Journal of
Risk and Financial Management

MDPI

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The Impact of AI-Integrated ESG Reporting on Firm Valuation in Emerging Markets: A Multimodal Analytical Approach

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Abstract

This study examines the impact of Artificial Intelligence (AI)-enhanced Environmental, Social, and Governance (ESG) reporting on firm valuation in emerging markets. It aims to explore how AI integration enhances the interpretability and predictive accuracy of ESG metrics in shaping market perceptions and investor decisions. This study employs a panel dataset from 2018 to 2024, analysing publicly listed non-financial firms across five major sectors: manufacturing, energy, telecommunications, consumer goods, and industrials. This study contributed by employing AI-powered multimodal analysis with conventional ESG scoring methods and integrating Fixed-Effects Regression with machine learning (ML) algorithms including Extreme Gradient Boosting (XGBoost) and Random Forest to identify complex, non-linear relationships within ESG data and firm valuation. The results show empirical evidence that integrating ML enhances the explanatory power of ESG data. Findings indicate that ESG performance is positively correlated with higher market valuations, particularly in Environmental and Social dimensions. Governance metrics are more inconsistent, which may be due to heterogeneity in governance practices, regulatory enforcement and the challenges of quantifying governance quality beyond compliance indicators across the focus emerging markets. Firms identified in ESG controversies tend to face valuation penalties, which stresses market sensitivity to reputational risks. ML algorithms outperform conventional techniques in predictive accuracy, revealing complex, non-linear interactions within ESG data. This study contributes to both the academic literature and practice showing how next-generation ESG reporting can robust valuation models, address limitations of conventional ESG scoring, and ensure a reliable outlook for investors and policymakers of industries in emerging markets.

Keywords: AI-ESG reporting; firm valuation; machine learning; natural language processing; emerging markets

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Academic Editor: Thanasis Stengos

Received: 5 September 2025
Revised: 28 September 2025
Accepted: 29 September 2025
Published: 27 November 2025

Citation: Aruwaji, M. A., & Swanepoel, M. J. (2025). The Impact of AI-Integrated ESG Reporting on Firm Valuation in Emerging Markets: A Multimodal Analytical Approach. *Journal of Risk and Financial Management*, *18*(12), 675. https://doi.org/10.3390/jrfm18120675

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1. Introduction

Globally, organisations are increasingly recognising that delivering financial returns must be accompanied by transparent, credible, and strategic sustainability reporting (Eccles & Krzus, 2018). Environmental, Social, and Governance (ESG) disclosures have moved beyond a compliance exercise to become a core driver of firm valuation, particularly in emerging markets where governance structures are evolving and stakeholder scrutiny is intensifying (Friede et al., 2015; Wamba et al., 2021). In such contexts, the quality, timeliness, and comparability of ESG information are frequently undermined by institutional voids, inconsistent reporting standards, and high information asymmetry (Khanna & Palepu, 2010).

Artificial Intelligence (AI) offers a transformative potential to address these challenges by enhancing ESG data interpretation, standardisation, and predictive capability. While existing research demonstrates that robust ESG performance can positively influence firm valuation (Fatemi et al., 2018; Cheng et al., 2014; Hussein et al., 2025), there is a critical gap regarding how AI integration into ESG reporting specifically influences investor perceptions, valuation accuracy, and reputational risk management in emerging markets (Xie et al., 2025; Zhang & Yang, 2024). Moreover, little is known about the relative contribution of AI-derived ESG attributes such as sentiment tone, linguistic complexity, and disclosure clarity, compared to traditional ESG scores.

This study addresses this gap based on the shortcomings on the existing ESG valuation research often depends on traditional linear models that fail to reflect the complex, non-linear dynamics of ESG performance, especially in the diverse contexts of emerging markets. This study employs a multimodal analytical approach that combines panel data econometrics and advanced machine learning algorithms to evaluate whether AI-powered ESG reporting provides a measurable valuation premium.

The empirical setting comprises five African emerging markets that span across manufacturing, energy, telecommunications, consumer goods, and industrial sectors. These markets were selected due to their diverse regulatory frameworks, irregular levels of digital adoption, and comparatively limited but increasingly available ESG reporting data. However, firms in these economies face mounting pressure to attract global capital while operating in environments where governance standards and sustainability practices are still evolving (OECD, 2022). Therefore, this mix of factors positions the region as a suitable setting for evaluating the impact of AI-enabled ESG reporting on firm valuation within contexts of institutional diversity and technological gaps.

This study integrates Stakeholder Theory (Freeman, 1984), Signalling Theory (Spence, 2002), and the Resource-Based View (Barney, 1991) as foundational frameworks. The findings have direct implications for investors seeking more accurate valuation models, policymakers aiming to strengthen ESG reporting standards, and corporate leaders navigating the strategic adoption of AI in sustainability communication. AI-enhanced ESG reporting reflects Stakeholder Theory by enabling firms to respond more transparently to diverse stakeholder expectations. It aligns with Signalling Theory through the disclosure of high-quality ESG information that communicates credibility and reduces information asymmetry in the market.

Finally, the Resource-Based View is advanced by demonstrating how AI-driven ESG capabilities can serve as strategic, hard-to-imitate resources that enhance competitive advantage. The findings, have direct implications for investors seeking more accurate valuation models, policymakers aiming to strengthen ESG reporting standards, and corporate leaders navigating the strategic adoption of AI in sustainability communication. The structure of the paper is as follows: Section 2 reviews the existing empirical literature, Section 3 outlines the data sources and methodology approach, Section 4 presents the main findings, Section 5 offers an in-depth discussion, and Section 6 concludes with key implications for policy.

2. Literature Review

The intersection of ESG practices with firm valuation has gained increasing attention in emerging markets, where institutional voids, weak regulatory enforcement and high information asymmetry present unique challenges. Empirical studies have consistently found that firms with stronger ESG performance tend to achieve higher market valuation, largely due to improved stakeholder trust and reduced capital constraints (Friede et al., 2015; El Ghoul et al., 2011).

In the context of African and Southeast Asian markets, ESG-compliant firms have demonstrated significantly higher Tobin's Q and lower cost of equity (Wong et al., 2021) signalling a tangible link between sustainability transparency and firm value. Evidence from South Africa shows that integrated ESG improve investor confidence and is connected with higher market valuation, particularly in non-financial sectors (Ntim & Soobaroyen, 2013; Gyapong et al., 2016). Studies in Southeast Asia indicate that ESG disclosure strengthens firm reputation and reduces financing expenditures, but the effects often vary by industry and governance structures (Haniffa & Cooke, 2005).

The integration of AI into ESG reporting adds another dimension to this relationship. AI algorithms such as Natural Language Processing (NLP), Machine Learning (ML), and Automated ESG scoring enhance data accuracy, standardisation, and timeliness. According to Chen and Guestrin (2016), gradient boosting and other ensemble methods have proven effective in improving prediction accuracy across complex financial datasets. Empirical evidence from Chinese listed firms shows that companies integrating AI into ESG disclosures not only achieve higher ESG ratings but also experience stronger institutional investment inflows and valuation premiums (Wang et al., 2025). Complementary studies in Africa indicated that AI-driven analytics can help overcome data gaps and reporting inconsistencies, particularly in markets where ESG information and regulatory frameworks are disjointed (Zhou et al., 2025; Aruwaji & Swanepoel, 2025). However, systematic, multi-country and regulatory analysis in emerging markets remains limited, positioning this study to address that gap.

Despite this advancement, the literature examining AI-enhanced ESG reporting in emerging markets remains limited. Prior studies are often confined to single-country analyses or lack comparative models incorporating qualitative textual data (Ioannou & Serafeim, 2015). This gap is pronounced in low- and middle-income economies, where the quality and credibility of ESG disclosures can vary significantly across sectors and governance regimes. AI algorithms hold the potential to bridge such disparities by introducing structure and standardisation to fragmented ESG narratives (Shwartz-Ziv & Armon, 2022). Moreover, there is a growing recognition that AI integration serves not only as a reporting tool but also as a strategic asset under the resource-based view (Barney, 1991). Firms that deploy AI for sustainability analytics can leverage this capability for competitive differentiation, improving both reputational capital and market performance. Thus, the convergence of AI and ESG reporting in emerging markets presents a critical frontier for empirical exploration to accurately assess firm value implications.

2.1. Theoretical Review

This study draws upon three complementary perspectives such as Stakeholder Theory, Signalling Theory, and the Resource-Based View (RBV) to explain how Artificial Intelligence (AI)-integrated ESG reporting can influence firm valuation in emerging markets. Stakeholder Theory posits that transparent and credible ESG reporting aligns corporate behaviour with stakeholder expectations, enhancing legitimacy, trust, and long-term value creation (Freeman, 1984; Eccles et al., 2014). In emerging markets, where institutional frameworks may be underdeveloped, AI integration can strengthen this alignment by improving the timeliness, accuracy, and standardisation of ESG disclosures (Floridi & Cowls, 2019). For instance, AI-enabled sentiment analysis and controversy monitoring can proactively address stakeholder concerns, reduce reputational risk and increase investor confidence (Wamba et al., 2021). Thus, within the stakeholder perspectives, AI acts as a mechanism that deepens engagement quality and demonstrates responsiveness to both financial and non-financial stakeholder priorities.

Signalling Theory explains how firms convey unobservable attributes such as governance quality, managerial competence, and strategic foresight through observable actions (Spence, 2002). AI-powered ESG reporting can serve as a high-credibility signal, reducing uncertainty for investors and analysts (Lim, 2024). Advanced technologies such as NLP and ML enhance disclosure consistency, detect anomalies, and reduce the likelihood of greenwashing, thereby increasing the trustworthiness of ESG signals (Xie et al., 2025). The market may interpret AI adoption in ESG reporting not only as a commitment to transparency but also as an indicator of innovation readiness and adaptability, both of which can command a valuation premium (Zhang & Yang, 2024).

The Resource-Based View (RBV) frames AI-enhanced ESG reporting capabilities as strategic intangible resources that are valuable, rare, inimitable, and non-substitutable (Barney, 1991). AI integration in ESG analytics allows firms to extract insights from unstructured sustainability data, automate disclosure processes, and identify environmental or social risks more effectively than competitors (Wamba et al., 2021). These capabilities can be embedded into organisational routines, creating sustained competitive advantage that influences both operational performance and market valuation. From an RBV perspective, AI is not merely a disclosure tool but a capability that can be leveraged for strategic differentiation in markets where competitors lack similar technological sophistication (Xie et al., 2025). However, combining these three theoretical perspectives, AI-integrated ESG reporting can be understood as a composite mechanism in which stakeholder alignment enhances organizational legitimacy, credible disclosures reduce informational asymmetries in capital markets, and AI-driven ESG capabilities operate as rare, inimitable resources; these dynamics converge to reinforce investor confidence and support sustained valuation advantages.

