results.

Construct	Composite Reliability (rho_a)	Composite Reliability (rho_c)	Average Variance Extracted (AVE)
Automation & Transparency in Environmental Reporting	0.898	0.924	0.708
Predictive Analytics of Environmental Costs	0.901	0.926	0.716
Resource Allocation	0.899	0.924	0.708
Environmental	0.887	0.917	0.688
Social	0.902	0.927	0.717
Governance	0.887	0.917	0.688

Table 11 presents the results of CR and convergent validity for the study constructs. The values of CR (rho_a) range from 0.887 to 0.902, whereas the CR (rho_c) values range from 0.917 to 0.927, indicating a high level of internal consistency among the measurement items of all constructs. Moreover, the AVE values are between 0.688 and 0.717, greater than the threshold of 0.50, which proves that the constructs attain a satisfactory level of convergent validity. This shows that the indicators of both constructs are fitting in the explanatory power of their respective latent variables, demonstrating the reliability and validity of the measurement model.

Table 12. Model fit indices for the saturated and estimated models.

Fit Index	Saturated Model	Estimated Model
SRMR	0.034	0.036
d_ULS	0.538	0.604
d_G	0.504	0.549
Chi-squared	959.060	1013.055
NFI	0.906	0.901

Table 12 shows the model fit indices of the saturated model and the estimated model. The values of standardized root mean squared residual (SRMR) are 0.034 and 0.036 for the saturated and estimated models, respectively; the values are less than 0.08, indicating a good model fit. Also, the saturated model measures 0.906, with the estimated model measuring 0.901 with respect to the normed fit index (NFI), indicating adequately model fit. Close results are also present in the values of d ULS and d G between the two models, with chi-squared values of 959.060 and 1013.055, respectively. Overall, these findings imply that the suggested model has a satisfactory degree of fit to the observed data.

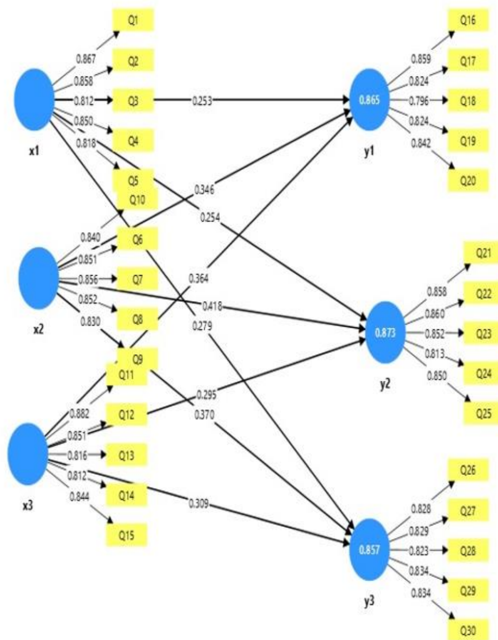

Figure 1. Structural model without mediator variable.

The three dimensions of the dependent construct are y1, y2, and y3, whereas those of the independent construct are x1, x2, and x3. Because the mediating variable is not present in the current model, the direct effects of the dimensions of the independent construct on the dimensions of the dependent construct can be examined. Without accounting for the mediating variable, the outcomes of these direct effects are shown in Table 13 along with path coefficients, t-values, and significance levels, which offer information on the strength and importance of the relationships.

Table 13. Path coefficients, significance, and effect sizes of the AI-Driven Green Accounting dimensions on ESG Reporting Excellence dimensions.

