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Big data and AI in Esg performance measurement: A bibliometric analysis

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Abstract: This study looks at how Big Data and Artificial Intelligence (AI) are used to measure Environmental, Social, and Governance (ESG) performance by analyzing 17 articles from Scopus and WoS published in the last ten years. The study adopts a systematic methodology using VOSviewer and Publish or Perish to map thematic clusters, citation networks, and emerging research trends. Findings reveal that AI, particularly machine learning and natural language processing, enhances ESG transparency by enabling anomaly detection, greenwashing identification, and real-time sustainability analytics. However, the lack of common guidelines, unclear algorithm processes, and mismatched regulations make it hard to effectively use AI in ESG reporting. The study concludes that interdisciplinary collaboration is essential to developing accountable, interpreted, and harmonized ESG evaluation systems. From a practical perspective, this research offers actionable insights for regulators, firms, and investors to refine ESG strategies by leveraging technological innovation. The study also highlights the need for integrating alternative data sources—such as IoT, blockchain, and remote sensing—to strengthen data reliability. By advancing a unified research agenda, this work contributes to bridging the methodological and conceptual divide between sustainability, accounting, and AI domains.
Keywords: *AI, Anomaly detection, Bibliometric analysis, Big data, ESG performance measurement.*

1. Introduction

Over the past decade, the concept of sustainability has evolved from a normative agenda into a fundamental metric for evaluating global corporate performance. Environmental, social, and governance (ESG) factors are now regarded not only as indicators of corporate social responsibility but also as proxies for long-term value and risk assessment by investors and regulators [1, 2]. Many studies show that how well a company performs in ESG areas affects what investors like, how much it costs to get capital, and the company's reputation [3, 4].

Even with its careful rules, ESG reporting is still unclear because of ongoing issues like different standards, personal judgments, and not enough data checks across countries [5, 6]. Notably, Chatterji, et al. [7] emphasize the low correlation between ESG ratings from different providers, reinforcing concerns over methodological bias and inconsistency. This divergence in assessment approaches is further supported by Christensen, et al. [8] who argues that the empirical validity of ESG as a performance measurement tool remains contested. Nonetheless, the social and governance dimensions are widely acknowledged to contribute significantly to corporate resilience, particularly during times of crisis [9, 10]. So, the research shows that people agree ESG is an important measure for strategy, but there are key differences in how it is applied, which is not consistent and has issues with proving its effectiveness.

One of the most critical and persistent challenges in ESG implementation lies in the limitation of the reporting mechanism. The absence of unified global standards, the subjectivity in the report, and the

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verifiable ESG data ecriss jurisdictions One of the most critical and persistent challenges in ESG implementation lies in the limitations of its reporting mechanisms. The lack of harmonized global standards, subjective judgment in ESG reporting, and the absence of real-time, reliable data across jurisdictions make it difficult to compare, interpret, and place trust in the information disclosed [5, 11, 12]. Numerous studies have underscored that variations among ESG frameworks such as GRI, SASB, and TCFD result in fragmented information, hinder meaningful cross company comparisons, and allow firms to selectively disclose favorable sustainability narratives while omitting material risks [13-15]. These issues have made it easier for companies to engage in greenwashing, where they twist or overstate their sustainability claims to look good without making real improvements in ESG; some experts warn that even standardized metrics can be manipulated if there isn't strong data management and auditing in place [1, 16, 17]. Although ESG is widely acknowledged as strategically important, research reveals substantial disagreement regarding how it should be measured, verified, and implemented underscoring the necessity of reliable and verifiable ESG data for it to be considered a valid performance evaluation metric. The advancement of big data and AI technologies not only presents a transformative opportunity but also fundamentally redefines how ESG performance is measured and communicated. Unlike traditional systems that rely on companies to report their information periodically often in a selective and incomplete manner AI leverages natural language processing (NLP), machine learning, and deep learning to automatically collect and analyze unstructured ESG data in real time from sources such as sustainability reports, social media, financial news, and capital market disclosures. At the same time, big data helps gather a large amount of diverse ESG related information from different sources, making it possible to find subtle patterns and unusual occurrences that traditional analysis methods couldn't detect [18-21]. Many studies show that these technologies greatly improve how quickly, in detail, and fairly ESG assessments are done [22-24]. However, divergence arises in terms of implementation complexity and interpretability. While some scholars advocate for AI-driven ESG systems as a solution to greenwashing and information asymmetry [3, 25] others caution that the “black box” nature of certain AI models may introduce new forms of opacity, particularly when used without clear governance mechanisms [8, 26]. So, while the combination of AI and big data can bring significant changes, its acceptance as a reliable system for ESG reporting depends on being clear, able to be checked, and fitting in with standard sustainability guidelines.

The foundation of AI as a field was first laid in the 1956 Dartmouth Conference by MacNeil and Esser [27] who coined the term “artificial intelligence” to describe systems capable of performing tasks that typically require human intelligence. In parallel, the concept of big data began to gain academic traction in the early 2000s, notably through Doug Laney’s 3V model (volume, velocity, and variety) as a framework for understanding large-scale, complex datasets. Over time, AI systems have evolved into several functional classifications, including expert systems, planning systems, machine learning, cognitive computing, and natural language processing [28]. Within ESG applications, the two most widely used AI categories are machine learning (supervised, unsupervised, and reinforcement learning) and NLP (sentiment analysis, topic modeling, and text mining), which fall under the limited memory type of AI. These systems demonstrate particular efficacy in processing unstructured ESG data, uncovering latent patterns, and detecting anomalies in disclosures making them highly valuable for enhancing the accuracy of ESG assessments and identifying potential fraud.