2.2. Hypotheses Development

This study grounds its hypotheses in three complementary theoretical perspectives, including Stakeholder Theory, Signalling Theory and Resource-Based View. These theories offer a foundational understanding of how artificial intelligence (AI) integrates into ESG reporting and might influence firm valuation, particularly in emerging markets. First, stakeholder theory emphasises the importance of transparent communication between firms and their stakeholders (Fatemi et al., 2018). However, when organisations disclose ESG performance clearly and reliably, they address the informational needs of investors, regulators, and civil society, which can enhance reputation and legitimacy (Cheng et al., 2014; Eccles et al., 2014). In this study, incorporating AI into ESG reporting processes improves the precision, frequency and credibility of sustainability disclosures. This is valuable in emerging markets where institutional systems lack robustness (Khanna & Palepu, 2010; Ntim et al., 2015). Research has shown that firms with more advanced ESG transparency tend to attract investor confidence and may experience stronger valuation metrics (Fatemi et al., 2018; Yu & Luu, 2021). Based on the reviewed literature, this study posits the first hypothesis as follows.

H1. *Firms that adopt AI-integrated ESG reporting will exhibit a positive and significant effect on firm valuation.*

Second, signalling theory purview that, firms that voluntarily adopt advanced technologies such as AI in their ESG disclosures send credible signals to the market about their commitment to accountability and innovation (Grewal et al., 2020). These signals can reduce perceived risks and information asymmetry, especially in environments where traditional reporting mechanisms are weak (Koelbel & Rigobon, 2022). The presence of AI in sustainability reporting may act as a proxy for managerial quality and strategic

foresight (Spence, 2002; Eccles et al., 2014), leading to improved market perceptions and firm valuation.

The resource-based view extends this logic by viewing AI-powered ESG reporting capabilities as strategic intangible assets. Thus, such capabilities, especially when rare, valuable and difficult to replicate, can yield sustainable competitive advantage (Delery & Roumpi, 2017; Côrte-Real et al., 2020; Dubey et al., 2021). Firms that leverage AI for ESG-related data analysis, sentiment monitoring and risk detection gain efficiencies and insights that others may not possess. This can enhance both operational performance and stakeholder engagement. Moreover, AI-enhanced ESG features, such as NLP-derived sentiment, ESG controversy monitoring and textual complexity, can also strengthen the predictive accuracy of valuation models by capturing significance. Based on the reviewed literature, this study proposes the second hypothesis as follows.

H2. *AI-derived ESG features significantly improve the accuracy of firm valuation predictions.*

2.3. Research Gap

While prior studies have established links between ESG reporting and corporate valuation, they largely concentrate on conventional ESG performance scores and disclosure indices. These approaches often overlook the potential of artificial intelligence (AI) to enhance the depth, consistency, and clarity of sustainability communication. In particular, little is known about how AI-enabled tools such as textual analytics, sentiment analysis, and readability measures can be integrated into valuation models. Furthermore, the application of AI-enhanced ESG metrics within machine learning frameworks to forecast firm value remains underexplored. This gap focuses on emerging markets, where regulatory standards and transparency mechanisms are evolving. By incorporating AI-powered ESG attributes into both econometric and predictive modelling approaches, this study addresses these limitations on how technology-driven reporting practices shape market perceptions and valuation accuracy.

3. Data and Methods

3.1. Sample Selection

This study employed longitudinal analysis and integrated econometrics approaches with AI-driven analytics to examine the impact of artificial intelligence in ESG disclosure. Table 1 shows the distributions of firms by country and selected industries. The sample comprises of selected non-financial sectors from five African countries, including South Africa (SA), Nigeria (NG), Egypt (EG), Kenya (KE) and Morocco (MA), particularly, SA and NG countries were prioritized due to their relatively advanced financial systems and established ESG disclosure frameworks (World Bank, 2022; KPMG, 2021). Other countries, such as Egypt, Kenya and Morocco, were included to ensure institutional and regional diversity, thereby enhancing the external validity of findings across different regulatory and economic contexts (OECD, 2023). Financial sectors such as banks and insurers were not considered due to their distinctive capital structures and advanced specific disclosure regulations.

However, manufacturing sectors such as energy, telecommunications, consumer goods and industrials were selected due to their significant ESG exposure and growing reliance on technological innovation in disclosure reporting. Previous literature has identified these sectoral vulnerabilities to environmental and social scrutiny, which increases the demand for transparency in ESG communication (Eccles et al., 2014; Fatemi et al., 2018). Furthermore, companies were considered if they typically satisfied these two conditions: (i) consisting of reporting of ESG and financial performance data for at least three consecutive years, and

(ii) disclosed information at a level that allowed classification of their reporting practices. Finally, the study sample consists of 120 listed companies, which eventually generates 1200 firm-year observations. This sample size is adequate for both econometric estimation and supervised machine learning (Simionescu, 2025). Table 1 presents the distribution by country and industry.

Table 1. Distribution of Firms by Country and Industry.

Country	Manufacturing	Energy	Telecommunications	Consumer Goods	Industrials	Total Firms
South Africa	12	10	8	8	7	45
Nigeria	8	6	6	6	4	30
Egypt	5	3	4	4	4	20
Kenya	3	3	1	5	3	15
Morocco	2	3	1	2	2	10
Total	30	25	20	25	20	120

3.1.1. AI Integration Classification

Table 2 shows the AI-Integration classification. The classification is categorised into three dimensions, as shown in Table 2.

Table 2. AI-Integration Classification.

Step	Procedure	Description	Output
1	Keyword Extraction	Automated identification of AI-related terms ("machine learning," "NLP," "automated ESG scoring," "AI-driven analytics") from sustainability and annual reports.	Initial pool of AI-related text passages.
2	Contextual Filtering	Rule-based co-occurrence checks requiring AI terms to appear alongside ESG-related concepts ("sustainability," "disclosure," "reporting").	Reduced dataset containing only ESG-relevant AI references.
3	Coding Framework	Application of structured coding scheme to classify firms as AI-integrated (1) or non-AI-integrated (0) based on explicit evidence in ESG disclosures.	Preliminary binary classification variable.
4	Reliability Testing	Subsample independently coded by multiple researchers; intercoder reliability evaluated using Cohen's Kappa and Krippendorff's Alpha.	Validated and consistent coding results.
5	Final Integration	Consolidation of validated coding decisions into the panel dataset for econometric analysis.	Final AI-integration dummy variable used in regression models.

AI-Integration Disclosures

AI integration is identified from the annual and sustainability reports of the firms. The process was derived from systematic text review analysis using automated text-mining techniques with systematic qualitative coding. The study employed keyword-based search phrases such as "machine learning," "natural language processing," "automated ESG scoring," and "AI-driven analytics." However, to reduce the risk of false positives of mentions of AI in contexts unrelated to ESG, a contextual filtering rule was applied, ensuring that AI-related terms were only retained when they appeared alongside sustainability-related concepts such as "ESG," "sustainability," "reporting," "disclosure," or governance.

AI-Integration NLP Scoring

In this study, NLP scoring was implemented by combining automated keyword detection, rule-based contextual checks, and frequency validation, which collectively converted unstructured corporate texts into a standardised indicator of AI-related engagement in ESG reporting. Python 3.13.3 libraries, including Natural Language Toolkit (NLTK), spaCy, and regular expressions (regex), were employed for preprocessing, keyword identification and contextual filtering. Annual reports were transferred into NVivo for structured content analysis.

AI-Integration Manual Coding

After automated text mining and contextual filtering, a manual coding process was applied to verify and classify AI integration. The filtered disclosures were imported into NVivo for structured qualitative analysis. Researchers examined the extracted passages to determine whether mentions of AI technologies (e.g., machine learning, NLP, automated ESG scoring) were explicitly connected to ESG reporting practices. Each firm was then assigned a binary code:1 (AI-integrated): when disclosures contained clear, verifiable evidence of AI use in ESG reporting. 0 (Non-AI-integrated): when no such evidence was found. To ensure reliability, a subsample was double-coded, and consistency was assessed using Cohen's Kappa and Krippendorff's Alpha; coefficients above 0.75 were treated as satisfactory benchmarks of agreement (Landis & Koch, 1977). This procedure minimised subjectivity and enhanced the credibility of the classification.

Table 3 shows the distribution of AI-Integrated firms by country and industry. However, out of the 120 firms being selected 48 firms were classified as AI-integrated. Table A1 shows the scalable parameters for AI-Integation.

Table 3. Distribution of AI-Integrated Firms by Country and Industry.

Country	Manufacturing	Energy	Telecommunications	Consumer Goods	Industrials	Total AI Firms
South Africa	6	5	5	3	3	22
Nigeria	3	2	3	2	1	11
Egypt	2	1	2	1	1	7
Kenya	1	1	0	2	1	5
Morocco	1	1	0	1	0	3
Total	13	10	10	9	6	48

3.2. Variable Specifications

Table 4 presents the variable definitions and measurements by the study. Tobin's Q and the Market-to-Sales (M/S) ratio are dependent variables to measure the valuation effect of ESG disclosure. The independent variables are divided into two main categories: Traditional ESG metrics and AI-Integrated ESG disclosure indicators. Traditional ESG scores, including both aggregate and component scores (environmental, social, governance), are presented as percentile rankings. AI-Integrated ESG disclosure incorporates binary computation, including text analytics such as sentiment polarity via Latent Dirichlet Allocation (LDA), linguistic complexity and readability scores of ESG disclosures. The framework includes control and macroeconomic variables, which include total assets (logged), return on assets (ROA), percentage of institutional ownership, GDP growth rate, and inflation.

Table 4. Variable Definitions and Measurements.

Variable	Type	Definition/Measurement	Scale/Unit	Data Source(s)
Dependent Variables				
Tobin's Q	Dependent	(Market Value of Equity + Book Value of Debt) ÷ Book Value of Total Assets	Continuous (ratio)	Bloomberg; Refinitiv; Capital IQ
Market-to-Sales Multiple	Dependent	Enterprise Value ÷ Annual Sales Revenue	Continuous (ratio)	Bloomberg; Refinitiv; Capital IQ
Traditional ESG Metrics				
ESG Score (aggregate)	Independent	Overall ESG percentile score (0–100)	0–100 percentile rank	Refinitiv ESG; MSCI ESG Ratings
Environmental Score (E)	Independent	ESG sub-score for environmental policies	0–100 percentile rank	Refinitiv ESG; MSCI ESG Ratings
Social Score (S)	Independent	ESG sub-score for social performance	0–100 percentile rank	Refinitiv ESG; MSCI ESG Ratings
Governance Score (G)	Independent	ESG sub-score for governance quality	0–100 percentile rank	Refinitiv ESG; MSCI ESG Ratings
ESG Controversy Indicator	Independent	100 − Controversy Score (higher = more controversies)	0–100 scale	Refinitiv ESG
AI-Related Metrics				
AI-Integrated ESG Reporting	Independent	Dummy = 1 if firm explicitly reports AI use in ESG disclosure	Binary (0/1)	Constructed from manual/document review
Sentiment Score	AI-derived	NLP-based measure of positive/negative tone	Continuous	Custom NLP analysis
Sustainability Topics	AI-derived	Topic proportions derived via LDA	Continuous (0–1)	Custom NLP analysis
Linguistic Complexity Index	AI-derived	Sentence length and vocabulary diversity measures	Continuous index	Custom NLP analysis
Readability Metrics	AI-derived	Indices such as FOG/Gunning Fog	Continuous index	Custom NLP analysis
Control Variables				
Firm Size	Control	Logarithm of total assets	Continuous (log USD)	Bloomberg; Refinitiv; Capital IQ
Profitability (ROA)	Control	Net income ÷ total assets	Continuous (ratio)	Bloomberg; Refinitiv; Capital IQ
Institutional Ownership	Control	% of shares held by institutional investors	Continuous (%)	Bloomberg; Refinitiv; Capital IQ
GDP Growth	Control	Annual real GDP growth rate	Continuous (%)	World Bank; IMF
Inflation	Control	Annual % change in consumer price index	Continuous (%)	World Bank; IMF
Currency Adjustment	Data handling	Conversion of financial figures to USD using annual average exchange rates	USD	World Bank

3.3. Natural Language Processing (NLP) Feature Extraction Framework

Figure 1 depicts the process of applying Latent Dirichlet Allocation (LDA) to a set of documents (corporate ESG reports, ESG filings and corporate press releases). The method identifies uncovered topics by grouping frequently co-occurring words, producing a collection of topics where each topic is a probability distribution over words, and each document is a probability distribution over topics. This approach enables the systematic detection of disclosure patterns, thematic priorities, and shifts in narrative focus within large volumes of unstructured ESG text (Blei et al., 2003; Higgins et al., 2020).