Path	Original sample (O)	Sample mean (M)	SD	T-statistics	f2	P-values	Result
x1 -> y1	0.253	0.254	0.048	5.232	0.071	.000	Significant
x1 -> y2	0.254	0.255	0.043	5.857	0.076	.000	Significant
x1 -> y3	0.279	0.279	0.053	5.252	0.081	.000	Significant
x2 -> y1	0.346	0.345	0.046	7.506	0.135	.000	Significant
x2 -> y2	0.418	0.417	0.041	10.212	0.209	.000	Significant
x2 -> y3	0.370	0.370	0.051	7.216	0.146	.000	Significant
x3 -> y1	0.364	0.365	0.047	7.680	0.149	.000	Significant
x3 -> y2	0.295	0.295	0.042	6.990	0.103	.000	Significant
x3 -> y3	0.309	0.310	0.047	6.598	0.101	.000	Significant

R-squared (y1) = .865
R-squared (y2) = .873
R-squared (y3) = .857

As indicated in Table 13, the complete dimensions of AI-Driven Green Accounting have a significant positive impact on the dimensions of ESG Reporting Excellence, with a p-value of .000 and t-test values of 5.232–10.212, showing that all the relationships in the model are statistically significant. Predictive analytics show that the Environmental Costs (x2) to Social (y2) pathway (path coefficient = 0.418, f2 = 0.209) is the most influential, and the other paths show at least moderate to strong effects. The R2 values are high (y1 = 0.865, y2 = 0.873, y3 = 0.857), showing that the AI-Based Green Accounting dimensions explain a large percentage of the difference in ESG Reporting Excellence, indicating that the model is highly predictive and underscoring the significance of AI tools in improving the performance of ESG reporting.

Table 14. Composite reliability and convergent validity results including the mediator variable.

Construct	Composite Reliability (rho_a)	Composite Reliability (rho_c)	Average Variance Extracted (AVE)
Data Granularity	0.938	0.948	0.696
Automation & Transparency in Environmental Reporting	0.898	0.924	0.708
Predictive Analytics of Environmental Costs	0.901	0.926	0.716
Resource Allocation	0.899	0.924	0.708
Environmental	0.887	0.917	0.688
Social	0.902	0.927	0.717
Governance	0.887	0.917	0.688

Table 14 shows the findings for CR and convergent validity for all the study constructs with the

Data Granularity mediator included. The CR (rho_a) values span from 0.887–0.938 and the rho_c values from 0.917–0.948, indicating that the internal consistency is high in all constructs. The values of the AVE vary from 0.688– 0.717, which are greater than the 0.50 threshold that validates acceptable convergent validity. Notably, the Data Granularity mediator has a very high level of reliability (rho c = 0.948) and a high AVE (0.696), indicating that it is a strong and valid construct in the model. Overall, the findings indicate that each measurement item is an effective indicator of the latent variables that it aims to describe, justifying further analysis of the validity of the measurement model's structure.

Table 15. Model fit indices for the saturated and estimated models including the mediator variable.

Fit Index	Saturated Model	Estimated Model
SRMR	0.031	0.032
d_ULS	0.725	0.753
d_G	0.711	0.737
Chi-squared	1349.539	1380.019
NFI	0.901	0.899

Table 15 shows the model fit indices of the saturated and estimated models, which also include the saturated and estimated mediator, Data Granularity. The saturated model and estimated model have SRMR values of 0.031 and 0.032, respectively, which are less than 0.08, indicating good model fit. The two models have similar values of d ULS (d 0.725 and 0.753, respectively) and d G (d 0.711 and 0.737, respectively), indicating that there is no significant difference in the observed and predicted correlations. The chi-squared values (1349.539 and 1380.019, respectively) and NFI values (0.901 and 0.899, respectively) also confirm that the model fits the data reasonably well. Overall, it is shown that the inclusion of the mediator does not negatively affect the model fit and further confirms the validity of the proposed structural model.

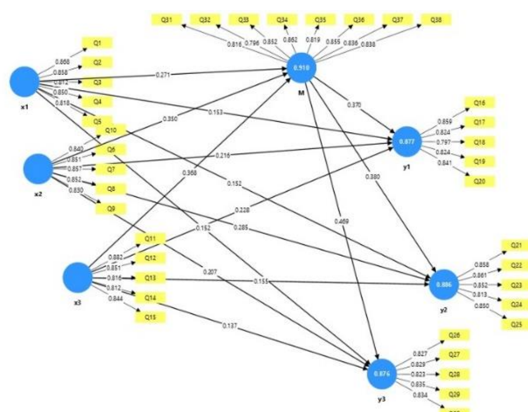

Figure 2. Structural model including mediator variable.