Despite its transformative potential, the integration of big data and AI into ESG performance measurement introduces a complex set of methodological, ethical, and institutional challenges. While AI can handle large and messy ESG data, its results often miss important details without human input, especially when understanding complex sustainability reports [29-31]. One recurring concern in the literature is the limited explainability and transparency of AI algorithms, especially deep learning models, which may function as “black boxes” and hinder stakeholder trust [8, 26]. Additionally, differences in technology resources, data management skills, and knowledge about technology in different countries have led to uneven use and development of AI-based ESG systems [21, 32]. Many bibliometric reviews show that there is a lack of clear connections and consistent language between the fields of AI, ESG, and accounting [12, 33]. Some researchers believe that AI and big data help improve ESG monitoring and transparency, while others think they are game-changing tools that make us rethink how we measure performance [3, 34-36]. These divergent perspectives underscore a continuing academic debate about whether such technologies should merely be considered supportive tools or regarded as transformative drivers reshaping ESG reporting and governance paradigms.

Despite the widely acknowledged potential of integrating big data and artificial intelligence (AI) into ESG performance measurement, systematic and data-driven academic research in this area remains remarkably limited. Existing literature tends to be fragmented, predominantly descriptive, and often reliant on case-based analyses within a unified conceptual framework [34, 35]. Although many studies have looked at how AI is used in ESG, like using predictive modeling, sentiment analysis, or automatically sorting sustainability reports, there hasn't been much effort to bring these findings together into a clear and unified understanding [37-40]. There are not many studies that look at how ESG and technology research have changed over time, even though these studies are important for understanding how major topics, collaborations between authors, and relationships between countries are evolving globally [41, 42]. A common theme is found when the methods, terms, or topics are similar across the ESG, AI, and accounting fields [11, 43, 44]. Differences among studies lie primarily in their organization; some emphasize the technical aspects of AI and big data implementation, while others stress the epistemological need to link technological innovation with sustainability accountability and long-term performance governance. Therefore, a comprehensive bibliometric analysis is urgently needed to bridge these disciplinary gaps and lay the groundwork for a more coherent and integrated research agenda.

Moreover, the failure to foster interdisciplinary integration in ESG performance research leveraging big data and AI remains a significant barrier to achieving comprehensive understanding and advancement in this field. Most existing research is still confined within disciplinary silos; accounting tends to focus on issues of accountability and sustainability reporting; information technology emphasizes algorithmic sophistication, while sustainability studies concentrate on normative and ethical concerns [45, 46]. This means there are not many new ideas or methods that connect the technical, social, and organizational aspects of ESG measurement [47-50]. A recurring theme across the literature is the recognition of the importance of technological integration to enhance ESG reporting quality, particularly through NLP, machine learning, and predictive analytics [51, 52]. However, disciplinary emphases diverge: while technology studies primarily focus on enhancing data efficiency and accuracy, accounting research points to the critical importance of verification, transparency, and information reliability for stakeholders. Therefore, the development of an integrated framework that bridges technical and social perspectives is urgently needed to comprehend the transformative role of AI and big data in ESG measurement, and to reconceptualize organizational performance through the lens of long-term sustainability [53, 54].

This research will fill the ongoing gaps in understanding how big data and artificial intelligence (AI) are used in measuring ESG performance by providing three connected contributions. This research will fill the ongoing gaps in understanding how big data and artificial intelligence (AI) are used in measuring ESG performance by providing three connected contributions. First, it plans to look at recent academic articles about how big data and AI technologies are used in measuring ESG, focusing on trends, growth in the literature, and connections between different fields [32, 41, 55, 56]. Second, the study aims to find important opportunities and major challenges related to using these technologies, such as how reliable the data is, how clear the algorithms are, and differences in how widely they are adopted around the world [57-60]. Third, it develops a bibliometric map based on reputable scientific databases such as WOS and Scopus to visualize author collaborations, institutional affiliations, and the evolution of key terms that reflect the intellectual development of this field [61, 62]. A common observation in the research is that the use of AI and big data in ESG-related studies has grown rapidly in the last five years, mainly due to the need for automation and real-time analysis [61, 62]. However, the literature also reveals divergent approaches; some studies prioritize technological perspectives, while others emphasize governance, regulatory frameworks, and social accountability [63-65]. Therefore, the bibliometric approach used in this study aims to not only create a quantitative overview of the research field but also to lay the groundwork for better combining accounting, information technology, and sustainability in measuring ESG performance.

In line with the research gaps found, this study has two main goals: first, to look at how the academic literature describes the role of big data and AI in making ESG performance measurement more accurate and efficient; and second, to find the research trends and thematic clusters related to AI's ability to spot errors, inconsistencies, and fraud in ESG reporting. Given the growing use of technology in sustainability disclosure, this study seeks to fill the evident gap in the literature by addressing the following research questions:

RQ1: How have scholarly discussions framed the role of big data and AI in improving the accuracy and efficiency of ESG performance measurement?

RQ2: What research trends and thematic clusters have emerged around AI's potential to detect anomalies and manipulation in ESG reporting?

This study contributes in two major ways: it strengthens the theoretical foundations of ESG performance measurement and offers valuable practical insights into how technology can enhance its assessment. This research contributes to the field of accounting and sustainability by integrating digital methods leveraging big data and artificial intelligence (AI) into the evaluation of ESG performance, which has traditionally relied on conventional methods [11]. This perspective not only broadens the intellectual boundaries across disciplines, but also acknowledges AI as a pivotal force in redefining how corporate sustainability is assessed in the digital era [3, 8].