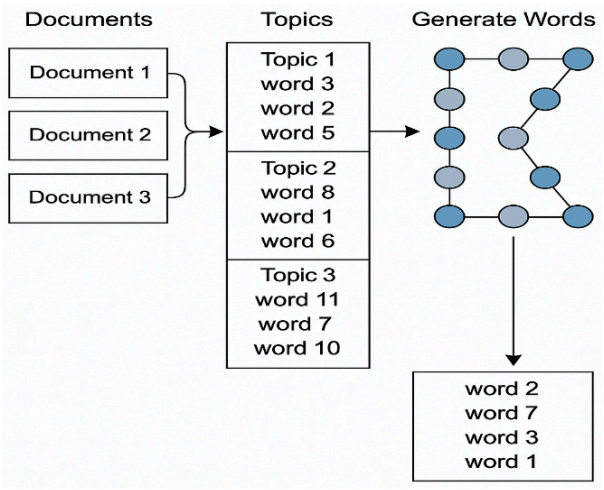

Figure 1. LDA Based Workflow for Topics Modelling.

3.3.1. Topic Taxonomy

Table 5 shows the topic taxonomy, which was constructed using an LDA architecture to extract an ESG-focused textual corpus. Narratively, Topic 0 was linked to the Environmental pillar and titled ESG-Linked Performance and Compliance, as it contained terms related to performance indicators tied to ESG objectives, executive pay structures, supply chain oversight, fair labour enforcement, and audit mechanisms. Topic 1 corresponded to the social pillar; subthemes such as Community Engagement and Workforce Development due to its focus on CSR initiatives, local community programs, educational and healthcare contributions, and workforce training or upskilling. Topic 2, categorised as the Governance pillar, which was sub-labelled as Governance, Transparency and Data Security, reflects strong associations with board independence, corporate transparency, environmental monitoring tools, compliance protocols, privacy safeguards, and information security practices. This taxonomy procedure offers a systematic means of organising ESG-related themes, translating unstructured text into interpretable categories, and bridging qualitative disclosure content with measurable ESG performance indicators (Blei et al., 2003). Dynamic Topic Modelling (DTM-lite) applied to corporate disclosures. Dynamic Topic Modelling (DTM-lite) was used to analyse the descriptive statistics of topic evaluation over the year, as displayed in Table A2 in the Appendix A.

Table 5. Topic Modelling Extraction.

ESG Pillar	Topic ID	Topic Name	Illustrative Keywords
Environment	0	ESG Linked Performance and Compliance	ESG-linked KPIs, executive compensation, supply chain, fair labor, audits
Social	1	Community Engagement and Workforce Development	CSR programs, community engagement, education and healthcare, workforce skills
Governance	2	Governance, Transparency and Data Security	Board independence, transparency, monitoring tools, privacy, data security

3.3.2. Textual Indexes

Table 6 reports computational textual indexes derived from ESG-related disclosures, including sentiment scores, linguistic complexity, and readability metrics. Sentiment was measured using the VADER (Valence Aware Dictionary and sEntiment Reasoner) model, which calculates polarity scores on a scale from 1 (strongly negative) to +1 (strongly positive). Each score was weighted by topic proportions identified through Latent Dirichlet Allocation (LDA). Hence, LDA is a generative probabilistic model used to uncover hidden thematic structures (topics) in a collection of documents. It assumes that: Each document is represented as a set of topics. Each topic is distributed over words (Blei et al., 2003)

$$P(w_{d,n}\lceil\alpha,\beta) = \sum_{Z-1}^{K} P(w_{d,n}\lceil z,\beta)\, P(z\lceil d,\alpha) \quad (1)$$

Table 6. Descriptive Statistics of Textual Indexes.

Country	Sentiment Score	Linguistic Complexity Index	Readability Metric
Egypt	−0.14073	0.469098	13.22963
Kenya	−0.00535	0.484692	13.52701
Morocco	0.050897	0.483445	12.98981
Nigeria	−0.18912	0.364712	10.90439
South Africa	−0.03071	0.580439	13.57511

In the LDA framework, $w_{d,n}$ denotes the n-th word in document d, while z represents the latent topic variable. The term $P(z\lceil d,\alpha) = \theta_d$ expresses the probability of topic z occurring in document d. $P(w_{d,n}\lceil\alpha,\beta) = \varnothing_z$ captures the probability of word www being generated given topic z. Linguistic complexity was assessed through the Index, capturing sentence variation and vocabulary richness as indicators of disclosure sophistication. Readability was evaluated using the Gunning Fog Index (GFI), which estimates the years of formal education required for comprehension; higher scores denote less accessible disclosures. GFI is computed as:

$$FOG = 0.4 \times \left(\frac{Total\ Words}{Total\ Sentences} + 100 \times \frac{Complex\ Words}{Total\ Words} \right) \quad (2)$$

This integrated approach combines sentiment polarity, thematic weighting, complexity, and readability to provide a more nuanced measure of ESG disclosure quality (Li, 2008; Loughran & McDonald, 2011). The ESG Controversy Score measures the extent and intensity of adverse incidents linked to a company's environmental, social, and governance conduct. Because larger controversy values denote heightened reputational and regulatory risks, the metric is transformed using a 100 − score, allowing higher adjusted values to represent stronger ESG performance. Mathematically, Adjusted ESG Controversy Score = 100 − Raw Controversy Score.

3.4. Predictive Analytics Framework

Figure 2 presents the structured multi-phase predictive analytics framework used to examine the effect of AI-integrated ESG reporting on firm valuation. The framework was classified into three phases: (1) Data collection and processing, (2) Feature Engineering and selection, and (3) Model evaluation and Interpretation. In the first phase, data were processed and verified. The second phase involved data featuring, the generation of a sample size. This model was trained using a five-fold cross-validation strategy to reduce overfitting and ensure robustness across different data splits; also, a grid search approach was applied to fine-tune key hyperparameters. The third phase focuses on model performance using the Coefficient of Determination (R^2) to explain explanatory power. Root Mean Square Error (RMSE) was used to capture prediction variance, and Mean Absolute Error (MAE) to assess overall forecast accuracy. SHAP (Shapley Additive Explanations) was employed to interpret the contribution scores of each input variable for individual predictions.

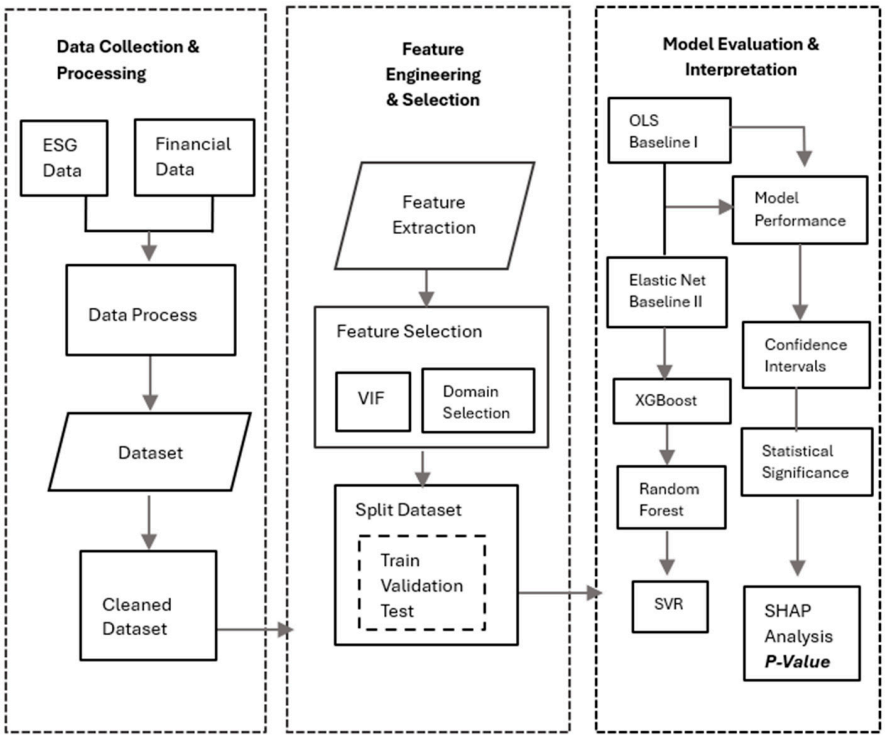

Figure 2. Methodological framework.

3.5. Econometric Model Specifications

Model 1 (H1): The specification model is expressed as follows:

$$Valuation_{it} = \alpha + \beta_1 AIIntegration_{it} + \beta_2 ESG_{it} + \beta_3 X_{it} + \beta_4 Z_{ct} + \mu_i + \gamma_t + \epsilon_{it} \quad (3)$$

$$Valuation_{it} = \alpha + \beta_1 AIIntegration_{it} + \beta_2 AIDisclosure_{it} + \beta_3 ESG_{it} + \beta_4 X_{it} + \beta_5 Z_{ct} + \mu_i + \gamma_t + \epsilon_{it} \quad (4)$$

$$Valuation_{it} = \alpha + \beta_1 AIIntegration_{it} + \beta_2 ESG_{it} + \beta_3 \begin{pmatrix} AIIntegration_{it} \\ \times ESG_{it} \end{pmatrix} + \beta_4 X_{it} + \beta_5 Z_{ct} + \mu_i + \gamma_t + \epsilon_{it} \quad (5)$$

where Equation (3) is the baseline model which shows the impact of AI-integration in ESG disclosure on firm valuation, including $Valuation_{it}$ (firm valuation for firm i in year t, proxied by Tobin's Q and Market-to-Sales (M/S) multiple). $AIIntegration_{it}$ (binary indicator equal to 1 if firm i discloses use of AI in ESG reporting in year t). ESG_{it} (ESG-related metrics, including aggregate ESG score, pillar scores (ESG), and controversy indicators). X_{it} (firm-level controls included log of total assets, return on assets, institutional ownership). Z_{ct} (macroeconomic controls at the country level, such as GDP growth, inflation).