The three dimensions of the independent construct are X1, X2, and X3, whereas those of the dependent construct are Y1, Y2, and Y3. The inclusion of the mediating variable (M: Data Granularity) in the current model enables the investigation of both the direct and indirect effects of the independent construct's dimensions on the dimensions of the dependent construct. Table

16 shows the outcomes of these effects, along with path coefficients, t-values, and significance levels, shedding light on the importance and intensity of the associations when the mediating variable is present.

Table 16. Path coefficients, significance, and effect sizes of AI-Driven Green Accounting dimensions on ESG Reporting Excellence dimensions, including the mediator variable.

Path	Original sample (O)	Sample mean (M)	SD	T-statistics	f2	P-values	Result
M -> y1	0.370	0.371	0.057	0.370	0.101	.000	Significant
M -> y2	0.380	0.381	0.056	0.380	0.114	.000	Significant
M -> y3	0.469	0.470	0.059	0.469	0.159	.000	Significant
x1 -> M	0.271	0.270	0.041	0.271	0.122	.000	Significant
x1 -> y1	0.153	0.155	0.050	0.153	0.026	.002	Significant
x1 -> y2	0.152	0.153	0.047	0.152	0.027	.001	Significant
x1 -> y3	0.152	0.151	0.050	0.152	0.025	.002	Significant
x2 -> M	0.350	0.349	0.040	0.350	0.207	.000	Significant
x2 -> y1	0.216	0.215	0.046	0.216	0.048	.000	Significant
x2 -> y2	0.285	0.284	0.045	0.285	0.089	.000	Significant
x2 -> y3	0.207	0.207	0.053	0.207	0.044	.000	Significant
x3 -> M	0.368	0.369	0.042	0.368	0.228	.000	Significant
x3 -> y1	0.228	0.228	0.052	0.228	0.052	.000	Significant
x3 -> y2	0.155	0.154	0.045	0.155	0.026	.001	Significant
x3 -> y3	0.137	0.137	0.048	0.137	0.019	.004	Significant

R-squared (M) = .910
R-squared (y1) = .877
R-squared (y2) = .886
R-squared (y3) = .876

Table 16 shows the results of the structural model that measures the direct and indirect impacts of the AI-Driven Green Accounting dimensions (x1–x3) on the ESG Reporting Excellence dimensions (y1–y3) with the mediator, Data Granularity (M). All the paths are statistically significant, with p-values of .000 (except one at .026), and the t-statistics show strong significance throughout the model. The Data Granularity mediator shows significant positive effects on all the dimensions of ESG (y1: 0.370, y2: 0.380, y3: 0.469), with moderate effect sizes (f2 = 0.101–0.159), and is therefore important in indicating the influence of AI-driven accounting practices. There are also strong direct effects of all AI dimensions on the mediator (0.271–0.368) and weaker yet significant direct effects on the ESG dimensions, representing partial mediation. The R2 values are very large (M = .910, y1 = .877, y2 = .886, y3 = .876), indicating that the model can explain a high percentage of the variance in both the mediator and ESG reporting dimensions. This shows that AI-assisted green accounting strongly contributes to the excellence of ESG reporting, both directly and indirectly via data granularity.

Table 17. Indirect effects of AI-Driven Green Accounting dimensions on ESG Reporting Excellence dimensions through Data Granularity (mediating effect).

