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THE DIGITAL FRONTIER OF GOVERNANCE: IMPACT OF ARTIFICIAL INTELLIGENCE ADOPTION ON ESG DISCLOSURE QUALITY: EVIDENCE FROM SAUDI VISION 2030

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Abstract

This study explores the link between corporate artificial intelligence (AI) adoption and the quality of environmental, social, and governance (ESG) disclosure among firms listed on the Tadawul All Share Index (TASI) from 2018 to 2024. Set within the transformative framework of Saudi Vision 2030, we develop a firm-level AI adoption index using natural language processing (NLP) analysis of annual reports and examine its impact on ESG scores obtained from Refinitiv. Using Agency Theory and Signalling Theory, we suggest that AI acts as a "digital monitor" that reduces information asymmetry, limits opportunistic managerial behaviour, and increases the credibility of non-financial disclosures. To address endogeneity and dynamic panel bias, we utilise the Two-Step System Generalised Method of Moments (GMM) estimator, alongside Propensity Score Matching (PSM) as a robustness check. Findings from a sample of 826 firm-year observations strongly support our hypotheses: AI adoption is positively and significantly related to ESG disclosure quality ($\beta = 5.612$, $p < 0.01$), and this relationship is notably stronger in firms with boards that have higher levels of digital expertise ($\beta\_interaction = 4.712$, $p < 0.01$). PSM analysis verifies that firms adopting AI outperform matched non-adopters by roughly 13.2 ESG score points. We also observe that the 2021 introduction of the Saudi Exchange ESG Disclosure Guidelines marks a distinct positive structural break in disclosure practices. These results add to the emerging research on digital governance, extend Agency Theory into the era of algorithms, and have direct policy implications for the Saudi Capital Market Authority (CMA) and comparable regulators in other emerging markets.

Keywords: *Artificial intelligence; ESG disclosure quality; digital governance; Saudi Vision 2030; agency theory; System GMM; emerging markets; Tadawul.*

JEL Classification: G34; M14; O32; Q56.

1. Introduction

The intersection of artificial intelligence (AI) and corporate governance (CG) represents one of the most consequential frontiers in contemporary business research. As machine learning algorithms, robotic process automation, and big data analytics permeate organisational decision-making, scholars and regulators alike are grappling with a fundamental question: does the digitisation of corporate operations enhance or erode accountability? This study addresses that question in a context where the stakes are particularly high, the Kingdom of Saudi Arabia, the Middle East's largest economy and a G20 member state in the midst of its most ambitious structural transformation in modern history.

Saudi Vision 2030, launched under the leadership of Crown Prince Mohammed bin Salman, represents a comprehensive blueprint to reduce the Kingdom's oil dependence and build a diversified, knowledge-driven economy (Al-Sulami, 2023). A central pillar of this program is digital transformation: firms listed on the Tadawul All Share Index (TASI) are incentivised through regulatory signals, capital market pressures, and sovereign wealth fund priorities to embed advanced technologies into their operations. Simultaneously, the Saudi Capital Market Authority (CMA) and the Saudi Exchange have intensified their push for transparency, culminating in the 2021 release of mandatory ESG Disclosure Guidelines for listed companies. This convergence of technological adoption and governance reform creates a natural laboratory for examining whether AI can serve as a mechanism for improving the quality of environmental, social, and governance (ESG) reporting.

The relevance of this question extends well beyond the Saudi context. ESG disclosure quality remains uneven across global capital markets, but the problem is particularly acute in emerging economies where "greenwashing", the strategic exaggeration or fabrication of sustainability performance, poses a systemic risk to market integrity and investor trust (Wang et al., 2025). Traditional governance mechanisms, such as board independence and audit committee oversight, have been the primary lines of defence against opportunistic disclosure behaviour (Jensen & Meckling, 1976). However, recent scholarship argues compellingly that these human-centred mechanisms are increasingly inadequate in processing the sheer volume and complexity of data that modern ESG reporting demands (Li et al., 2024; Chen & Zhang, 2023). AI, by contrast, can process vast quantities of unstructured data in real time, identify inconsistencies, and generate auditable documentation trails that are difficult for human actors to manipulate.

We conceptualise this process through the lens of two established theoretical frameworks. Agency Theory (Jensen & Meckling, 1976) provides the foundational logic: AI adoption reduces the monitoring cost that shareholders bear in overseeing managerial behaviour, thereby attenuating the agency conflict that gives rise to opportunistic or selective disclosure. Signalling Theory (Spence, 1973) adds a complementary dimension: by voluntarily adopting and disclosing AI-driven governance practices, firms transmit credible signals of organisational sophistication and commitment to transparency to external stakeholders. Together, these two frameworks generate testable predictions about the directionality and magnitude of the AI–ESG relationship, and about the conditions under which this relationship is amplified.

A key moderating condition identified in the Upper Echelons Theory literature (Hambrick & Mason, 1984) is the strategic orientation of the board. Smith and Brown (2024) argue persuasively that AI tools are only as effective as the human governance infrastructure that frames their deployment. A board lacking digital literacy may fail to recognise AI-generated insights, misallocate AI resources, or perpetuate the "productivity paradox" in which technology investments do not translate into governance improvements. Accordingly, we hypothesise that the positive effect of AI adoption on ESG disclosure quality is amplified in firms whose boards include directors with information technology, engineering, data science, or digital transformation expertise.

To test these hypotheses, we assembled a panel dataset comprising all firms listed on TASI over the period 2018–2024, yielding 826 firm-year observations. AI adoption was measured by constructing a novel index based on NLP analysis of corporate annual reports, capturing both the frequency and variety of AI-related terminology. ESG disclosure quality was sourced from Refinitiv Eikon, cross-validated against Saudi Exchange reporting guidelines. We estimated our models using the Two-Step System GMM estimator (Arellano & Bover, 1995; Blundell & Bond, 1998) to address the dynamic endogeneity inherent in the relationship between AI investment and ESG performance, specifically, the concern that firms with superior ex-ante governance may simultaneously exhibit higher AI adoption and higher ESG quality. As a further robustness check, we employed Propensity Score Matching (PSM) to compare AI-adopting firms against observationally equivalent non-adopters under matched financial conditions.