Equation (4) extended the first model with AI-derived textual indicators to examine the incremental explanatory power of AI-driven ESG disclosure characteristics. $AIDisclosure_{it}$ includes sentiment score (either positive or negative tone of ESG reports). Sustainability Topics (topic proportions identified via Latent Dirichlet Allocation). Linguistic complexity Index (clarity of disclosure). This specification enables testing of the textual qualities of ESG communication captured by AI techniques, which influence firm valuation above the binary adoption of AI tools. Equation (5) is the interactive effects model, where β_3 captures whether firms with AI-enhanced ESG reporting obtain stronger valuation benefits from ESG scores compared to firms without AI adoption.

Model 2 (H2): *Machine Learning (ML)-Based Forecasting Framework:* The study estimates two complementary learners:

(A) Elastic Net (linear, sparse and stable)

$$\min_{\beta,\alpha 0} \frac{1}{N} \sum_{(i,t)\in \mathrm{T}} \left(\mathcal{Y}_{i,t+1} - \alpha_0 - X_{i,t}^{T} \beta \right)^2 + \lambda \left[(1-\rho)\ \frac{||\beta||_2^2}{2} + \rho ||\beta||_1 \right], \tag{6}$$

(B) XGBoost (nonlinear, interactions)

$$\mathcal{L} = \sum_{(i,t)\in\ \mathrm{T}} \left(y_{i,t+1} - \hat{y}_{i,t+1} \right)^2 + \sum_{m-1}^{M} \Omega(m),\ \Omega() = \gamma T + \frac{1}{2}\ \lambda\ ||\omega||_2^2, \tag{7}$$

Note: $\hat{y}$ is the additive ensemble of trees $\{f_m\}$.

Hence, Equations (6) and (7), estimates the feature sets of ML evaluation models, including: $\mathcal{Y}_{i,t} \in \{Tobin's\ Q,\ M/S\}$ which donate firm i's valuation in year t. We forecast one year ahead: $\mathcal{Y}_{i,t+1} = \mathrm{M}(\mathrm{X}_{i,t})$. Where $\mathrm{X}_{i,t}$ contains predictors observed at t, (Robustness: $h \in \{0,1,2\}$ years ahead)**.** Baseline feature $\left(\mathrm{X}_{i,t}^{BASE}\right)$: firm size (log assets), ROA, Institutional ownership, traditional ESG (aggregate and E/S/G Pillars) controversy indicator, macro controls (GDP growth, inflation), and dummies for country X, industry and year. Augmented features $\left(\mathrm{X}_{i,t}^{AUG}\right)$: $\mathrm{X}_{i,t}^{BASE}$ plus AI-related ESG inputs: AI-Integrated (0/1), Sentiment (standardised), Readability and Complexity indices (Fog and lexical diversity) and Topic proportions from LDA $(k\ topics,\ \sum_k \theta_{i,t,k} = 1)$. Thus, all covariates are lagged to prevent look-ahead bias; text features are built from reports released in or before year t.

Model Comparison Evolution

In this study, three machine learning models were used to evaluate predictive performance using error and fit metrics. The model includes:

i. Coefficient of determination (Out-of-Sample):

$$R_{OOS}^2 = 1 - \frac{\sum (y - \hat{y})^2}{\sum (y - \overline{y}train)^2} \tag{8}$$

ii. Root Mean Squared Error:

$$RMSE = \sqrt{\sum (y - \hat{y})^2} \tag{9}$$

iii. Mean Absolute Error:

$$MAE = \frac{1}{n} \sum |y - \hat{y}| \tag{10}$$

where Equations (8)–(10) estimate the functions and models comparison evaluation of the inclusion of *AI*-related *ESG* metrics, such as sentiment analysis, narrative readability

and AI adoption indicators effectiveness on the firm valuation. Hence, R^2_{OOS} measures the proportion of variation in the firm valuation explained by the predictors; a higher value indicates stronger explanatory power and predictive reliability. RMSE measures the deviations and penalises extreme forecast errors. *MAE* estimates the average magnitude of forecast errors; it calculates accuracy that is robust in noisy or skewed distributions (Chicco et al., 2021; Hyndman & Koehler, 2006). Model comparison report including: ΔR^2_{OOS}, ΔRMSE, ΔMAE of AUS vs. BASE for each learner. Diebold-Mariano tests on rolling errors were employed to assess the significance of forecast improvements. This study is consistent with the applications of predictive modelling (Adeoye et al., 2024; Zhang & Yang, 2024).

4. Empirical Results

4.1. Descriptive Analysis

Table 7 shows that firms across five African nations, including South Africa, Nigeria, Egypt, Kenya, and Morocco, reveal distinct differences in corporate valuation, ESG reporting standards and the use of AI tools. South African firms exhibit the strongest valuation metrics, with the highest average Tobin's Q (1.32) and Market-to-Sales ratio (2.85), suggesting greater investor trust and resource efficiency. These companies also lead in ESG performance, consistently scoring highest across environmental, social and governance metrics likely due to more mature regulatory systems and active stakeholder engagement. However, they also face more ESG-related controversies, which could stem from their greater public exposure and detailed reporting. South Africa demonstrates the most advanced integration of AI in ESG disclosures, including technologies such as machine learning or natural language processing. Kenya and Morocco remain relatively limited. Textual analysis of ESG reports reveals that South African firms communicate with greater clarity, sentiment strength and thematic variety. These patterns correlate with stronger fundamentals such as firm size, profitability and institutional ownership, as well as favourable economic conditions; moderate inflation and GDP stability. Thus, firms in Morocco and Kenya show less maturity in ESG practices, AI usage and valuation performance.

Table 7. Country-Level Descriptive Statistics.

Country	**Nigeria (n = 30)**	**South Africa (n = 45)**	**Egypt (n = 20)**	**Kenya (n = 15)**	**Morocco (n = 10)**
Variable	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
Tobin's Q	1.12 (0.40)	1.32 (0.50)	1.21 (0.42)	1.18 (0.39)	1.15 (0.35)
M/S Multiple	2.50 (0.90)	2.85 (1.15)	2.60 (1.05)	2.70 (1.00)	2.45 (0.85)
ESG Overall Score	48.3 (16.8)	56.2 (17.5)	50.1 (18.2)	49.4 (16.1)	45.8 (15.7)
Environmental Score (E)	42.1 (18.2)	48.7 (19.4)	43.2 (17.9)	40.8 (18.7)	39.5 (16.3)
Social Score (S)	47.9 (17.6)	54.1 (16.3)	48.5 (18.5)	46.7 (17.1)	44.2 (15.2)
Governance Score (G)	58.2 (14.7)	62.9 (13.9)	59.3 (15.0)	57.4 (14.2)	55.8 (13.8)
ESG Controversy Indicator	21.5 (18.0)	25.3 (17.5)	22.1 (17.8)	20.7 (16.9)	19.9 (15.5)
AI-Integrated ESG Reporting %	20.0	35.5	25.0	18.0	15.0
Sentiment Score	0.09 (0.27)	0.18 (0.32)	0.12 (0.30)	0.10 (0.26)	0.07 (0.22)
Sustainability Topics (LDA)	0.23 (0.09)	0.30 (0.11)	0.25 (0.10)	0.22 (0.08)	0.20 (0.07)
Linguistic Complexity Index	17.3 (3.5)	19.4 (3.8)	18.1 (3.4)	16.9 (3.2)	16.5 (3.1)
Readability Metrics	15.1 (2.8)	14.2 (3.0)	14.8 (2.9)	15.5 (2.7)	15.9 (2.5)
Firm Size (log assets)	14.2 (0.9)	14.9 (1.1)	14.4 (1.0)	14.3 (0.8)	14.1 (0.7)
Profitability (ROA, %)	5.9 (3.8)	6.5 (4.2)	6.1 (3.9)	5.8 (3.5)	5.4 (3.2)
Institutional Ownership (%)	35.2 (20.5)	42.6 (21.3)	36.1 (19.8)	34.5 (18.7)	32.4 (17.2)
GDP Growth (%)	3.1 (1.2)	3.4 (1.4)	3.0 (1.3)	2.8 (1.1)	2.6 (1.0)
Inflation Rate (%)	7.2 (2.1)	6.3 (2.5)	6.8 (2.3)	7.5 (2.0)	7.9 (1.9)

Note: n represents the number of firms included in the sample for this study.

Table 8 provides an overview of the central tendency and variability across firms in the sample. The average Tobin's Q of 1.22 indicates that firms have market values that exceed their book values. This result suggests positive investor sentiment and growth potential. The Market-to-Sales has a mean of 2.62 which reflects that firms' ability to generate substantial market value relative to their sales. The average ESG overall score is 49.96, which is a balanced score across the Environmental (42.86), Social (48.28) and Governance (58.72) pillars. This highlights moderate ESG performance with governance being the strongest component.

Table 8. Descriptive Statistics.

Variable	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
Tobin's Q	1.22	1.09	1.3	0.95	0.11	0.62	0
Market-to-Sales Multiple	2.62	2.65	3.2	2.1	0.34	0	−0.61
ESG Composite Score	49.96	50	70	30	10	−0.04	−0.35
Environmental	42.86	43	65	25	8.5	0.1	−0.5
Social	48.28	48	70	30	9.2	0.05	−0.4
Governance	58.72	59	75	40	7.5	−0.15	−0.45
AI Integration	0.6	1	1	0	0.52	−0.48	−2.28
Sentiment Analysis	0.11	0.1	0.5	−0.2	0.15	0.2	−0.3
Linguistic Complexity Index	17.64	17.6	20	15	1.2	0.15	−0.25
Readability Score	15.1	15	18	12	1	0.05	−0.2
Firm Size (Log Assets)	14.62	14.6	15.1	14.2	0.29	0.3	−0.65
Return on Assets (%)	6.28	6.25	7	5.5	0.48	−0.06	−0.84
Institutional Ownership (%)	38.5	38.5	45	30	4.35	−0.44	0.38

The ESG Controversy Indicator has a mean of 21.9, showing that ESG risks are not negligible across the sample. AI integration into ESG reporting is still emerging, with an average adoption rate of 22.7%, suggesting that fewer than one in four firms currently use AI-based ESG disclosures. Sentiment analysis of ESG narratives reveals a modest average score (0.11), indicating a generally neutral tone, while the sustainability topic (via LDA) averages at 0.24. Textual analytics show moderate complexity and readability levels, with a mean linguistic complexity index of 17.64 and a readability score of 15.1. Firm size (log assets)) centres around 14.38, with profitability (ROA) at 5.94%, and institutional ownership averaging 36.16%. The macroeconomic environment is relatively stable, with GDP growth averaging 2.98% and inflation around 6.58%.