Figure 1, analyzed using VOSviewer, highlights the centrality of big data and AI in ESG performance measurement research particularly within accounting due to their strong interconnection with accounting and finance. The results of this study help companies, regulators, and stakeholders create ESG reporting systems that are more precise, efficient, and better at meeting growing regulatory demands and data-focused investor needs [66, 67]. Several studies underscore that technological integration can reduce greenwashing risks and enhance disclosure transparency [26, 39]. However, notable disparities remain regarding implementation readiness and digital infrastructure gaps across countries [66, 67]. While there is growing consensus on the critical role of big data and AI in improving the quality of sustainability reporting, scholarly approaches differ in emphasis: technology oriented research typically prioritizes automation and efficiency, whereas accounting literature places greater weight on governance, auditability, and information legitimacy [8, 36]. In today's digital world, using big data and AI is essential for creating flexible, trustworthy, and forward-looking ESG accountability systems.

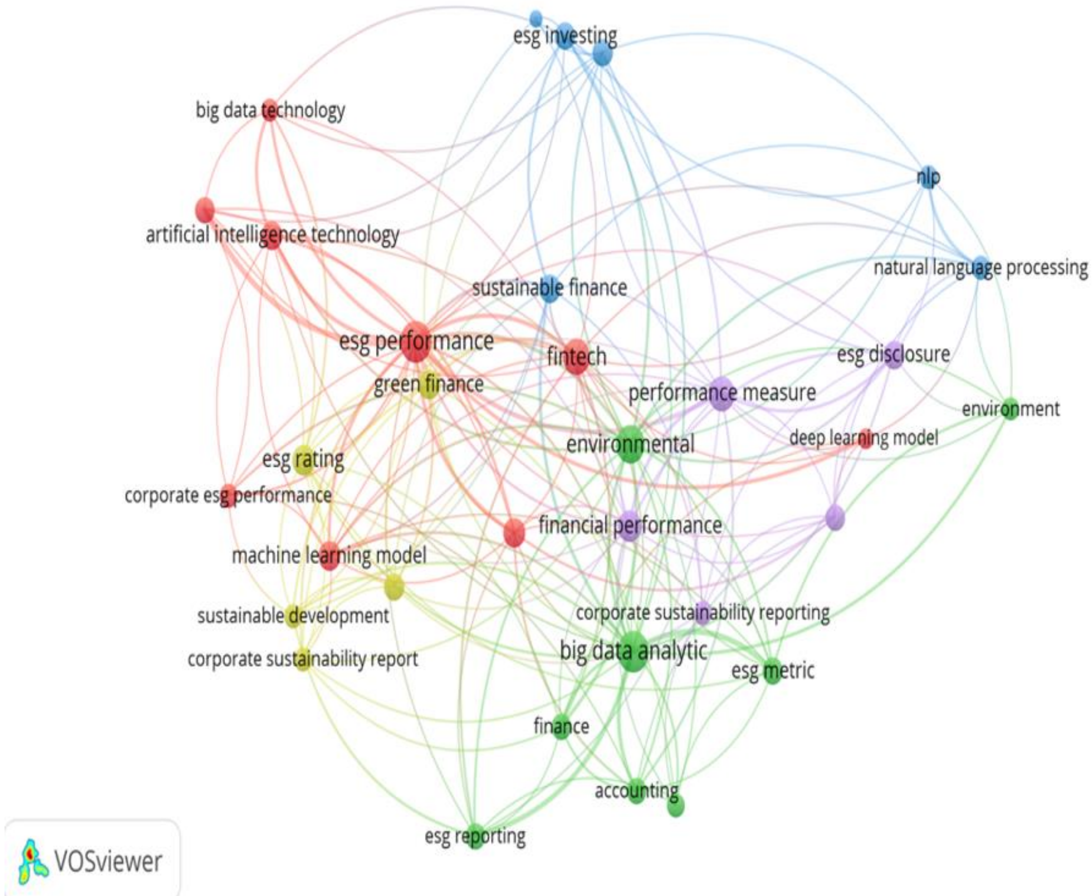

Figure 1.
Mapping subject.

Table 1.
Inclusion and Exclusion Criteria.

Category	**Inclusion Criteria**	**Exclusion Criteria**
Language	Only articles published in English	Articles published in languages other than English
Document Type	Peer reviewed journal articles	Conference papers, book chapters, review papers, editorials
Database	Articles indexed in Web of Sciences (WoS) and Scopus	Articles not indexed in WoS of Scopus
Subject Area	Research categorized under business finance in WoS	Studies outside the Business Finance category
Relevance	Studies explicitly discussing big data and AI in ESG performance measurement	Studies focusing on general ESG topics without AI or Big Data integration
Duplication	Uniqe article with No. duplicates	Duplicate articles from the same sources