Our results yielded four primary findings. First, AI adoption is positively and significantly associated with ESG disclosure quality across all model specifications, with effect sizes remaining economically meaningful after controlling for firm size, leverage, profitability, board size, and regulatory year effects. Second, the interaction term between AI adoption and board digital expertise is positive and highly significant, confirming the moderating role of digital board capital. Third, PSM analysis confirms that the ESG disclosure advantage of AI adopters is not merely a selection artefact, treated firms outperform matched controls by approximately 13.2 ESG score points, an effect equivalent to more than two-thirds of a standard deviation. Fourth, we documented a discrete positive structural break in 2021 corresponding to the Saudi Exchange ESG Disclosure Guidelines, validating the importance of regulatory catalysts in shaping disclosure quality.

This paper makes three primary contributions to the literature. First, it provides the first systematic empirical evidence on the AI–ESG nexus in the Middle East's largest capital market, addressing a significant geographic and contextual gap in the corporate governance literature. Second, it extends Agency Theory into the digital age by proposing and validating the concept of "digital agency," in which algorithmic tools serve as institutional monitors that substitute for, or complement, human oversight mechanisms. Third, it offers direct, evidence-based policy guidance to the Saudi CMA and to regulators in comparable emerging market contexts on the role of technology in advancing market integrity.

The remainder of the paper is organised as follows. Section 2 reviews the relevant literature and develops the study's hypotheses. Section 3 presents the research methodology, including data collection procedures, variable definitions, and econometric identification strategy. Section 4 reports the empirical results and robustness tests. Section 5 provides discussion and conclusions, including theoretical implications, policy recommendations, and directions for future research.

2. Literature Review and Hypothesis Development

2.1 Effect of AI adoption on ESG, Board AI experience, size, leverage, ROA, and board size

Using ESG/sustainability disclosures of listed Chinese companies from 2015 to 2022, Naveed, Farooq, Zahir-Ul-Hassan, and Rau (2025) noted that AI adoption enhanced both the overall quality of sustainability reporting and the pillar-specific quality of ESG disclosures. This positive effect was further strengthened by the presence of sustainability committees. Analysis of heterogeneous impacts revealed that committee specialisation was particularly associated with improved disclosure quality across ESG pillars, except governance, indicating that specialist committees can drive more effective reporting outcomes. Within non-state-owned enterprises, governance-focused committees positively moderated the AI–disclosure relationship, underscoring a nuanced ownership-based effect.

The study by Hamdouni (2025) examined how Saudi banks' internal adoption of AI-enabled FinTech-related digital tools was correlated with their financial performance, sustainability performance, and financial stability over the period 2015–2024 using a panel dataset of 10 banks. The analysis examined how the adoption of AI-driven technologies, such as machine-learning credit assessment, robo-advisory systems, and automated compliance tools, was related to market performance (Tobin's Q), accounting performance (ROA and ROE), financial stability (Z-Score), and sustainability outcomes measured by both Bloomberg ESG Disclosure Score and the LSEG ESG performance-oriented score. The authors obtained a positive relationship between banks' internal adoption of AI-enabled digital/FinTech-related technologies and their financial performance, sustainability performance, and financial stability.

(Zhang & Yang, 2024) evaluated the influence of AI adoption on the ESG performance of Chinese firms. AI adoption significantly improved environmental and social performance but had a limited impact on governance aspects. The absorptive capability partially mediated this relationship, suggesting AI enhances ESG performance both directly and indirectly by enhancing firms' ability to assimilate and apply sustainability knowledge. Heterogeneity analyses indicate that AI's sustainability benefits vary across organisational life cycles. Mature firms showed the strongest effects. Across industry types, non-polluting sectors showed greater improvements.

By analysing 23,094 firm-year observations of Chinese A-share listed firms from 2009 to 2021, Li (2024) observed that AI significantly improves firm ESG performance. The impact was higher in non-state-owned enterprises, compared to state-owned enterprises (SOEs), and in central SOEs than in local SOEs. AI helped the firms to alleviate financing constraints, enhance internal control, and improve overall firm performance, leading to enhanced ESG performance over time. The impact was higher in regions with high fintech activity, strict environmental regulations, and high bank concentration.

Using a sample of 4858 listed companies in China from 2007 to 2022, Xie and Wu (2025) showed that corporate application of AI technology enhanced corporate ESG performance. The degree of corporate digitalisation had a positive moderating effect on how AI technology affects corporate ESG performance. The application of AI technology enhanced environmental (E) performance by strengthening corporate green technology innovation, social (S) performance by improving corporate philanthropic responsibility, and overall ESG performance, with the above two sub-items as the main aspects. However, AI technology weakened the effectiveness of corporate internal control, leading to a decline in corporate governance (G) performance. AI technology promoted ESG in more competitive industries and technology-intensive firms, and in the eastern and central regions than in the western and northeastern regions, and in large- and medium-sized firms are similarly superior to small-sized firms. While medium-sized firms have more room for upward mobility than large-sized firms, the promotion effect was higher than in large enterprises.

Textual analysis of the annual reports of a sample of Chinese A-share listed companies from 2009 to 2020 by Jia (2025) showed that the extent of AI-related information disclosed in corporate annual reports was positively correlated with their ESG ratings, even after controlling for firm characteristics.

Tian, Wang, and Cai (2025) observed that AI use by Chinese listed firms improved their ESG performance by reducing the financing constraints, enhancing information transparency, and corporate innovation. The impact of the use of AI on firms' ESG performance was more conspicuous in regions with highly developed factor markets, in asset-intensive industries, and in industries characterised by high levels of competition.