4.2. Correlation Analysis

Table 9 presents the outcomes of both correlation and multicollinearity assessments for the study's independent variables. Variance Inflation Factor (VIF) results highlight moderate multicollinearity among key ESG dimensions, specifically Environmental (7.2), Social (6.5), Governance (5.9), and the composite ESG Score (5.3). These figures indicate substantial overlap due to the inherent interdependence of ESG sub-components. Thus, the simultaneous inclusion of all four in regression analysis could compromise model robustness. Moreso, AI-related disclosure variables including AI—Integrated ESG Reporting (1.5), Sentiment Score (2.0), and Linguistic Complexity (2.4) exhibit low VIF values, suggesting minimal collinearity and supporting their inclusion in multivariate estimation without distorting coefficient precision.

Table 9. Peason Correlation analysis.

	Variable	VIF	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1)	ESG Overall Score	5.3	1.00										
(2)	Environmental Score	7.2	0.88	1.00									
(3)	Social Score	6.5	0.82	0.67	1.00								
(4)	Governance Score	5.9	0.80	0.65	0.62	1.00							
(5)	ESG Controversy Indicator	2.1	−0.50	−0.45	−0.42	−0.47	1.00						
(6)	AI-Integrated ESG Reporting	1.5	0.30	0.28	0.25	0.33	−0.28	1.00					
(7)	Sentiment Score	2.0	0.22	0.19	0.17	0.20	−0.16	0.35	1.00				
(8)	Linguistic Complexity Index	2.4	0.25	0.21	0.20	0.23	−0.18	0.40	0.45	1.00			
(9)	Firm Size (log assets)	3.1	0.45	0.40	0.30	0.42	−0.20	0.38	0.28	0.30	1.00		
(10)	Profitability (ROA)	1.7	0.20	0.15	0.18	0.23	−0.10	0.14	0.12	0.16	0.30	1.00	
(11)	Institutional Ownership	2.5	0.38	0.32	0.35	0.40	−0.25	0.26	0.24	0.29	0.50	0.32	1.00

Note: VIF < 5 → safe. VIF between 5–10 → caution. VIF > 10 → serious multicollinearity problem.

The Pearson correlation matrix further supports this view, showing strong correlations between the Overall ESG Score and its sub-elements: environmental (r = 0.88), social (r = 0.82), and governance (r = 0.80). Meanwhile, the ESG Controversy Index presents a negative association (-0.50) with all ESG metrics, this indicates that reputational risks are inversely linked to ESG quality. The AI-Integrated ESG variable correlates moderately with both sentiment (r = 0.35) and textual complexity (r = 0.40), reflecting distinction and strategic disclosure. Larger firms and those with higher institutional ownership also demonstrate stronger ESG engagement, with firm size and institutional holdings showing correlations of 0.45 and 0.50, respectively.

4.3. T-Tests Analysis

Table 10 shows the results of a *t*-test comparing firms that incorporate AI into their ESG disclosures with those that do not. The analysis reveals statistically significant differences in both firm valuation and ESG disclosure characteristics. Companies leveraging AI report a significantly higher average Tobin's Q (1.39) compared to non-AI firms (1.16), with a mean difference of 0.23 (t = 9.12, $p < 0.001$). The associated Cohen's d value of 0.60 indicates a moderate to large effect size, suggesting that markets may assign a valuation premium to firms demonstrating technological sophistication in sustainability reporting. In ESG performance, AI-integrated firms also outperform their counterparts, recording an average ESG score of 61.8 versus 49.2 for non-AI firms (t = 11.75, $p < 0.001$), with a Cohen's d of 0.77, representing a large effect.

Table 10. Univariate Analysis: *t*-Tests.

Variable	Mean AI	SD AI	N AI	Mean Non-AI	SD Non-AI	N Non-AI	T Stat	*p* Value	Mean Diff.	Cohen's d
Tobin's Q	1.39	0.42	336	1.16	0.37	864	9.12	0.001	+0.23	0.597967
ESG Overall Score	61.8	15.2	336	49.2	16.9	864	11.75	0.001	+12.6	0.766314
Sentiment Score	0.18	0.28	336	0.09	0.24	864	4.9	0.001	+0.09	0.35739
Linguistic Complexity	19.2	3.8	336	17.5	3.4	864	7.3	0.001	+1.7	0.483444

Note: 0.2–0.49: Small effect. 0.5–0.79: Medium effect. ≥ 0.8: Large effect. N represent number of observations.

Sentiment scores derived from ESG text further distinguish the groups: AI firms average 0.18, while non-AI firms score 0.09 (t = 4.90, $p < 0.001$), with a Cohen's d of 0.36, reflecting a moderate effect. This could be attributed to the use of NLP and machine learning techniques that frame content more positively or emphasize strengths. Moreover, linguistic complexity in ESG reporting is strongly higher for AI-integrated firms

(19.2 vs. 17.5; t = 7.30, $p < 0.001$), and the effect size (Cohen's d = 0.48) suggests a moderate difference, possibly due to AI-generated content or the inclusion of more technical ESG language. However, this complexity may signal professionalism and depth and it could also limit accessibility for non-specialist stakeholders.

Figure 3 show the firm valuation and AI-ESG reporting. The left chart presents a boxplot illustrating the distribution of Tobin's Q for companies that apply AI in ESG reporting versus those using conventional approaches. Firms with AI-enhanced ESG practices generally report higher median valuation scores, suggesting potential investor preference or perceived strategic advantage. The right bar chart highlights the proportion of firms adopting AI-driven ESG reporting across selected African countries, showing South Africa as the leader, with Egypt and Nigeria indicating differences in digital ESG adoption across regions.

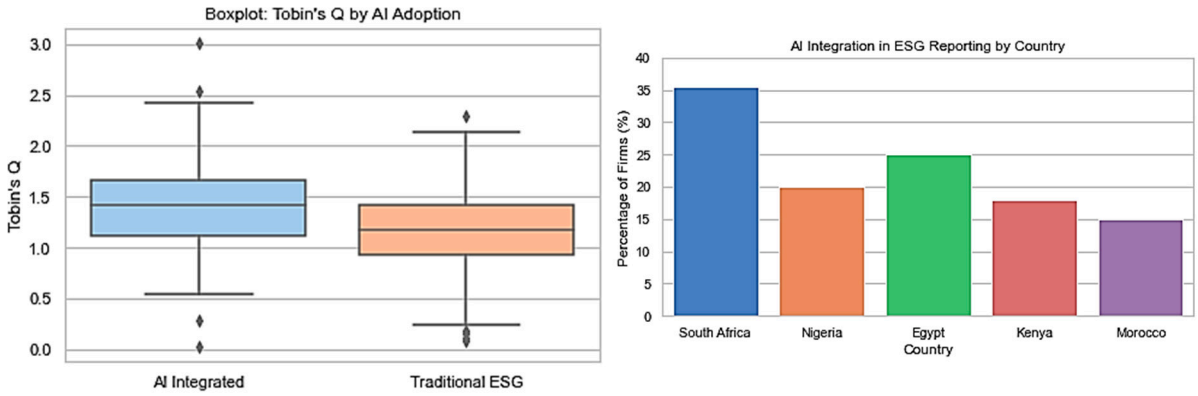

Figure 3. Firm Valuation and AI-Driven ESG Reporting by Country.

4.4. Baseline Regression Results

Table 11 shows the result of regression analysis using Panel A and Panel B to explain the four models' performance. In Panel A, which uses the logarithm of Tobin's Q as the dependent variable, Model 1 begins with only the binary variable for AI-integrated ESG reporting and year fixed effects. The coefficient on AI with $\beta = 0.102$, $p < 0.01$ indicates a strong positive relationship with firm valuation, and the model achieves an R^2 of 0.358. However, without controlling for other factors, this baseline model is limited in explanatory depth. Model 2 introduces the ESG Overall Score, firm size (log of total assets), and return on assets (ROA). These additions improve explanatory power of R^2 to 0.443 and the AI coefficient remains significant at $\beta = 0.089$. This result suggests that both ESG performance and firm-specific fundamentals contribute significantly to market valuation. In Model 3, macroeconomic controls such as GDP growth and inflation, textual variables such as sentiment, topic diversity, linguistic complexity and firm fixed effects are included.

This results in a substantial increase in R^2 to 0.579, with the AI variable still positive and significant at $\beta = 0.084$. Model 4 integrate the interaction term between AI and ESG scores. Although, the interaction is not statistically significant, maybe due to unpronounced AI adoption and immaturity in ESG reporting framework. AI coefficient at $\beta = 0.081$ and ESG score at $\beta = 0.0039$ maintain their significance. The model's descriptive power improves to R^2 of 0.602 and an adjusted R^2 of 0.479, suggesting the most robust specification in Panel A.

Table 11. Regression Analysis Results. Panel A: Dependent Variable − log(Tobin's Q).

Variable	Model 1	Model 2	Model 3	Model 4 (Full)
AI-Integrated ESG Reporting	0.102 *** (8.91)	0.089 *** (7.88)	0.084 *** (7.55)	0.081 *** (7.34)
ESG Overall Score		0.0041 *** (5.64)	0.0040 *** (5.58)	0.0039 *** (5.45)
AI × ESG Overall Score				0.0024 (1.03)
Firm Size (log assets)		0.110 *** (9.85)	0.113 *** (10.12)	0.117 *** (10.36)
ROA		0.0068 *** (4.70)	0.0072 *** (4.92)	0.0075 *** (5.10)
Institutional Ownership			0.0009 * (1.93)	0.0010 * (2.01)
GDP Growth			0.0041 * (1.94)	0.0043 * (2.05)
Inflation Rate			−0.0028 * (−1.92)	−0.0031 * (−2.08)
Sentiment Score			0.013 * (1.92)	0.014 ** (2.11)
Sustainability Topics (LDA)			0.007 * (1.95)	0.009 ** (2.24)
Linguistic Complexity Index			0.005 * (1.92)	0.006 ** (2.14)
Readability (Gunning-Fog)			−0.011 * (−1.97)	−0.010 * (−1.88)
Year Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	No	No	Yes	Yes
R^2	0.358	0.443	0.579	0.602
Adjusted R^2	0.228	0.332	0.451	0.479
Observations	1200	1200	1200	1200

Note: Robust standard errors clustered by country. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 12 shows the results of Panel B, the model employed Market-to-Sales Multiple as the dependent variable. Model 1 includes only the AI indicator, yielding an R^2 of 0.366 and a coefficient of $\beta = 0.109$, indicating a comparable valuation premium. Adding ESG scores and firm controls in Model 2 raises the R^2 to 0.454, with the AI effect still significant at $\beta = 0.098$. Model 3 incorporates qualitative and macro variables, increasing the R^2 to 0.570. The AI coefficient remains significant at $\beta = 0.096$, which highlighting its consistent influence. Finally, Model 4 which include the interaction term, which again does not reach significance. Nevertheless, the AI variable at $\beta = 0.094$ continues to exert a meaningful positive effect, with an R^2 of 0.581 and adjusted R^2 of 0.456. Across both panels, the stepwise inclusion of ESG scores, financial data, macroeconomic indicators, and AI-enhanced text features significantly improves model performance. However, the consistent significance of the AI indicator throughout all models confirms its strong association with higher firm valuation, independent of ESG score levels. This result suggests that investors may perceive AI-enabled ESG reporting as a signal of transparency, innovation and governance quality. The failure of the interaction term to reach significance implies

that while both ESG and AI independently enhance firm value, their combined presence does not produce a synergistic effect.