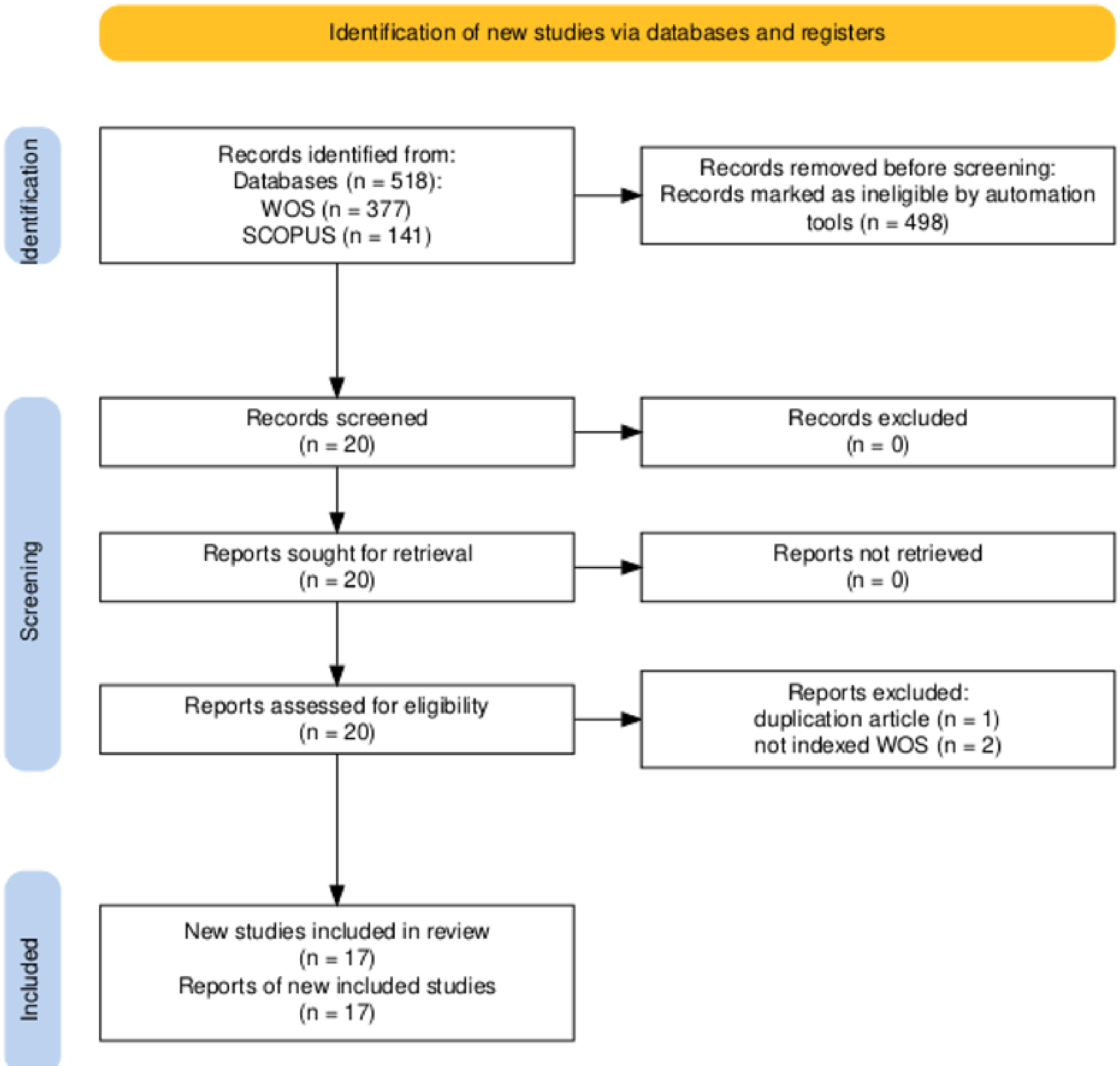

Figure 2.
PRISMA Diagram.

2. Research Method

This study employs a bibliometric approach to analyze trends in big data and artificial intelligence (AI) in ESG performance measurement. This method facilitates the identification of publication patterns, academic collaborations, and key topics emerging in the relevant scientific literature. By utilizing this approach, the study offers context for the academic landscape and the evolution of research in this domain.

The research data were obtained from two major academic databases: WoS and Scopus, using carefully selected keywords relevant to the study's scope: "Artificial intelligence in ESG measurement," "Big data for ESG performance," "AI and Sustainability Reporting," and "Machine Learning in ESG Analysis." The initial search yielded 518 documents (WoS = 377, Scopus = 141) before undergoing further screening.

Below is a structured Table 1, outlining the inclusion and exclusion criteria. The tables ensure clarity in the research selection process and maintain the study's focus on big data and AI in ESG performance measurement. Based on these criteria, 498 documents were excluded, leaving 20 articles for further analysis. After additional screening for duplicates and indexing verification, the final dataset comprised 17 articles. The study and screening process adhered to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines to ensure transparency and systematic literature selection. The PRISMA flow diagram in Figure 2 used in this study outlines the selection process, from initial identification to final inclusion of articles for analysis.

We conducted bibliometric analysis using two primary software tools: VosViewer, which visualizes author collaboration networks, co-occurrence keyword analysis, and thematic trends in the field. We extract and manage bibliometric data from the selected databases using Publish or Perish. Through this approach, this study identifies conceptual relationships, publication trends, and research areas that offer opportunities for further exploration.

Table 2.
Breakdown of Reviewed of Studies.