Using panel data from 22,953 Chinese listed firm-year observations spanning 2011–2023, Liu, Song, Zhou, and Liu (2025) showed that AI adoption improved overall ESG performance by enhancing all three individual pillars. However, this positive effect was most pronounced in large firms and those in non-heavily polluting industries, showing the effect of boundary conditions. Green innovation and supply chain efficiency helped AI to enhance ESG outcomes. Digital transformation positively moderated this relationship. Thus, firms with greater digital maturity benefited more significantly from AI applications.

From a study using a mixed-methods design with a longitudinal quantitative analysis of 600 publicly traded companies over 3 years and in-depth and unstructured qualitative interviews, Younus and Kashif (2025) observed that AI investments were positively related to ESG scores. Industry influences on AI investments were very strong in industries with high AI intensity, like technology. Qualitative responses indicated that AI helped to monitor the environment in real time, engage stakeholders, and uphold ethical standards, thus changing routine organisational processes and decision-making.

From an analysis of panel data from 3,048 listed firms across Germany, France, Italy, Spain, and Finland over the period 2019–2023, Al Amosh and Khatib (2026) noted a positive relationship between ESG commitment and technological innovation capability (TIC). Gender diversity on boards negatively moderated this relationship. Thus, although ESG fosters innovation, board gender diversity may not always enhance this process, possibly due to integration challenges or tokenism.

Thus, all papers report a positive effect of AI in improving ESG and some board characteristics influencing their relationship. This observation leads to the following hypothesis:

H1: AI adoption is positively and significantly associated with ESG disclosure transparency.

2.2 Effect of AI adoption on ESG: impact of board directors with information technology, engineering, data science, or digital transformation expertise

An analysis of data from Chinese A-share mining-listed companies (MLCs) from 2010 to 2024 by Umair, Gulzar, and Rahman (2025) showed that the digital orientation of executives exerted a positive impact on overall ESG performance, especially strengthening the governance and environmental pillars. Green innovation capability mediated this relationship. Thus, digitally oriented leaders enhanced ESG outcomes by enabling process innovation, energy efficiency, and transparent disclosure.

Using empirical analysis of Chinese A-share listed companies from 2010 to 2019, Yang and Jin (2024) noted that digital transformation promoted ESG performance in the manufacturing industry. The educational level, CEO tenure, and diversity of professional backgrounds in senior management teams moderate this relationship, thereby improving ESG performance.

In the studies of Qiao, Zhao, Fung, and Fung (2025), digital leadership led to excellence in ESG performance and promoted progress in digital transformation and stock trading. The effect on ESG was particularly pronounced in the case of female executives, executives with environmental expertise, firms offering liability insurance to board members and executives, and those operating in regions with robust government environmental policies.

Zada, Zada, Dhar, Ping, and Sarkar (2025) used a three-phase time-lagged data collection approach to mitigate common method bias and ensure robust analysis, with responses from 413 employees representing diverse roles. Digital leadership positively influenced the green innovation process. It also partially mediated the relationship between digital leadership and firm sustainability. Top management innovativeness expanded the positive effects of digital leadership on green innovation, thus reinforcing the importance of leadership-driven sustainability strategies.

An analysis of panel data from 19,155 Chinese A-share listed companies (2011–2020) by Gao, Li, and Guo (2023) showed that the top management team's career experience heterogeneity positively influenced green innovation, strengthened by digital transformation.

Agnese, Arduino, and Di Prisco (2025) suggested establishment of an AI committee consisting of experts with technical knowledge dedicated to managing artificial intelligence-related potential threats and opportunities on the board to implement AI in the company and obtain maximum benefits through its relationship with ESG.

An analysis of 432 valid responses from private commercial, service, and industrial organisations in Oman by Youssef and Almaqtari (2025) showed that digital technologies improved board effectiveness. There was no effect of board characteristics on AI. But it positively influenced blockchain technologies. Blockchain and digital transformation mediated the relationship between board characteristics and board effectiveness, whereas AI showed only a limited mediating role. Directors viewed AI and digital transformation as drivers of board effectiveness. However, their weak performance showed that implementation and capability-building were challenging, especially in an emerging market like Oman.

An analysis of 863 firms by Marrone, Pontrelli, and Oliva (2023) showed that board characteristics consisting of gender diversity, independence, size, members' average age and membership in the high-tech sector positively influenced the level of ESG disclosure. However, board tenure negatively influenced the ESG disclosure level.

The above results suggest a moderating effect of board expertise (BEXP) on AI adoption, influencing ESG. On this basis, the following hypothesis is proposed:

H2: Board expertise in digital technology, AI, ESG and engineering moderates the relationship between AI adoption and ESG score.

2.3 Regulation and technology are complements in improving market transparency

Based on a critical review of the existing EU regulations by Bobinaite, Di Somma, Graditi, and Oleinikova (2019) suggested respecting the valid provisions on market transparency while tailoring them to the Web of Cells (WoC)-based architecture. The need to integrate some provisions of the current regulations to improve market transparency was also proposed.

The EU has introduced some modest AI transparency requirements as part of its General Data Protection Regulation. However, two years after their introduction, the effectiveness of these rules remains questionable. Using semi-structured interviews with 75 participants, Seizov and Wulf (2020) showed that the existing implementation of the EU's informed consumer framework has not achieved a sufficient standard of consumer protection and information in the online space. If basic technological tools like cookies are still unclear to consumers, the present strategies are entirely inadequate for tackling the challenges posed by complex AI technologies.

In producing a transformative and transparency impacts of AI and other digital technologies and regulatory compliance of auditing, data visualisation for better stakeholder engagement and predictive insights is necessary (Thanasas, Kampiotis, & Karkantzou, 2025). A theoretical framework was developed by Granados, Gupta, and Kauffman (2006) to explain the role played by IT in affecting market information, transparency and market structure.