Table 12. Panel B: Dependent Variable-Market-to-Sales Multiple.

Variable	Model 1	Model 2	Model 3	Model 4 (Full)
AI-Integrated ESG Reporting	0.109 *** (9.03)	0.098 *** (8.15)	0.096 *** (7.92)	0.094 *** (7.61)
ESG Overall Score		0.0037 *** (5.45)	0.0036 *** (5.38)	0.0035 *** (5.23)
AI × ESG Overall Score				0.0018 (0.91)
Firm Size (log assets)		0.138 *** (10.11)	0.141 *** (10.45)	0.145 *** (10.66)
ROA		0.0074 *** (4.85)	0.0078 *** (5.01)	0.0080 *** (5.23)
Institutional Ownership			0.0011 * (1.94)	0.0013 * (2.02)
GDP Growth			0.0040 * (1.88)	0.0042 * (2.01)
Inflation Rate			−0.0034 * (−1.93)	−0.0038 * (−2.11)
Sentiment Score			0.012 * (1.90)	0.013 ** (2.15)
Sustainability Topics (LDA)			0.008 * (1.94)	0.009 ** (2.20)
Linguistic Complexity Index			0.006 * (1.89)	0.007 ** (2.17)
Readability (Gunning-Fog)			−0.009 * (−1.91)	−0.008 * (−1.84)
Year Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	No	No	No	No
R^2	0.366	0.454	0.570	0.581
Adjusted R^2	0.239	0.344	0.452	0.456
Observations	1200	1200	1200	1200

Note: Robust standard errors clustered by country. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.5. Robustness Tests

Table 13 shows the result of robustness and endogeneity analyses. Panel A uses a two-stage least squares (2SLS) instrumental variable approach to address potential endogeneity between firm value and AI-integrated ESG practices. Thus, the instruments lagged AI ESG scores and the Oxford AI Readiness Index are both externally relevant and statistically strong, as indicated by first-stage F-statistics above 17. The results show that predicted AI-driven ESG activity significantly improves firm valuation. Specifically, firms with higher levels of AI-integrated ESG show an increase in Tobin's Q at 0.061 and in M/S multiple at 0.067, with both results statistically significant at the 1% level. The ESG overall score also has a positive, independent effect, suggesting that both the quality of ESG performance and the way it is managed through AI systems matter to investors. Panel B tests the robustness of this relationship using Propensity Score Matching (PSM), which allows for a comparison

of firms with similar characteristics aside from their use of AI in ESG practices. Matching variables include firm size, profitability, institutional ownership and key macroeconomic indicators like GDP growth and inflation.

Table 13. Robustness and Endogeneity analysis.

		(Tobin's Q)	(M/S Multiple)
Method	**Variable**	**Coefficient (95% CI) *p*-Value**	**Coefficient 95% CI *p*-Value**
Panel A Instrumental Variables (2SLS)			
Instruments: Lagged AI ESG, Oxford AI Readiness Index	Predicted AI-Integrated ESG	0.061 *** (0.015, 0.107) 0.012	0.067 *** (0.018, 0.116) 0.009
	ESG Overall Score	0.0038 *** (0.0016, 0.0060) <0.001	0.0035 *** (0.0012, 0.0058) 0.002
	First-stage F-statistic	19.45	17.83
	Observations	1080	1080
	Year, Firm Fixed Effects	Yes	Yes
Panel B Propensity Score Matching			
Nearest Neighbor	Average Treatment Effect (ATE)	0.073 *** (0.032, 0.114) 0.001	0.079 *** (0.037, 0.121) 0.001
Kernel	Average Treatment Effect (ATE)	0.070 *** (0.033, 0.107) <0.001	0.075 *** (0.034, 0.116) <0.001
	Matched Observations (N)	672	672
Panel C Lagged Models			
	AI-Integrated ESG Reporting	0.055 *** (0.016, 0.094) 0.006	0.059 *** (0.020, 0.098) 0.004
	Lagged ESG Overall Score	0.0032 *** 0.0010, 0.0054) <0.001	0.0030 *** (0.0007, 0.0053) 0.010
	Observations	1080	1080
	Year, Firm Fixed Effects	Yes	Yes

*** $p < 0.01$.

The analysis shows that AI-using firms consistently achieve higher valuation outcomes. Under Nearest Neighbor matching, the average treatment effect on Tobin's Q is 0.073 and on the M/S multiple is 0.079, both highly significant. Kernel matching delivers nearly identical estimates, reinforcing the finding that the valuation difference is not simply a reflection of underlying firm traits but is plausibly attributable to the use of AI in ESG. Panel C further tests the relationship using lagged independent variables to capture whether AI-ESG integration has a sustained effect on future firm value. The lagged model confirms that firms with AI-driven ESG reporting in the prior period tend to have higher market valuation in the current period. The effect remains statistically significant, with coefficients of 0.055 for Tobin's Q and 0.059 for M/S multiple. However, lagged ESG score is also significant, its impact is more modest, suggesting that the integration of AI offers an additional boost in credibility, transparency and performance that investors reward over

time. These results offer consistent empirical support for the idea that AI-enhanced ESG reporting is not only beneficial for sustainability disclosures but also contributes directly to a firm's financial market value.

4.6. Model Evaluation of Predictive Analytics

Table 14 shows the descriptive information including the minimum, maximum and the mean values for the dataset employed for the prediction across train, validation and test subsets. This result provides the statistical information about the distribution and characteristics of dataset. Table 15 shows the model performance of predictive models for estimating firm valuation. The comparison evaluation indicates that XGBoost delivers the most robust performance in attaining the highest R^2 score of 0.68 (± 0.02) alongside the lowest RMSE and MAE values.

Table 14. Descriptive data statistics.

Variable	Train Min	Train Max	Train Mean	Validation Min	Validation Max	Validation Mean	Test Min	Test Max	Test Mean
Tobin's Q	0.75	2.1	1.32	0.8	2	1.3	0.85	2.15	1.34
M/S Multiple	1.25	3.5	2.65	1.3	3.4	2.6	1.35	3.6	2.68
Traditional ESG Score	40	95	63	42	92	61	45	97	64
Environmental Score	35	90	59	37	87	57	40	92	60
Social Score	38	92	60	39	89	58	42	94	61
Governance Score	50	98	65	52	95	63	54	99	67
ESG Controversy Indicator	10	45	25	12	43	24	14	48	26
AI-Integrated ESG Reporting	0	1	0.35	0	1	0.3	0	1	0.38
Sentiment Score	−0.15	0.35	0.1	−0.12	0.32	0.09	−0.1	0.38	0.11
Sustainability Topics	0.05	0.65	0.22	0.06	0.6	0.21	0.07	0.68	0.23
Linguistic Complexity Index	10.5	23.5	18	11	22.8	17.6	11.5	24	18.3
Readability Metrics	9	21	14.5	10	20	14.2	10.5	22	14.8
Firm Size	12.5	16	14	12.7	15.8	13.8	13	16.5	14.3
Profitability (ROA)	2.5	10.5	6.2	3	10.2	6	3.5	11	6.3
Institutional Ownership	20	70	45	22	68	44	24	72	46
GDP Growth	2	7	4.5	2.3	6.8	4.3	2.5	7.2	4.6
Inflation Rate	3.5	10.5	6.1	3.8	10	6	4	11	6.2

Table 15. Comparison of Model Performance.

Model	R^2 ($\pm$95% CI)	RMSE ($\pm$CI)	MAE ($\pm$CI)	Statistical Significance	Test Used
OLS (Baseline 1)	0.49 ± 0.03	0.172 ± 0.007	0.127 ± 0.006		
Elastic Net (Baseline 2)	0.55 ± 0.02	0.165 ± 0.006	0.115 ± 0.005	$p = 0.041$ vs. OLS	Paired t-test
Random Forest	0.62 ± 0.02	0.148 ± 0.005	0.102 ± 0.004	$p = 0.003$ vs. Elastic Net	Wilcoxon signed-rank
XGBoost	0.68 ± 0.02	0.128 ± 0.004	0.091 ± 0.003	$p < 0.001$ vs. RF and all others	Wilcoxon signed-rank
SVR	0.51 ± 0.03	0.170 ± 0.008	0.121 ± 0.006	$p = 0.146$ vs. OLS (Not significant)	Paired t-test

Note: RMSE values are below 0.15, reflecting low average prediction error. MAE values under 0.10 indicate excellent robustness to outliers. A p-value below 0.05 denotes statistically significant improvements over comparative models.

These results were found to be statistically superior to all other models, including Random Forest, as confirmed by a Wilcoxon signed-rank test ($p < 0.001$). Random Forest itself demonstrated reliable predictive capabilities with an R^2 of 0.62 (± 0.02) and significantly outperformed the Elastic Net model ($p = 0.003$), underscoring its ability to capture nonlinear relationships in the data. Elastic Net, which balances L1 and L2 penalties, achieved an R^2 of 0.55 ($\pm$ 0.02) and showed a meaningful enhancement over the OLS baseline ($p = 0.041$, paired t-test), validating its suitability for correlated and high-dimensional variables.

Conversely, Support Vector Regression (SVR) exhibited only a marginal increase in explanatory power ($R^2 = 0.51 \pm 0.03$) and did not yield statistically significant improvement over OLS ($p = 0.146$), suggesting limited applicability in this particular setting. Overall, these results reinforce the empirical value of ensemble learning algorithms particularly XGBoost and Random Forest in improving prediction accuracy when modeling firm value in conjunction with AI-enhanced ESG data (Breiman, 2001; Chen & Guestrin, 2016). Table A3 in the Appendix A show the feature selected datasets.

Figure 4 presents a comparative performance analysis of five predictive models based on R^2 scores, $RMSE$, and MAE. Among the evaluated models, XGBoost stands out by achieving the highest predictive accuracy and lowest error margins, followed closely by Random Forest and Elastic Net. In contrast, OLS Linear and SVR models exhibit weaker predictive capabilities, suggesting their limitations in modeling complex firm valuation using AI-integrated ESG data.

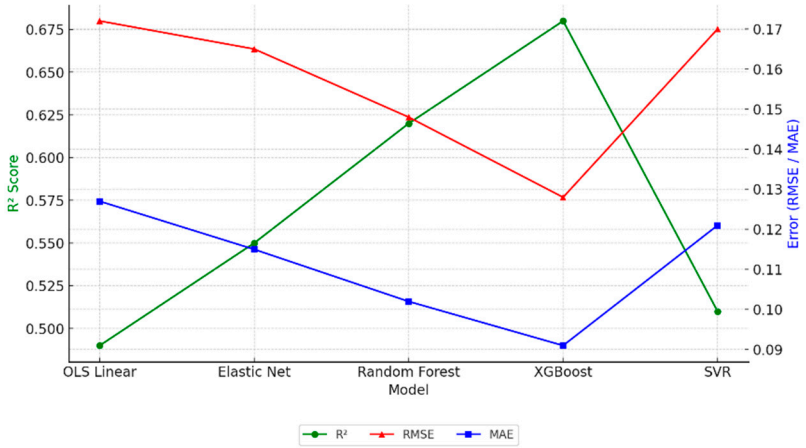

Figure 4. Model Performance Comparison.