No	Nama of Source	Total Citations (2020-2024)	Source
1	Journal of Financial Reporting and Accounting	2.974	WOS
2	Sustainability Accounting Management and Policy Journal	6.183	WOS
3	International Journal of Accounting Information Systems	4.472	WOS
4	Risks	4.993	WOS
5	Financial Innovation	6.964	WOS
6	Research in International Business and Finance	23.348	WOS
7	Journal of Corporate Accounting and Finance	1.388	WOS
8	Journal of Sustainable Finance & Investment	4.591	WOS
9	Green Finance	1.083	WOS
10	Oeconomia Copernicana	2.992	SCOPUS
11	Accounting Horizons	12.212	SCOPUS
12	Cleaner Logistics and Supply Chain	655	SCOPUS
13	Industrial Marketing Management	72.193	SCOPUS
14	International Journal of Financial Studies	3.086	SCOPUS
15	Journal of Applied Accounting Research	3.530	SCOPUS
16	Equilibrium Quarterly Journal of Economics and Economic Policy	2.320	SCOPUS

3. Result and Discussion

The bibliometric analysis reveals that big data and AI in ESG performance measurement remain an emerging yet underdeveloped research area within the accounting discipline. Table 2 shows that high-impact journals like Industrial Marketing Management (72.193 citations) and International Reviews of Financial Analysis (33.501 citations) talk about sustainability issues in finance in a general way, but they don't talk about AI and big data applications in measuring ESG performance.

In contrast, journals more closely related to this study, such as the Journal of Financial Reporting and Accounting (2.974 citations) and the Journal of Corporate Accounting & Finance (1.388 citations), exhibit significantly lower citation counts. This difference indicates that even though ESG research is growing, there is still a need for a more organized study of how big data, AI, and ESG performance measurement are connected in the current literature using a bibliometric approach. So, this study is important for showing how these technologies influence academic discussions about ESG performance measurement and for finding research areas that haven't been fully explored [68, 69].

Table 3.
Literature Review.

No	Title of Paper & Authors (years)	Name of Journals	Total Citations*)	AI Method used	Contribution to subject	Main Findings	Methodology	Big Data and AI
1	AI human impact: toward a model for ethical investing in AI-intensive companies Brusseau [70]	Journal of sustainable Finance & Investment	10	ML for AI impact evaluation	AI Ethics in investment and regulation, emphasizing the aspects of autonomy, dignity, privacy, and the performance of AI technology for investors, regulators, and financial analysts.	The AI ethical investment model complements ESG to assess the impact of AI	Qualitative research, with a multidisciplinary conceptual analysis of AI ethics	Big data based personalized AI and its impact on individual autonomy
2	AI-powered information and Big Data: current regulations and ways forward in IFRS reporting Leitner-Hanetseder and Lehner [71]	Journal of Applied Accounting Research, 24(2), pp. 282–298	15	ML for IFRS financial reporting	Integration of AI and Big Data in IFRS reporting for intangible asset reporting	FAIIBD (Framework for AI-powered Information and Big Data Reporting): AI and Big Data for more accurate IFRS reporting	Qualitative research, with conceptual analysis of IFRS and AI	Big data and AI drive predictive analytics and operational efficiency in business.
No	Title of Paper & Authors (years)	Name of Journals	Total Citations*)	AI Method used	Contribution to subject	Main Findings	Methodology	Big Data and AI
3	Current Issues Faced by Controllers Bucaro, et al. [72]	Accounting Horizons, 38(4), pp. 31–49	0	The impact of digital transformation and AI on controllership	The role of AI and digital transformation in the challenges of controllers and chief accounting officers	Dgital Transformation and AI are changing the role of controllers in accounting and ESG reporting	Qualitative research, semi structured interviews with thematic analysis	AI and big databased ERP transform financial reporting and decision making.
4	Disclosures about algorithmic decision making in the corporate reports of Western European companies Bonsón, et al. [73]	International Journal of Accounting Information Systems	13	NLP and ML for ADM (Automated Decision Making) disclosure analysis	Transparancy of AI Disclosure in ADM for regulators, accountants, and investors	ADM disclosure is still limited, there needs to be a transparency standard in company reports	Quantitative Research, NLP Text Mining, and Logistic Regression for Company ADM Disclosure Analysis	AI processes big data for ADM, needs transparency regulations and bias mitigation.
5	Does ESG Predict Business Failure in Brazil? An Application of Machine Learning Techniques Kaleem, et al. [74]	Risks, 12(12), 185	0	ML for predicting business failure based on ESG	ML and ESG for predicting business failure in emerging markets	ESG and ML for predicting business failure in Brazil	Quantitative research, ML, and PCA for Business Failure Prediction Classification in Brazil	AI and big data predict bankruptcy and enhance financial risk management.
No	Title of Paper & Authors	Name of	Total	AI Method used	Contribution to subject	Main Findings	Methodology	Big Data and AI