An examination of four cases (the Netherlands, Australia, the United States, and Singapore) of successful eXtensible Business Reporting Language (XBRL) by Chen (2012) showed the importance of program goals and strategic alignment in achieving information transparency and efficiency, the advantage of strategies correlating to institutional setting, the critical need to provide incentives for adoption, and the usefulness of incremental implementation. Hodge, Kennedy, and Maines (2004) observed that search-facilitating technologies, like XBRL, help financial statement users by improving the transparency of firms' financial statements and how managers' report such information.

Trienekens, Wognum, Beulens, and Van Der Vorst (2012) noted the need for transparency in the food supply chain to ensure food quality and provenance to all users of food and food products. There is a need for intensified information exchange and integrated information systems involving all chain actors to achieve transparency with respect to a multitude of food properties.

Amroni, Darmawan, and Pangilinan (2025) observed that blockchain improves transparency and traceability through a decentralised, secure system. Big data helps in real-time data processing to optimise operational efficiency and reduce environmental impact. The synergy between these technologies can be leveraged by businesses to improve sustainability and maximise performance. Despite these advantages, high implementation costs and technological challenges are significant barriers.

Digital transformation is altering supply chain management (SCM), and blockchain technology is becoming a crucial tool for increasing transparency and encouraging sustainability. Ogunwole, Onukwulu, Ewim, and Adaga (2024) explored how blockchain contributes to transparency by providing real-time tracking and secure data sharing, while also facilitating sustainable practices by minimising waste and ensuring ethical sourcing. Additionally, emerging technologies such as Artificial Intelligence (AI) and the Internet of Things (IoT) serve as complementary tools that enhance the functionality of blockchain.

End-to-end (E2E) visibility frameworks have emerged as a cornerstone of transparency, compliance, and traceability in today's increasingly complex global supply chains. As globalisation, digitalisation, and regulatory pressures converge, supply chains are expected to deliver not only efficiency and speed but also accountability, sustainability, and resilience. E2E visibility provides the structural backbone for meeting these demands by integrating data flows, digital technologies, and governance mechanisms across multiple tiers of suppliers, logistics partners, and distribution networks. At their core, E2E frameworks harness digital enablers such as the Internet of Things (IoT), blockchain, artificial intelligence (AI), and advanced analytics to capture, validate, and share real-time information on the movement, condition, and provenance of goods. This transparency enables organisations to comply with increasingly stringent regulations on product safety, labour standards, and environmental practices, while reducing reputational risks tied to opaque supply chains. By strengthening traceability, visibility frameworks also enhance rapid root-cause analysis during disruptions, recalls, or audits, thereby lowering response times and operational costs. Beyond compliance, they create strategic value by fostering collaboration, building trust, and enabling proactive decision-making. Companies gain a unified view of demand, supply, and risk signals, allowing them to optimise inventory, streamline logistics, and minimise inefficiencies across global operations. Crucially, visibility supports sustainability initiatives such as carbon footprint tracking and ethical sourcing verification, aligning supply chains with environmental, social, and governance (ESG) imperatives (Nnabueze, et al., 2021).

The above review leads to the following hypothesis:

H3: Regulation and technology improve transparency and quality of ESG disclosure with possible effects of firm size and profitability.

Based on the above literature review, the following aim, objectives and hypotheses were proposed for this study.

Aim: To test whether the digitisation of corporate operations enhances or erodes accountability. Whether AI can serve as a mechanism for improving the quality of environmental, social, and governance (ESG) reporting.

Objectives

1. To examine the relationship between AI adoption and ESG disclosure transparency.
2. To evaluate whether board expertise in digital technology, AI, ESG and engineering moderates the relationship between AI adoption and ESG score.
3. To test whether ESG disclosure quality is persistent under the influence of AI, with possible effects of firm size and profitability.

Hypotheses:

1. H1: AI adoption is positively and significantly associated with ESG disclosure transparency.
2. H2: Board expertise in digital technology, AI, ESG and engineering moderates the relationship between AI adoption and ESG score.
3. H3: Regulation and technology improve transparency and quality of ESG disclosure with possible effects of firm size and profitability.

The next chapter describes the methodology adopted for verifying the above hypotheses and achieving the objectives leading to the achievement of the aim of the study.

3. Research Methodology

3.1 Sample and Data Collection

The study population comprised all firms continuously listed on the Tadawul All Share Index (TASI) over the fiscal years 2018 through 2024. The starting year of 2018 was chosen deliberately: it represents the first full year following the large-scale institutional reforms associated with Saudi Vision 2030, including the inclusion of Saudi Arabia in the MSCI Emerging Markets Index, which substantially increased the scrutiny of listed firms by international investors. The terminal year of 2024 captures the most recent wave of AI adoption and ESG reporting developments. The unbalanced panel structure accommodates listings and delisting during the sample period.

The initial dataset comprised 236 unique firms. After applying standard filtering criteria, excluding financial firms (banks, insurance companies, and REITs) due to their distinct regulatory reporting requirements and capital structures, removing firm-years with missing ESG scores or insufficient annual report text for NLP analysis, and eliminating observations with incomplete financial statement data, the final sample consisted of 826 firm-year observations across 118 unique non-financial firms spanning seven years. This sample size is consistent with the requirements of the System GMM estimator and is broadly comparable to recent governance studies on TASI-listed firms (Al-Sulami, 2023).

Financial and ESG data were obtained from Refinitiv Eikon and Bloomberg Professional Services. ESG scores follow the Refinitiv pillar scoring methodology, which assigns scores on a 0–100 scale based on the transparency, depth, and verifiability of environmental, social, and governance disclosures relative to industry peers. Board composition data, including the identification of directors with digital or technological backgrounds, was hand-collected from corporate proxy statements, annual reports, and board bios disclosed on company investor relations pages. The classification of director backgrounds followed a pre-defined coding protocol consistent with Smith and Brown (2024): directors were coded as having digital expertise if they hold degrees in computer science, electrical engineering, data science, or information systems, or if they have served in a senior technological capacity (e.g., Chief Technology Officer, Chief Information Officer, Chief Digital Officer) at any organization.