Path	Original sample (O)	Sample mean (M)	SD	T-statistics	P-values
x1 -> M -> y1	0.100	0.100	0.020	4.895	.000
x1 -> M -> y2	0.103	0.103	0.022	4.586	.000
x2 -> M -> y1	0.129	0.130	0.025	5.131	.000
x1 -> M -> y3	0.127	0.127	0.025	4.989	.000
x2 -> M -> y2	0.133	0.133	0.024	5.513	.000
x3 -> M -> y1	0.136	0.137	0.028	4.878	.000
x2 -> M -> y3	0.164	0.164	0.028	5.870	.000
x3 -> M -> y2	0.140	0.141	0.027	5.215	.000
x3 -> M -> y3	0.172	0.173	0.029	5.899	.000

Table 17 shows the indirect relationship between the AI-Driven Green Accounting dimensions (x1, x2, x3) and the ESG Reporting Excellence dimensions (y1, y2, y3) using the mediator Data Granularity (M). The t-statistics are statistically significant (0.000), ranging from 4.586–5.899, proving a significant mediating effect. These findings show that data granularity partially moderates the connection between AI-based accounting and ESG reporting. That is, although the AI accounting dimensions directly affect ESG performance, their effects are intensified and more widely distributed due to increased data granularity, so the mediator is an important element of enhancing ESG reporting. The highest mediation effect is found to be Resource Allocation (x3) -> M -> y3, with a coefficient of 0.172, which explains the significance of accurate resource-related data to the improvement of governance practices. In general, the results prove that data granularity is a crucial element in transforming AI-based accounting practices into more efficient ESG reporting, as detailed and organized data are essential to organizational decision-making and reporting superiority.

Discussion

The study results show that AI-Driven Green Accounting positively affects ESG Reporting Excellence, both directly and indirectly via Data Granularity. The participants were more likely to agree on the importance of AI-driven practices on environmental reporting, particularly on automation, transparency, and predictive analytics. The results show that the organizations are coming to recognize the significance of using AI in improving environmental performance, in quality of reporting, and in integrating sustainability issues into the strategic decision-making process. The discussion illustrates that the measurement constructs are effective and confirm the power of the proposed model. The structural model was also used to demonstrate that the overall dimensions of AI-Driven Green Accounting positively and significantly influence ESG reporting, which demonstrates the strategic position of AI technologies in ESG practices. These results affirm the idea that introducing new technology in accounting systems, such as advanced analytics and automation, enhances an organization's capacity to report sustainability and establish transparency.

Regarding the role of data granularity, the results show that detailed, high-quality environmental data effectively mediate the effects of AI-based accounting practices on ESG reporting. This demonstrates the importance of adequate and holistic information in informing judgments and making sustainability practices effective. Altogether, the research highlights that integrating AI-based accounting with comprehensive environmental information is crucial to companies that aim to excel at reporting their social and environmental performance in the long term.
The results of the present research suggest that AI-driven green accounting has a considerable positive impact on ESG reporting excellence, directly as well as indirectly via data granularity. These findings are in line with previous studies and highlight the vital role of combining environmental accounting and advanced technologies. The findings align with the work of Zik-Rullahi and Jide (2023) and Sudarminto and Harto (2023) who found that green accounting helps to introduce an environmental focus to conventional accounting frameworks and improves the process of sustainability reporting. The results equally affirm the work of Shaheen et al. (2024) and Faieq and Cek (2024) who contend that environmental accounting enhances transparency and plays a role in sustainable decision-making in organizations. The findings also parallel those of Tariq and Rahim (2024) and Mayegun and Nwanevu (2025) who note that AI is relevant in enhancing the accuracy of environmental accounting through automation, predictive analytics, and real-time data analysis, as well as the arguments of Zaman et al. (2022) and Uddin et al. (2024) that detailed, high-quality data are beneficial in sustainability analysis and reporting quality, which is corroborated by the substantial mediating effect of data granularity.
Nevertheless, the findings are somewhat inconsistent with those of Rahman and Islam (2023) and Dye et al. (2021) who report that the practice of environmental accounting can be associated with issues of measurement errors and standardization of reporting. The present study indicates that AI and the development of sophisticated analytics can mitigate such constraints and enhance the quality of environmental reporting. All in all, the current research contributes to the existing literature by offering empirical evidence that AI-assisted green accounting with elaborated environmental data can contribute immensely to excellence in ESG reporting.