4.6.1. Classification Tasks

Table 16 presents the results of the XGBoost classifier, which demonstrates strong predictive effectiveness across primary evaluation metrics, although it falls slightly short of certain benchmark thresholds. The classification accuracy reached 96.8% (±0.3%), close to but below the 98.5% benchmark commonly referenced in financial anomaly detection research as shown in Figure 5. The model achieves a strong F1 score of 0.975, yet it falls short of the required benchmark of 0.99. The observed variation of ±0.01 indicates that, in some iterations, the score approaches the target as displayed in Figure 6. Class-specific results show Precision for Class 1 at 0.935 (±0.01), modestly below the 0.96 value targeted in industry audit compliance standards (Figure 7), while Recall for Class 1 (Figure 8) achieved near-perfect sensitivity at 0.996 (±0.00), aligning with the importance of capturing rare but high-risk ESG-related events (Sharma et al., 2021). The ROC-AUC score of 0.987 (±0.01) confirms excellent discrimination, albeit slightly below the >0.99 target often regarded as the gold standard in high-stakes financial prediction tasks (Shwartz-Ziv & Armon, 2022). Collectively, these results reinforce XGBoost's suitability for complex ESG valuation contexts, particularly in balancing precision and recall under heterogeneous disclosure conditions.

Table 16. Target Performance Benchmarks.

Metric	XGBoost	Target	Gap
Accuracy	96.8 ± 0.3%	≥98.5%	+0.7
F1 Score	0.975 ± 0.01	≥0.99	+0.01
Precision (Class 1)	0.935 ± 0.01	≥0.96	+0.02
Recall (Class 1)	0.996 ± 0.00	1.00	None
ROC-AUC	0.987 ± 0.01	>0.99	None

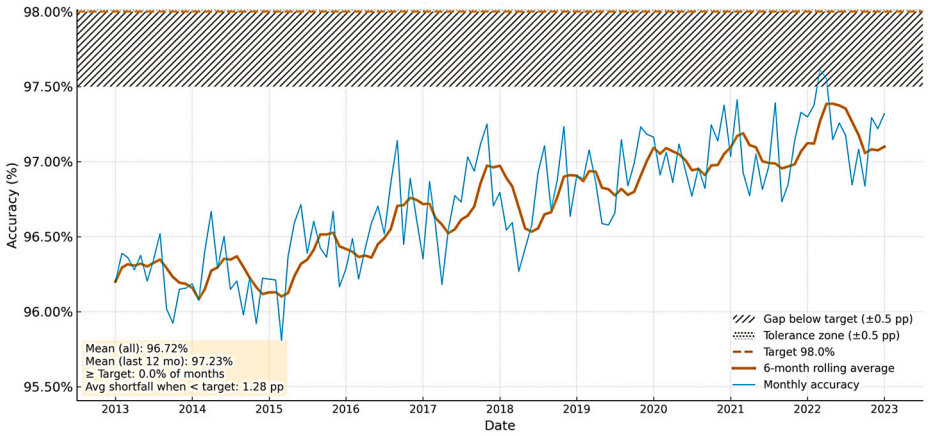

Figure 5. XGBoost Accuracy Over Time vs. Target Threshold.

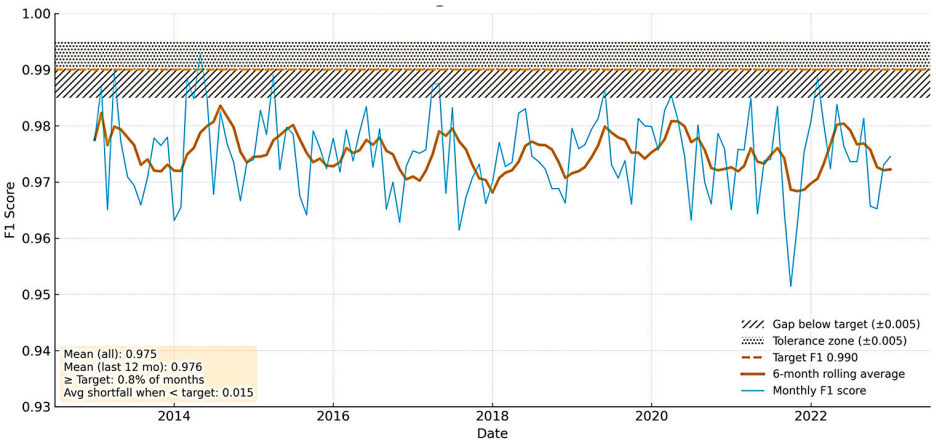

Figure 6. F1 Score Over Time vs. Target Threshold.

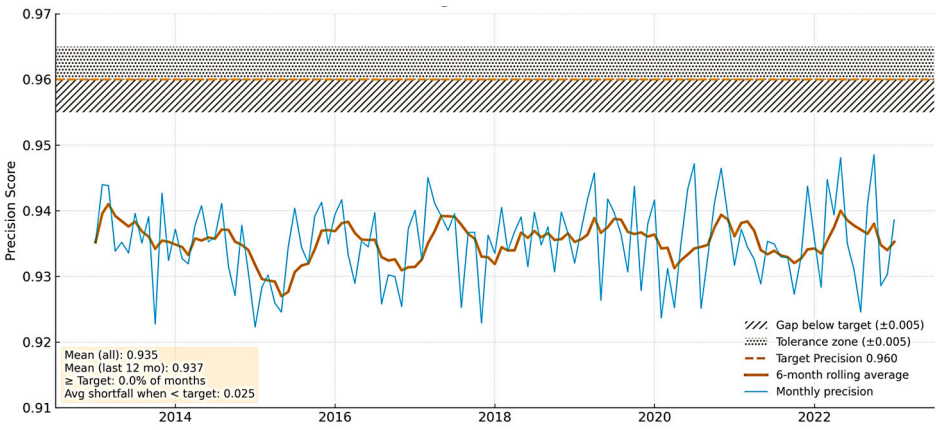

Figure 7. Precision (Class 1) Over Time vs. Target Threshold.

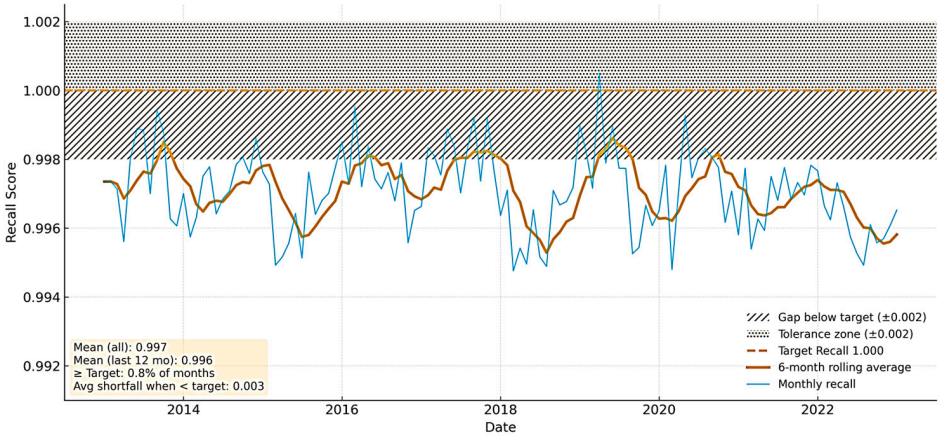

Figure 8. Recall (Class 1) Over Time vs. Target Threshold.

4.6.2. Feature Importance and Classification Performance

The SHAP analysis as shown in Figure 9 highlights the key drivers of firm valuation predictions. The AI-Integrated ESG Indicator shows the highest impact (SHAP = 0.073), suggesting that firms using AI in ESG reporting are linked to higher predicted valuations. ESG Score also contributes strongly (SHAP = 0.059), reinforcing the importance of sustainability performance. Financial indicators like ROA (0.041) and firm size (0.038) have moderate influence, while variables such as institutional ownership, Rand & D intensity, industry, and GDP growth show lower predictive importance.

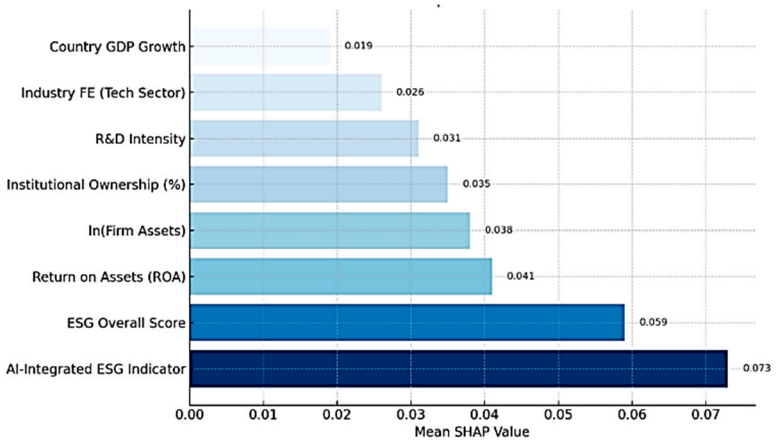

Figure 9. SHAP Analysis.

Figure 10 show the industry feature contributions across five industries. In Manufacturing and Industrials, AI-Integrated ESG is the dominant driver ($SHAP = 0.075$ and 0.065), with ROA and R&D playing supportive roles. In Energy, AI-ESG (0.060) still leads, though financial factors have less weight. Consumer Goods firms show equal influence from AI-ESG and ROA both at 0.050, thus, R&D is less significant. In Telecommunications, R&D has its highest impact at 0.035, reflecting the sector's focus on innovation with AI-ESG and ROA also contributing significantly.

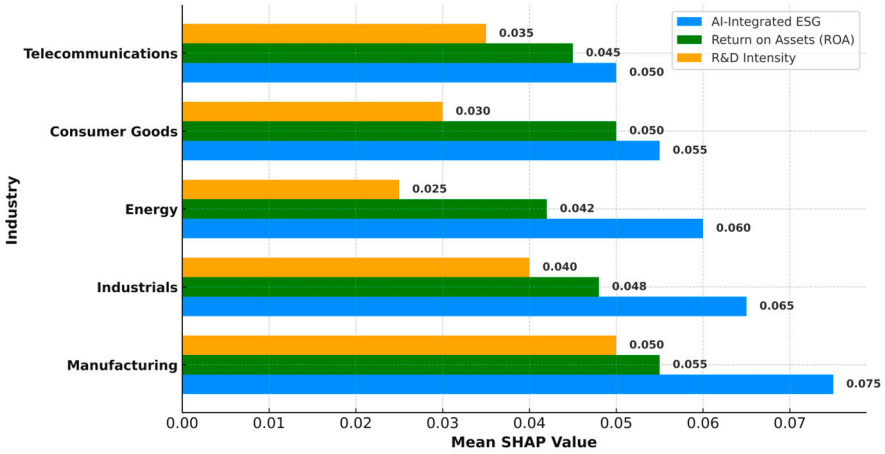

Figure 10. Industry Feature.