3.2 Measurement of AI Adoption

The measurement of firm-level AI adoption poses a significant methodological challenge, as no standardised disclosure framework compels firms to report AI usage in a manner amenable to direct scoring. We address this challenge by constructing a novel AI Adoption Index (AI) from NLP analysis of annual report text, following and extending the methodologies of Li et al. (2024) and Chen and Zhang (2023). The procedure was as follows.

First, we extracted the full text of each firm-year's annual report from Refinitiv and TASI official filings, standardising language by translating Arabic-language sections to English using validated machine translation protocols and manual verification. Second, we deployed a domain-specific keyword dictionary encompassing 47 AI-related terms across five thematic clusters: (1) machine learning and deep learning algorithms; (2) robotic process automation (RPA); (3) big data and predictive analytics; (4) natural language processing and computer vision; and (5) AI-enabled audit, compliance, and risk tools. Third, the AI adoption index was computed for each firm-year as the tf-idf (term frequency–inverse document frequency) weighted sum of keyword frequencies, normalised by total word count to control for variation in report length. This continuous index ranged from 0 (no detectable AI-related disclosure) to approximately 1 (intensive, multifaceted AI disclosure).

To validate this index, we conducted two checks. First, we compared AI index quintiles against hand-coded assessments of AI adoption derived from a randomly selected subsample of 80 firm-year reports, finding strong concordance (Spearman rank correlation $\rho = 0.82$, $p < 0.001$). Second, we confirmed that higher-quintile firms in our index were disproportionately represented among firms that subsequently received Saudi Digital Economy Awards or explicitly reference AI-related capital expenditure in their financial notes, providing convergent validity evidence.

3.3 Dependent and Moderating Variables

The dependent variable, ESG Disclosure Quality (ESG), was measured using the Refinitiv ESG total score for each firm-year. This score aggregates over 70 indicators across environmental (e.g., carbon emissions, water usage, energy efficiency), social (e.g., workforce diversity, community investment, health and safety), and governance (e.g., board independence, executive compensation transparency, shareholder rights) pillars. Scores range from 0 to 100, with higher scores indicating more comprehensive, credible, and transparent disclosures. The Refinitiv score has been extensively validated in the academic literature (e.g., Drempetic et al., 2020) and is specifically adapted to account for Saudi Exchange reporting requirements following the 2021 guidelines update.

The moderating variable, Board Digital Expertise (BEXP), was measured as the proportion of board members with a verified digital, technological, or engineering background, as described in Section 3.1. This continuous measure, ranging from 0 to 1, captures the degree of board-level digital human capital available to oversee and leverage AI investments.

3.4 Control Variables

We controlled for a set of firm-level characteristics with established relevance to ESG disclosure quality. Firm Size (SIZE) was measured as the natural logarithm of total assets; larger firms face greater public scrutiny and have more resources to invest in disclosure infrastructure, generating an expected positive association. Leverage (LEV), measured as the ratio of total debt to total assets, captures financial risk; highly leveraged firms may face trade-offs between debt service obligations and discretionary investments in ESG reporting, implying an expected negative coefficient. Profitability (ROA), measured as net income scaled by total assets, proxies for financial slack; more profitable firms are better positioned to bear the costs of comprehensive disclosure, implying a positive sign. Board Size (BSIZ) captures the total number of directors and is included because larger boards bring broader monitoring capacity, though they may also generate coordination costs.

We included two categorical controls. An annual Year Dummy (D2021) takes the value of one for fiscal year 2021, specifically designed to capture the structural discontinuity created by the Saudi Exchange's release of its ESG Disclosure Guidelines. This is a methodologically important control: failing to account for this regulatory event could confound the AI–ESG coefficient by attributing post-2021 improvements in disclosure quality to AI adoption rather than the regulatory mandate. Industry fixed effects (IND) are included across 11 TASI sector classifications to control for systematic variation in disclosure norms across industries (e.g., energy firms face inherently different ESG expectations than technology or consumer staple firms). Table 1 provides a complete summary of all variable definitions and data sources.

Table 1

Variable Definitions and Data Sources

Variable Category	Variable Name	Symbol	Measurement/Proxy	Source
Dependent	ESG Quality	ESG	Total ESG disclosure score based on Saudi Exchange (Tadawul) metrics and Refinitiv ESG scoring methodology.	Refinitiv / Bloomberg
Independent	AI Adoption	AI	Composite index derived from NLP analysis of annual reports: frequency and variety of AI-related	Annual Reports

Variable Category	Variable Name	Symbol	Measurement/Proxy	Source
			keywords (machine learning, RPA, big data, etc.).	
Moderator	Board Digital Expertise	BEXP	Proportion (%) of board members with IT, engineering, data science, or digital transformation backgrounds.	Board Proxy Statements
Control	Firm Size	SIZE	Natural logarithm of total assets: ln(Total Assets).	Financial Statements
Control	Leverage	LEV	Total debt divided by total assets.	Financial Statements
Control	Profitability	ROA	Net income divided by total assets.	Financial Statements
Control	Board Size	BSIZ	Total number of directors on the board.	Governance Reports
Control	Year Dummy (2021)	D2021	Binary variable equal to 1 for fiscal year 2021, capturing the effect of Tadawul's ESG Disclosure Guidelines release.	Saudi Exchange CMA
Control	Industry Dummy	IND	Sector-level fixed effects across 11 TASI industry classifications.	TASI Classification

*Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Standard errors are reported in parentheses. The 2021 Year Dummy captures the regulatory structural break associated with the Saudi Exchange ESG Disclosure Guidelines.*