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	(years)	Journals	Citations*)					
6	Exploring accounting and AI using topic modelling Murphy, et al. [75]	International Journal of Accounting Information Systems, 55, 100709	4	NLP with Laten Dirichlet Allocation (LDA) technique and ML for AI Accounting trend analysis	Mapping AI topics in accounting with LDA for academics and practitioners	ADM disclosure is still limited and needs consistent reporting standarts	Quantitative research, Text Analysis with LDA for identifying AI and Accounting research patterns	Big data and AI reveal trends in automated accounting and audit literature.
7	Exploring the linkages between FinTech and ESG: A bibliometric perspective TROTTA	Research in International Business and Finance	14	ML and NLP for FinTech and ESG analysis	The role of AI in FinTech and ESG for sustainability and financial investment	Integrated FinTech and ESG, need a strong theoretical framework and research consolidation	Quantitative research, bibliometrics and Content Analysis for mapping trends in FinTech and ESG Research	AI and big data strengthen ESG rating and financial risk management.
8	Generative artificial intelligence in FinTech: Applications, environmental, social, and governance considerations, and organizational performance: The moderating role of ethical dilemmas Zada, et al. [76]	Oeconomia Copernicana, 15(4), pp. 1303–1347	0	Generative AI and ML for FinTech Innovation	The impact of GenAI in FinTech for innovation, ESG, and Operational efficiency	GenAI drives FinTech and ESG innovation, ethical challenges still need to be addressed	Quantitative research, SEM Smart-PLS and CFA for variable relationship analysis in the FinTech industry	GenAI and big data optimize investments, facing challenges of ethics and transparency
No	Title of Paper & Authors (years)	Name of Journals	Total Citations*)	AI Method used	Contribution to subject	Main Findings	Methodology	Big Data and AI
9	Green bond market boom: did environmental, social and governance criteria play a role in reducing health-related uncertainty? Ribeiro [77]	Green Finance	5	ML and Spatial econometrics for green bond analysis	The impact of ESG on Health Uncertainty and the Stability of the Green Bond Market	The social dimension of ESG reduces health uncertainty and encourages green bond growth	Quantitative research, Dynamic spatial Durbin model and ML for ESG analysis and health uncertainty	AI and big data connect ESG and health risks in the green bond market

No	Title of Paper & Authors (years)	Name of Journals	Total Citations*)	AI Method used	Contribution to subject	Main Findings	Methodology	Big Data and AI
10	How will AI text generation and processing impact sustainability reporting? Critical analysis, a conceptual framework and avenues for future researchDe Villiers, et al. [78]	Sustainability Accounting Management and Policy Journal	26	NLP and ML for sustainability reporting analysis	The role of generative AI in sustainability reporting and prevention of Greenwashing	Generatif AI increases reporting efficiency, but risks encouraging greenwashing	Qualitative research, Critical conceptual analysis based on the three-stage alvesson and deetz framework for AI analysis in sustainability reporting	GenAI processes big data for sustainability reporting, facing the risk of greenwashing.
No	Title of Paper & Authors (years)	Name of Journals	Total Citations*)	AI Method used	Contribution to subject	Main Findings	Methodology	Big Data and AI
11	Implementation of deep learning models in predicting ESG index volatility Bhandari, et al. [79]	Financial Innovation	71	Deep learning (LSTM, GRU, CNN) for predicting ESG volatility	Deep Learning for predicting ESG Volatility and making decisions on sustainable investment strategies	LSTM excels in predicting ESG volatility, helping investors manage market risk	Quantitative research, Deep learning (LSTM, GRU, CNN) with RMSE, MAPE, and Welch's t-test evaluation for ESG time series prediction	LSTM and GRU analysis ESG volatility from financial big data.
12	Nexus among artificial intelligence implementation, healthcare social innovation, and green image of hospitals' operations management in Egypt Adel, et al. [80]	Cleaner Logistics and Supply Chain, 11, 100156	5	ML for efficiency and sustainability in hospital operations	AI for innovation, operational effiency, and hospital sustainability	AI enhances social innovation, which mediates the relationship between AI and the green image of hospitals	Mixed Methods with quantitative PLS-SEM and qualitative interview and Focus group for AI and social innovation analysis	AI and big data enhance the efficiency and transparency of hospital services.
No	Title of Paper & Authors (years)	Name of Journals	Total Citations*)	AI Method used	Contribution to subject	Main Findings	Methodology	Big Data and AI
13	Sustainable development goals and assurance of non-financial information reporting in Spain Sierra García, et al. [36]	Sustainability Accounting Management and Policy Journal	26	Quantitative analysis for assurance and reporting of SDGs	The role of external assurance in transparency and disclosure of SDGs in sustainability report	Assurance High quality assurance enhances SDG reporting and company ESG performance	Quantitative research, logistic regression, and chi square test	Big data ESG helps the potential automation of SDG assurance with AI in the future.
14	The Impact of Artificial Intelligence Disclosure on Financial Performance Shiyyab, et al. [81]	International Journal of Financial Studies, 11(3), 115	15	NLP and ML for AI disclosure analysis	AI Disclosure and its impact on financial performance in the banking sector	AI disclosure improves performance and efficiency, but standards are still inconsistent	Quantitative research, content analysis, and OLS (Ordinary Least Square)	AI and big data drive bank efficiency and more transparent AI disclosures

No	Title of Paper & Authors (years)	Name of Journals	Total Citations*)	AI Method used	Contribution to subject	Main Findings	Methodology	Big Data and AI
15	The role of Industry 4.0 technologies in driving the financial importance of sustainability risk management Turek, et al. [82]	Equilibrium. Quarterly Journal of Economics and Economic Policy, 18(4), pp. 1009–1044	23	ML and Big Data for sustainability risk management	The role of AI and industry 4.0 in sustainability risk management and financial performance	Industry 4.0 technology has not yet significantly impacted short-term financial performance	Mixed Methods, survey, Mann-Whitney U Test, Case Studies, and in-depth interviews	AI and Big Data for sustainability risk management based on industry 4.0 technology
No	Title of Paper & Authors (years)	Name of Journals	Total Citations*)	AI Method used	Contribution to subject	Main Findings	Methodology	Big Data and AI
16	Unleashing the power of artificial intelligence for climate action in industrialAkter, et al. [83]	Industrial Marketing Management, 117 , pp. 92–113	14	ML and Deep Learning for climate service innovation	AI for climate service innovation, industrial sustainability, and market efficiency	AI improves environmental performance and competitiveness, but implementation is still fragmented	Quantitative research, PLS SEM with surveys of fast fashion sector managers and regression for analyzing AI innovation and fast fashion sustainability	Big Data and predictive AI for supply chain efficiency and climate mitigation
17	Where and how machine learning plays a role in climate finance research Alonso-Robisco, et al. [84]	Journal of Sustainable Finance & Investment	240	ML, NLP, Deep Learning for climate finance	ML in climate finance for ESG, Risk and Market Transparency	ML encourage climate finance research, but challenges in transparency and energy remain	Quantitative approach, SLR, using LDA (Latent Dirichlet Allocation), and Bibliometrics for Climate Finance ML research trend analysis	Big Data ESG and Green AI for sustainability climate finance