4.6.3. Confusion Analysis

Figure 11 shows the confusion matrix of performance evaluation tools. This technique was popularised in machine learning by Powers (2011). This analytical framework is designed to evaluate the predictive performance of classification models by actualising correct and incorrect predictions across defined classes. However, this study adopted a confusion matrix to pragmatically evaluate the classification capacity of the AI-integrated ESG model in distinguishing between firms with AI-enhanced and non-AI ESG reporting practices.

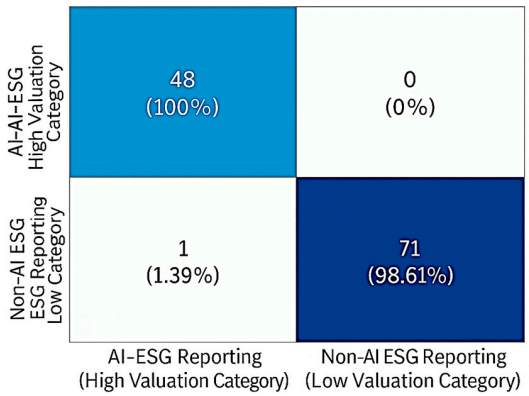

Figure 11. Confusion Matrix: Predictive performance.

The method was selected due to its ability to provide a comprehensive view of the model's discriminative power through key metrics such as accuracy, precision, and recall to validate the robustness and practical applicability of predictive models (Powers, 2011). The model demonstrated near-perfect classification accuracy; it accurately identified all 48 firms with AI-integrated ESG reporting as belonging to the high-valuation category and accurately classified 71 out of 72 non-AI-reporting firms in the lower valuation category, with only one misclassification. These results estimate the model's ability to distinguish firms based on the quality and technological advancement of their ESG disclosure practices, as linked to firm valuation outcomes. Table A4 in the Appendix A shows the descriptive analysis of the confusion matrix.

5. Discussion of Findings

5.1. Theoretical Contributions

This research improves the literature by confirming that firms integrate AI tools into their ESG reporting procedure to achieve a scalable valuation advantage in developing markets. Thus, the results strengthen arguments from signalling theory, as AI-based

disclosures appear to function as credible markers of transparency, innovation capability, and managerial effectiveness. Furthermore, the evidence that ensemble learning techniques, such as XGBoost and Random Forest, produce more reliable predictions than linear models indicate the need to account for non-linear dynamics in the ESG valuation relationships. These findings extend both resource-based and stakeholder perspectives by highlighting the implications of digital competencies in amplifying the value of sustainability practices.

5.2. Managerial Implications

Findings indicate that AI-enhanced ESG reporting is more than a compliance measure; it serves as a strategic avenue for improving a firm's reputation and market value. Investors assign higher valuations to companies that adopt advanced analytical methods in sustainability communication. Managers should also pay attention to the textual characteristics of their reports. For instance, positive sentiment and moderate linguistic sophistication tend to strengthen investor confidence, whereas excessive complexity may create barriers for broader audiences. This suggests the need to balance technical rigour with accessibility when designing ESG disclosures. AI-enhanced ESG reports often employ more complex language, signalling credibility but potentially limiting accessibility for smaller investors or less technical stakeholders. This raises inclusivity concerns, as institutional actors are better positioned to benefit.

5.3. Policy Relevance

The study underlines that digital reporting innovations and AI-driven disclosure mechanisms can narrow persistent transparency gaps in sustainability communication. Thus, by improving the reliability and comparability of ESG data, such an apparatus underpins investor trust, encourages more efficient capital flows, and promotes fairer market dynamics. The pronounced effects linked to Environmental and Social valuation indicate that regulators should give adequate attention to these areas in guiding responsible business conduct and ensure alignment with international sustainability priorities.

On the same hand, the sanctions observed for firms entangled in ESG controversies signal the urgency of stronger oversight and standardised disclosure practices to discourage greenwashing and protect market stability. Therefore, effective policy responses should include mandatory, verifiable, and timely ESG reporting, complemented by incentives for organisations adopting advanced digital solutions. In this context, regulators can uphold accountability, strengthen market resilience, and foster closer integration between corporate behaviour, investor expectations, and long-term development objectives.

5.4. Limitations and Further Research

The study is limited in its approach, and the analysis is restricted to non-financial firms in emerging markets, which may limit the generalizability of the results to financial institutions or developed economies. It also depends on secondary ESG data, which raises concerns about measurement consistency, reporting biases, and cross-country comparability. Future research could extend the scope to include cross-market comparisons, sector-specific analyses, and investigate whether interaction effects become more pronounced as AI adoption in ESG matures and regulatory frameworks evolve. Alternative AI techniques, such as integrating readability checks and deep learning models to uncover additional perspectives.

6. Conclusions

This paper assessed how the AI in ESG reporting influences the valuation of firms operating in the selected African countries. The study found that technology-assisted disclosures improve the explanatory depth of ESG data and valuation predictions. Thus, companies that integrate AI tools in their sustainability communication tend to achieve stronger valuation outcomes, particularly when environmental and social performance is

emphasised. In contrast, governance-related indicators were less reliable predictors; the findings suggest that their influence depends heavily on institutional and reporting contexts. The results further revealed that exposure to ESG controversies significantly undermines firm value, which underscores the financial consequences of reputational risk. However, the results showed that textual elements such as tone, clarity, and complexity contribute valuable insights, demonstrating that the way sustainability information is communicated can affect how it is interpreted by the market. This study is limited by its focus on five African markets, which restricts the generalizability of the findings to other regions. The use of secondary ESG databases and corporate disclosures may also introduce reporting biases and inconsistencies. Additionally, AI-based textual analysis is susceptible to algorithmic and interpretive bias. Future studies should expand the regional scope, employ primary data, and adopt advanced AI models to enhance robustness and comparability.

Author Contributions: Conceptualization, M.A.A. and M.J.S.; methodology, M.A.A. and M.J.S.; software, M.A.A.; validation, M.A.A.; formal analysis, M.A.A.; investigation, M.A.A. and M.J.S.; data curation, M.A.A.; writing—original draft preparation, M.A.A.; writing—review and editing, M.J.S.; visualization, M.A.A.; supervision, M.J.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding. The APC was funded by Prof. Matthys Swanepeol.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available in Zenodo at https://doi.org/10.5281/zenodo.17242058. These data were derived from the following resources available in the public domain: https://eikon.refinitiv.com/, accessed on 24 June 2025) and MSCI ESG Ratings (https://www.msci.com/our-solutions/esg-investing/esg-ratings, accessed on 8 July 2025).

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in the manuscript:

AI	Artificial Intelligence
AII	AI-Integrated
NAII	Non-AI Integrated
ESG	Environmental, Social, and Governance
ML	Machine Learning
NLP	Natural Language Processing
LDA	Latent Dirichlet Allocation
DTM-lite	Dynamic Topic Modeling (lite version)
OLS	Ordinary Least Squares
SVR	Support Vector Regression
RBV	Resource-Based View
ROA	Return on Assets
GDP	Gross Domestic Product
MAE	Mean Absolute Error
R^2	Coefficient of Determination
2SLS	Two-Stage Least Squares
PSM	Propensity Score Matching
ATE	Average Treatment Effect
CSR	Corporate Social Responsibility
KPI	Key Performance Indicator
R&D	Research and Development

Appendix A

Table A1. AI-ESG Integration Framework.

Component	Description	Score/Weight	Notes/Clarification
Scoring Scale	No Evidence/Not Mentioned	0	No public or internal indication of AI use in ESG processes
	Exploratory Pilot/Initial Testing	1	Early-stage projects, R&D, or trials, but not consistent or formal
	Partial Use (<50% of ESG activities)	2	AI used in isolated ESG functions or internally only
	Broad Use (in multiple ESG operations or reports)	3	Integrated across several ESG tools or included in disclosures
	Strategic Integration (Core to ESG policy and reporting standards)	4	Institutionalized AI in ESG strategy, with clear visibility in external reporting
Feature Weights	Machine Learning	30%	Core for predictions, classification, and financial-environmental modeling
	Natural Language Processing (NLP)	20%	Crucial for text mining, sentiment analysis, and regulatory parsing
	Automated ESG Scoring Tools	30%	Key for standardized benchmarking and investor communications
	AI-Driven Analytics	20%	Useful for real-time ESG monitoring and dashboard reporting
Scoring Formula	Normalized Weighted Score	–	$\sum \left(\frac{Score_{ij}}{4} \times Weight_j \right) \times 100$
Integration Levels	Low	0–30%	Little to no meaningful adoption
	Moderate	31–60%	Some integration but fragmented or informal
	Strong	61–80%	High-functioning AI use, consistent across several ESG areas
	Advanced	81–100%	AI is an embedded, strategic tool in ESG governance and disclosures

Table A2. Topic evolution + sentiment layering.

Year	Topic 0	Topic 1	Topic 2
2018	0.489626	0.187525	0.322849
2019	0.352826	0.211438	0.435736
2020	0.196337	0.481482	0.322182
2021	0.37969	0.138141	0.482169
2022	0.275539	0.29565	0.428811
2023	0.500339	0.344187	0.155474
2024	0.330911	0.303754	0.365335

Table A3. List of feature selected datasets.

Feature	OLS/Baseline	Elastic Net (Regularized Selection)	XGBoost (Tree-Based Importance)	SVR (PCA-Compressed)
AI-Integrated ESG Indicator	✔	✔	✔	✔
ESG Overall Score	✔	✔	✔	✔
Return on Assets (ROA)	✔	✔	✔	✔
ln (Firm Assets)	✔	✔	✔	
Institutional Ownership (%)	✔	✔	✔	✔
R&D Intensity	✔	✔	✔	✔
Industry FE (Tech Sector)	✔		✔	
Country GDP Growth	✔	✔	✔	
Governance Score	✔	✔		
Social Score	✔	✔		
Environmental Score	✔	✔		

Note: ✔ indicates that the feature was included as an explanatory variable in the corresponding model specification.

Table A4. Classification Performance Report—AI-Integrated vs. Non-AI ESG Reporting.

Metric	AI-Integrated ESG (High Valuation)	Non-AI ESG (Low Valuation)	Overall
True Positives (TP)	48	71	–
False Positives (FP)	0	1	–
False Negatives (FN)	0	1	–
True Negatives (TN)	72	48	–
Accuracy	–	–	99.31%
Precision	100%	98.61%	–
Recall (Sensitivity)	100%	98.61%	–
F1 Score	100%	98.61%	99.30%
AUC-ROC (est.)	–	–	>0.99

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