Conclusions

This study investigated how AI-driven green accounting influences ESG reporting excellence and examined the role of data granularity as a mediating variable. The results provide solid empirical evidence that ensuring the quality and effectiveness of organizations' ESG reporting by adopting AI-based environmental accounting practices is an important area of research. The findings of the descriptive analysis indicate that the respondents generally expressed a high degree of consensus in terms of using AI-based practices of green accounting and ESG reporting. Specifically, the AI-Driven Green Accounting dimension with the highest mean was Automation and Transparency in Environmental Reporting, which shows the increasing significance of digital technologies in enhancing the activities of environmental reporting. The findings of the structural model analysis also support the conclusion that the dimensions of AI-Based Green Accounting exert meaningful positive impacts on the dimensions of ESG Reporting Excellence. Such results demonstrate the significance of AI technologies, including predictive analytics and automated data processing, in enhancing ESG reporting performance.
Moreover, the study found that data granularity plays a major mediating role among other variables, which suggests that precise, high-quality environmental information can be used to enhance the association between AI-based accounting practices and ESG reporting excellence. This implies that organizations can greatly enhance sustainability reporting performance by

collecting environmental data of quality and depth. Overall, the results underscore that the application of AI in green accounting systems can be vital in promoting sustainable business operations, better reporting disclosure, and greater organizational capacity to address stakeholders' growing demands concerning ESG performance. The research thus adds to the extant literature on sustainability accounting and demonstrates the strategic value of technological innovation in terms of developing environmental and sustainability reporting.

6.1. Recommendations

The study outcomes inspire a number of recommendations to facilitate the power of AI-driven green accounting and the excellence of ESG reporting in organizations. To begin, organizations should invest in the use of AI in environmental accounting systems, as the accuracy, efficiency, and transparency of environmental data and sustainability reporting can be enhanced by integrating AI tools, including predictive analytics and automated reporting systems. Second, companies should improve their data management infrastructure to increase the degree of data granularity. Obtaining accurate, detailed, and appropriately structured environmental data enables organizations to conduct better analyses and create more credible ESG reports. Third, organizations are urged to make environmental reporting processes more automated and transparent. The use of digital dashboards and real-time monitoring systems can provide oversight of environmental performance indicators on a regular basis and enhance sustainability in decision-making. Fourth, managers and decision-makers are encouraged to work on a better strategy of resource allocation regarding environmental activities. The application of AI-based analytics can assist organizations in finding inefficiencies, environmental costs, and better ways to use resources in sustainable initiatives. Fifth, companies should invest in employee training and capacity-building in areas that pertain to AI, environmental accounting, and sustainability reporting. The acquisition of relevant skills will enable successful implementation of AI-driven green accounting practices. Lastly, organizations should foster a strategic dedication to ESG reporting measures by incorporating environmental, social, and governance issues in the organization's overall corporate strategy, which can enhance transparency, increase stakeholder confidence, and increase the longevity of the organization.

6.2. Future Research Directions

Although the present study provides a number of insights into the application of AI-driven green accounting to increase ESG reporting excellence via data granularity, future research directions may be proposed. To start, future research could examine the effect of AI-driven green accounting in other areas and industries to identify whether the correlations presented in this study repeat in other organizational settings. Second, future studies could add more variables as mediating or moderating factors, including organizational culture, technological readiness, or regulatory pressure, to better understand the processes that mediate or moderate the relationship between AI-based accounting practices and ESG reporting performance. Third, scholars should explore how sophisticated data analytics can be applied in enhancing environmental accounting and sustainability reporting, including big data and blockchain. Fourth, longitudinal research designs could be employed to investigate the evolution of AI-driven environmental accounting practices over time and how they influence long-term sustainability performance. Lastly, future studies should consider investigating obstacles and issues related to the adoption of AI-oriented green accounting systems, especially in small and medium-sized businesses, to gain further information about the feasible usage of this type of technological implementation.

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