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A thematic analysis performed using VOSviewer identified three principal clusters in the scholarly literature on big data and AI applications in ESG performance measurement. The first cluster focuses on machine learning applications for ESG risk assessment, highlighting studies that develop predictive models to quantify corporate sustainability risks [68, 69]. The second cluster emphasizes natural language processing (NLP) in ESG reporting, demonstrating how AI-driven sentiment analysis can improve transparency and detect greenwashing practices [26, 39]. The third cluster examines how data management and verification operate within AI-based ESG systems, raising concerns over the reliability of algorithmic evaluations and the ongoing challenges in developing consistent regulatory frameworks for AI-driven sustainability reporting [3, 8]. The third thematic cluster centers on data governance and auditability in AI-based ESG systems, raising critical concerns about the reliability of algorithmic evaluations and the regulatory complexities involved in standardizing AI-driven sustainability disclosures [3, 8].

Table 3 presents a comprehensive overview of existing research addressing the intersection of AI, big data, and ESG performance measurement. It shows the main research methods, areas of focus, and gaps that still need to be filled. According to the literature review, AI has been used a lot to automate ESG scoring. However, many studies don't have a solid framework for putting these technologies into standard ESG reporting systems [2, 85]. With the increasing use of AI in automated ESG risk assessment, the studies presented in Table 3 reveal persistent challenges, including data inconsistency, algorithmic bias, and misalignment with regulatory standards.

Table 4.
Several key insight emerge from this literature review.

Key insight	Findings and implications	Supporting Reference
Bias and data integrity issues	AI generated ESG ratings often rely on self-reported data, raising concern about accuracy and transparency	Hughes, et al. [86] and MacNeil and Esser [27]
Regulatory misalignment	The absence of standardized ESG disclosure regulations makes it difficult to compare ESG ratings across different markets	Mondal, et al. [87]
Greenwashing detection limitation	NLP and sentiment analysis improve ESG monitoring, but lack uniformity across industries, affecting robustness	Baumüller and Leitner-Hanetseder [88]

Some studies look at how AI can find problems in ESG reporting, but not many talk about how to make AI-driven assessments understandable and accountable, which is still a big problem for financial regulators and auditors [36, 89]. Another major concern arising from Table 3 is the imbalance in research methodologies. As the use of AI for automated ESG risk assessment continues to expand, the studies presented in Table 3 reveal persistent challenges, including inconsistent data, algorithmic bias, and non-compliance with established regulatory standards [90]. The lack of interdisciplinary studies further demonstrates that AI and big data have yet to be fully integrated into the accounting and sustainability domains [74]. The analysis of existing literature, as summarized in Table 4, reveals a growing interest in the application of AI and big data for ESG performance measurement. However, a closer examination of the research landscape uncovers several key insights that warrant further exploration. These results indicate that we need standardized AI-driven ESG measurement frameworks, collaborations between different fields, and more research into AI governance mechanisms to make sure that ESG reporting is open and honest.

Addressing RQ1: The role of big data and AI in improving ESG performance measurement

The findings indicate that big data and AI play a transformative role in enhancing ESG performance measurement by improving accuracy, efficiency, and scalability. The bibliometric analysis's VOSviewer mapping reveals the widespread use of AI in ESG research. Three primary applications of AI include risk assessment, anomaly detection, and real-time ESG analytics. First, machine learning (ML) models have been increasingly adopted for ESG risk assessment, allowing firms and investors to quantify corporate sustainability risks more objectively [37, 69]. Existing studies indicate that both supervised and unsupervised learning approaches have been applied to forecast ESG ratings, classify sustainability practices, and detect emerging ESG-related financial risks [27, 86, 91]. The accuracy of AI-driven ESG models depends critically on high-quality data and transparency, as substantial variation in ESG disclosures across industries complicates meaningful cross-sectoral comparisons [71, 89]. Additionally, NLP techniques have been very helpful in finding errors, strangeness, and possible fraud in ESG disclosures [26, 39]. Companies strategically lie about their ESG disclosures by pulling structured insights from unstructured corporate sustainability reports, financial news, and regulatory filings [36, 85]. Many have used NLP-based sentiment analysis to uncover these practices. Nevertheless, the application of NLP in ESG evaluation continues to face significant challenges, including linguistic diversity, inconsistent data quality, and the lack of standardized ESG terminology across markets [82]. According to [3, 83] real-time ESG analytics using big data and AI make it possible to continuously monitor and rate sustainability performance. This reduces the lack of information between companies, regulators, and investors. Big data technologies help collect and combine a lot of ESG data from various sources, like satellite images, IoT sensors, and other data sources, to give detailed and up-to-date information about how companies are doing in terms of sustainability [72, 78]. Big data technologies help collect and combine a lot of ESG data from various sources, like satellite images, IoT sensors, and other data sources, to give detailed and up to date information about how companies are doing in terms of sustainability.