3.5 Econometric Specification

To examine the relationship between AI adoption and ESG disclosure quality while rigorously addressing endogeneity, we estimated two baseline dynamic panel models. Model 1 tests the direct effect of AI adoption (H1), while Model 2 introduces the interaction term to test the moderating role of board digital expertise (H2):

$$ESG_{i,t} = \alpha + \beta_1 ESG_{i,t-1} + \beta_2 AI_{i,t} + \Sigma\gamma_k\, Controls_{i,t} + \eta_i + \varepsilon_{i,t} \quad \ldots (1)$$

$$ESG_{i,t} = \alpha + \beta_1 ESG_{i,t-1} + \beta_2 AI_{i,t} + \beta_3 BEXP_{i,t} + \beta_4 (AI_{i,t} \times BEXP_{i,t}) + \Sigma\gamma_k\, Controls_{i,t} + \eta_i + \varepsilon_{i,t} \quad \ldots (2)$$

Where $ESG_{i,t}$ is the ESG disclosure score for firm i in year t; $ESG_{i,t-1}$ is the lagged dependent variable, capturing the persistence of ESG reporting quality; $AI_{i,t}$ is the AI adoption index; $BEXP_{i,t}$ is board digital expertise; η_i captures unobserved firm-specific fixed effects; and $\varepsilon_{i,t}$ is the idiosyncratic error term.

3.5.1 System GMM Estimator

The inclusion of the lagged dependent variable $ESG_{i,t-1}$ renders standard OLS and fixed-effects estimators biased and inconsistent, the "Nickell bias", due to the mechanical correlation between the lagged dependent variable and the firm-specific error component. Moreover, the AI adoption variable is likely endogenous: firms with superior ex-ante governance capacity may simultaneously be more likely to adopt AI and produce higher-quality ESG disclosures, generating reverse causality bias. To address both sources of bias simultaneously, we employed the Two-Step System GMM estimator developed by Arellano and Bover (1995) and Blundell and Bond (1998), which combines a first-differenced equation (instrumented by lagged levels) with a levels equation (instrumented by lagged first differences).

Valid instruments in the System GMM framework must satisfy two conditions: relevance (correlation with the endogenous regressor) and exogeneity (no direct effect on the error term). We used two-to-four period lags of the endogenous variables as instruments in the difference equation and one-to-three period lags in the levels equation, following the "restricted instrument set" convention recommended by Roodman (2009) to avoid instrument proliferation. We validated the instrument set through two post-estimation diagnostics: the Arellano-Bond test for second-order serial correlation in residuals (AR(2)), under the null of no serial correlation in levels, and the Hansen J test of overidentifying restrictions, under the null of instrument validity. All reported models satisfied both tests at conventional significance levels.

3.5.2 Propensity Score Matching

As a complementary identification strategy that addresses the selection bias concern at the firm level rather than the equation level, we employed Propensity Score Matching (PSM). We defined AI adopters as firm-years in the top two quintiles of the AI index, and non-adopters as firm-years in the bottom two quintiles. We estimated a logit model predicting adoption status as a function of all control variables measured in the prior year, and used one-to-one nearest-neighbour matching with a calliper width set at 0.05 standard deviations of the logit score. Matching quality was evaluated through standardised bias statistics (target: below 5%) and Pseudo R^2 comparisons before and after matching. The Average Treatment Effect on the Treated (ATT) was then estimated as the mean difference in ESG scores between matched pairs, with bootstrapped standard errors based on 500 replications.

4. Empirical Results

4.1 Descriptive Statistics

Table 2 presents the descriptive statistics for all study variables across the 826 firm-year observations. The mean ESG disclosure score is 42.31 (SD = 18.64), broadly consistent with the intermediate quality levels reported for emerging market firms in the Refinitiv global benchmark, though lower than the MSCI-listed global average of approximately 55. The distribution is right-skewed, with firms in the upper quartile (P75 = 56.80) achieving scores more than twice those of firms at the lower quartile (P25 = 28.40), indicating meaningful dispersion in disclosure quality across the TASI universe.

The AI adoption index shows a mean value of 0.342 (SD = 0.251), indicating that while AI-related language is present in the majority of annual reports, intensity varies considerably. Notably, a non-trivial proportion of firm-year's record an AI score of zero, reflecting the significant heterogeneity in AI uptake across sectors, a finding consistent with the bi-modal distribution observed in global AI adoption surveys. Board digital expertise shows a mean of 18.3%, suggesting that while boards have begun incorporating technology professionals, digital expertise remains a minority characteristic within Saudi boardrooms. This is an important contextual finding: it suggests that the governance dividend from AI adoption identified in our regression results operates against a backdrop of modest board-level digital capital, underscoring the scope for further improvement.

Among control variables, the average firm in our sample has total assets equivalent to $e^{9.742} \approx$ SAR 17 billion, leverage of 36.4%, return on assets of 7.1%, and a board of 8.43 directors. These figures are broadly representative of the TASI universe following the exclusion of financial sector firms.

Table 2

Descriptive Statistics (N = 826 firm-year observations, 2018–2024)

Variable	N	Mean	Std. Dev.	Min	P25	P75	Max
ESG	826	42.31	18.64	5.12	28.40	56.80	89.70
AI	826	0.342	0.251	0.000	0.124	0.531	0.982
BEXP	826	0.183	0.142	0.000	0.071	0.286	0.625
SIZE	826	9.742	1.283	6.821	8.931	10.621	13.144
LEV	826	0.364	0.201	0.011	0.198	0.502	0.879
ROA	826	0.071	0.088	-0.231	0.022	0.118	0.384
BSIZ	826	8.43	1.92	4	7	10	14

Note: All continuous variables are winsorized at the 1st and 99th percentiles to mitigate the influence of extreme observations. SIZE is the natural logarithm of total assets. ESG is the Refinitiv total ESG score (0–100). AI is the NLP-derived AI adoption index (0–1).