Despite these technological advancements, challenges persist in ensuring the reliability and transparency of AI-driven ESG measurement systems. People are worried about how trustworthy and honest ESG ratings created by AI methods are because many AI models are hard to understand, have unclear processes, and can be biased. ESG reporting standards vary from jurisdiction to jurisdiction, which makes it challenging for AI-powered sustainability analytics to be used everywhere [27, 65, 86] and there are also different rules about how AI can be used and how it should be used ethically. So, even though AI and big data have made ESG performance measurement much more accurate, efficient, and in-depth, it is still difficult to incorporate them into standard ESG reporting frameworks. Getting AI used for ESG measurement to grow in the following years will depend on figuring out how to standardize data, hold algorithms accountable, and make sure that rules apply across borders [69, 89, 91].

Addressing RQ2: Research Trends and AI's Potential in detecting Anomalies and Manipulation in ESG Reporting

The bibliometric analysis and thematic mapping show that researchers are paying more attention to how AI can help find problems and fraud in ESG disclosure. As firms increasingly integrate sustainability metrics into corporate reporting, concerns over greenwashing, selective disclosures, and data manipulation have intensified [57, 72]. Recent improvements in AI-powered anomaly detection models have made it easier to spot false ESG claims, inconsistent sustainability reporting, and problems with how companies report their ESG metrics [92, 93]. First, AI-driven anomaly detection models are widely used to identify misreporting and fraudulent ESG claims. Machine learning techniques, particularly supervised and unsupervised learning models, are used to spot differences in ESG disclosures compared to what is typical in the industry, revealing ongoing problems in how sustainability practices are reported [27, 86, 94]. AI methods like unsupervised clustering and deep anomaly detection help researchers and regulators find mistakes in ESG reports, especially when companies share only positive sustainability information and leave out negative impacts [3, 89]. However, AI's ability to accurately find unusual patterns depends on having good, consistent ESG datasets, which can differ a lot between industries and regions [71, 82].

Second, sentiment analysis and NLP techniques play a crucial role in detecting greenwashing practices. Scientists have used AI to look at the tone, structure, and semantic pattern in ESG reports, annual filings, and corporate sustainability communications[40, 93] the reports and communications. NLP models that are specifically trained on ESG-related texts can identify differences between what companies say about their ESG efforts and the actual numbers they report, even if they haven't taken real steps to improve [71, 95]. However, using NLP to detect greenwashing is not very effective because of variations in context, unique industry terms, and the lack of a common vocabulary for ESG reporting. Third, AI's ability to compare ESG disclosures with financial performance metrics significantly enhances transparency and accountability. By integrating alternative data sources, such as satellite imagery, environmental sensor data, and supply chain records, AI models can provide evidence [83, 96]. These cross-validation techniques mitigate the risks of selective ESG disclosures and provide investors, regulators, and policymakers with more reliable sustainability assessments [36, 69]. However, even with these improvements, many AI-based ESG scoring systems still have issues with being difficult to understand and not clearly showing how they work, which raises worries about responsibility and ethical use of AI in ESG assessments [27, 86, 89].

Several key limitations hinder the effectiveness of AI in ESG anomaly detection, despite its transformative potential. First, ESG datasets are usually broken up, messy, and don't follow a standard format, which makes it hard for AI models to set reliable benchmarks for finding anomalies [82]. Second, subjective weighting schemes, inconsistent sustainability criteria, and corporations self-reporting can all cause biases in ESG rating models. These biases may make ESG misclassification risks worse rather than better [3, 8]. Third, because there isn't a consistent set of global rules for AI-driven ESG scoring methods, different ESG rating agencies have varying results, making it more difficult to compare companies in different markets [65, 94].

4. Conclusion

Big Data and AI in ESG Performance Measurement: A Bibliometric Analysis of Emerging Trends shows that artificial intelligence and big data analytics are being used in ESG performance measurement in new and intriguing ways. This use case is particularly evident in the detection of mistakes and fraud in sustainability reporting. Bibliometric analysis indicates that while AI has significantly contributed to enhancing the transparency and accuracy of ESG reporting, its adoption still faces methodological and regulatory challenges. This study found that there are different types of research, which means that there aren't any universal rules for using AI for ESG. This makes it harder to compare and be consistent between studies. Moreover, data bias and limitations in AI model interpretability remain major barriers to the widespread implementation of this technology.

This study acknowledges several limitations. While effective in identifying research trends, bibliometric methods do not directly explore the practical perspectives of regulators, investors, and corporations in implementing AI for ESG. Additionally, differences in the quality and availability of ESG data across industries and jurisdictions make it difficult to create AI-driven evaluation models that can be used by everyone. The continuously evolving policy and regulatory landscape further adds uncertainty to the sustainability of AI implementation in ESG performance measurement, which should be considered in future research.

To address these challenges, future studies should focus on three key aspects First, developing standardized AI-driven ESG reporting frameworks is critical to guaranteeing regulatory coherence and cross-regional data comparability. Second, enhancing NLP models with ESG-specific linguistic datasets can improve the detection of greenwashing and misreporting. Third, integrating alternative data sources such as blockchain, IoT, and remote sensing into AI-based ESG evaluation can reduce reliance on self-reported corporate data and improve verification accuracy. By addressing these challenges, AI and Big Data can play a more transformative role in ensuring ESG reporting integrity, reducing information asymmetry, and enhancing corporate accountability.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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