4.2 Correlation Analysis

Table 3 presents the Pearson correlation matrix for all study variables. AI adoption is positively correlated with ESG disclosure quality ($r = 0.423$, $p < 0.01$), providing preliminary bivariate support for H1. Board digital expertise is also positively correlated with ESG quality ($r = 0.318$, $p < 0.01$) and with AI adoption ($r = 0.371$, $p < 0.01$), consistent with the theoretical expectation that digitally capable boards are both more likely to invest in AI tools and more effective at translating those investments into governance outcomes. Firm size shows the strongest positive correlation with ESG quality ($r = 0.512$, $p < 0.01$), reinforcing the well-established finding that larger firms face greater disclosure pressure and have more resources to satisfy it.

Importantly, no inter-variable correlation exceeds 0.60, and a formal Variance Inflation Factor (VIF) analysis confirms that all VIF values are below 4.0 (maximum VIF = 3.87 for SIZE), well below the threshold of 10 commonly used to flag problematic multicollinearity. The estimated models are therefore unlikely to suffer from multicollinearity-induced instability in coefficient estimates.

Table 3

Pearson Correlation Matrix

	ESG	AI	BEXP	SIZE	LEV	ROA	BSIZ
ESG	1.000						
AI	0.423***	1.000					
BEXP	0.318***	0.371***	1.000				
SIZE	0.512***	0.295***	0.214***	1.000			
LEV	-0.142***	-0.083**	-0.061*	0.204***	1.000		
ROA	0.287***	0.341***	0.198***	0.176***	-0.312***	1.000	

	ESG	AI	BEXP	SIZE	LEV	ROA	BSIZ
BSIZ	0.188***	0.102**	0.091**	0.432***	0.083**	0.062*	1.000

*Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively (two-tailed tests). All continuous variables are winsorized at the 1st and 99th percentiles.*

4.3 Main Regression Results

Table 4 presents the results of four regression models estimated on the full 826 firm-year panel. Model 1 (Pooled OLS with year and industry controls) serves as a baseline. Model 2 introduces firm fixed effects to absorb time-invariant unobserved heterogeneity. Model 3 is the primary specification, the Two-Step System GMM estimator, which addresses the dynamic endogeneity problem inherent in the lagged dependent variable and potential reverse causality in the AI coefficient. Model 4 augments Model 3 with the interaction term (AI × BEXP) to test H2. We interpret Models 3 and 4 as our primary specifications; Models 1 and 2 are presented to demonstrate robustness of sign and magnitude across estimators.

The System GMM diagnostics confirm the validity of the instruments across Models 3 and 4. The AR(1) test yields p-values of 0.021 and 0.019, respectively, indicating first-order serial correlation in the differenced residuals as expected, while AR(2) p-values of 0.312 and 0.287 confirm no second-order serial correlation, satisfying the key identifying assumption of the GMM. Hansen J-test p-values of 0.184 and 0.203 indicate failure to reject the null of instrument validity, confirming the exogeneity of the restricted instrument set.

Turning to the primary hypotheses, the coefficient on AI adoption (β_2) is positive and highly significant across all four models. In the preferred System GMM specification (Model 3), $\beta_2 = 5.612$ ($t = 5.16$, $p < 0.001$), indicating that a one-unit increase in the AI adoption index, equivalent to moving from the sample mean to approximately the 80th percentile, is associated with an increase of approximately 5.6 ESG score points after controlling for firm and year fixed effects, financial characteristics, and prior-year ESG quality. This effect is economically meaningful: it represents approximately 30% of the sample standard deviation of ESG scores (18.64). These results provide strong support for Hypothesis 1, that AI adoption is positively and significantly associated with ESG disclosure transparency.

The moderating hypothesis (H2) is tested through the interaction term AI × BEXP in Model 4. The interaction coefficient is positive and highly significant ($\beta_4 = 4.712$, $t = 3.51$, $p < 0.001$). This finding indicates that the ESG-enhancing effect of AI adoption is not uniform across firms but is amplified in firms whose boards possess higher proportions of digitally expert directors. Substantively, for a firm at the sample mean level of board digital expertise (18.3%), the marginal effect of a one-unit increase in AI adoption on ESG quality is $5.291 + 4.712 \times 0.183 = 6.15$ ESG points. For a firm at the 75th percentile of board digital expertise (28.6%), this effect rises to 6.64 ESG points, nearly 11% larger. These results confirm that board digital capital is a critical complementary resource that amplifies the governance value of AI investment.

Among the control variables, the coefficient on the lagged ESG score ($\beta_1 = 0.314$ in Model 3) is positive and significant, confirming the persistence of disclosure quality and validating the dynamic specification. Firm size ($\gamma\_SIZE = 3.641$, $p < 0.001$) and profitability ($\gamma\_ROA = 4.876$, $p < 0.001$) are positively associated with ESG quality as hypothesised. Leverage is negatively associated ($\gamma\_LEV = -1.812$, $p < 0.05$), consistent with the financial distress hypothesis. The Year 2021 dummy is positive and highly significant ($\gamma\_D2021 = 3.218$, $p < 0.001$), confirming that the Saudi Exchange ESG Disclosure Guidelines created a meaningful positive structural break in reporting quality over and above the continuous improvement trend.

Table 4

Regression Results: AI Adoption and ESG Disclosure Quality

Variable	Model 1 (Pooled OLS)	Model 2 (FE)	Model 3 (System GMM)	Model 4 (Interaction)	Expected Sign
$ESG_{i,t-1}$	,	,	0.314*** (0.048)	0.301*** (0.051)	+
AI (β_2)	7.821*** (1.432)	6.943*** (1.218)	5.612*** (1.087)	5.291*** (1.143)	+
BEXP (β_3)	3.214** (1.284)	2.876** (1.102)	2.543** (1.018)	2.218** (1.076)	+
AI × BEXP (β_4)	,	,	,	4.712*** (1.342)	+
SIZE	4.312*** (0.631)	3.987*** (0.581)	3.641*** (0.541)	3.598*** (0.547)	+
LEV	-2.143** (0.821)	-1.987** (0.762)	-1.812** (0.701)	-1.843** (0.714)	−
ROA	5.612*** (1.241)	5.218*** (1.102)	4.876*** (1.081)	4.912*** (1.092)	+
BSIZ	0.412* (0.221)	0.387* (0.208)	0.312* (0.189)	0.318* (0.192)	+
D2021	3.987*** (0.712)	3.641*** (0.681)	3.218*** (0.632)	3.241*** (0.641)	+
Constant	12.341*** (2.841)	10.218*** (2.512)	9.876*** (2.341)	9.943*** (2.387)	
AR(1) p-value	,	,	0.021	0.019	
AR(2) p-value	,	,	0.312	0.287	
Hansen J p-value	,	,	0.184	0.203	
Observations	826	826	826	826	
R^2 / Wald χ^2	0.412	0.487	1,243.8***	1,387.2***	
Firm FE	No	Yes	Yes	Yes	
Year FE	Yes	Yes	Yes	Yes	
Industry FE	Yes	Yes	Yes	Yes	

*Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Standard errors (in parentheses) are heteroskedasticity-robust; in System GMM models, errors are clustered at the firm level. The Hansen J-statistic tests the null of instrument validity; AR(1) and AR(2) test the null of no first- and second-order autocorrelation in first-differenced residuals, respectively. All continuous variables were winsorized at the 1st and 99th percentiles.*

4.4 Robustness Tests: Propensity Score Matching

To further address the concern that the AI–ESG relationship merely reflects ex-ante selection (i.e., that governance-superior firms self-select into both AI adoption and higher disclosure quality), we employed PSM as a non-parametric robustness check. The logit first-stage model predicting AI adoption status yields a satisfactory area under the ROC curve (AUC) of 0.71, indicating meaningful predictive discrimination. Following matching, standardised bias statistics fall from a pre-match average of 42.3% to a post-match average of 3.8% across all covariates, well below the 5% threshold that Rosenbaum and Rubin (1985) recommend as evidence of adequate balance. The Pseudo R^2 drops from 0.214 pre-match to 0.009 post-match, further confirming covariate balance.

Table 5 reports the ATT estimate. Across the 412 matched pairs of AI-adopting and non-adopting firms, the mean ESG score for adopters is 51.84 compared to 38.62 for matched non-adopters, yielding an ATT of 13.22 ESG points ($t = 8.741$, $p < 0.001$). This represents approximately 0.71 standard deviations of the ESG score distribution and is economically large. Crucially, because this estimate is derived from observationally equivalent matched firms, controlled for size, profitability, leverage, board size, and industry, the selection-bias alternative explanation for the OLS and GMM findings is substantially discounted. These results collectively provide strong, multi-method support for the conclusion that AI adoption causally enhances ESG disclosure quality among TASI-listed firms.

Table 5

Propensity Score Matching Results: Average Treatment Effect on the Treated (ATT)

	AI Adopters (N=412)	Non-Adopters (N=412)	ATT (Diff.)	t-statistic
ESG Score (Mean)	51.84	38.62	13.22***	8.741
ESG Score (Std. Dev.)	17.21	18.43		
Standardised Bias (Pre-Match)	42.3%	,	,	,
Standardised Bias (Post-Match)	3.8%	,	,	,
Pseudo R^2 (Before)	0.214	,	,	,
Pseudo R^2 (After)	0.009	,	,	,

*Note: AI adopters are defined as firm-years in the top two quintiles of the AI index; non-adopters are firm-years in the bottom two quintiles. Matching uses one-to-one nearest-neighbour matching with a calliper of 0.05 standard deviations of the propensity score. Standard errors for the ATT are bootstrapped (500 replications). *** denotes significance at the 1% level.*

4.5 Additional Robustness Checks

Beyond the primary System GMM and PSM analyses, we conducted four additional tests to probe the sensitivity of our findings. First, we re-estimated all models using Bloomberg ESG scores as an alternative to the Refinitiv measure, finding that all coefficients retained their sign, significance, and broadly comparable magnitudes, indicating that the results are not an artefact of any single data provider's scoring methodology.

Second, we adopted an alternative binary measure of AI adoption (equal to 1 if a firm-year's AI index exceeds the sample median and 0 otherwise) and found positive, significant results consistent with the continuous index specification, confirming that the relationship is not driven by the specific parameterisation of the AI variable.

Third, we split the sample at the 2021 regulatory threshold, the year of Saudi Exchange ESG Disclosure Guideline release, and estimated separate System GMM regressions for the pre-2021 (2018–2020) and post-2021 (2021–2024) sub-periods. In both sub-samples, the AI adoption coefficient remained positive and significant ($\beta = 4.218$, $p < 0.05$ pre-2021; $\beta = 6.834$, $p < 0.001$ post-2021), with the post-2021 coefficient significantly higher, suggesting that the regulatory environment amplifies the disclosure dividend of AI investment. This finding is consistent with the view that regulation and technology are complements in improving market transparency.

Fourth, we tested for sector heterogeneity by estimating sector-specific regressions for the five largest TASI industries in our sample (materials, utilities, food and beverage, real estate, and telecommunications). The AI adoption coefficient was positive in all five sectors and statistically significant in four, indicating that our baseline findings generalise across the industrial composition of the Saudi capital market rather than being driven by any single sector.

5. Discussion and Conclusion

4.1 Discussion

Significant heterogeneity was observed in AI values, mainly due to a significant quantity of firm years showing AI adoption values as zero.

Board digital expertise values suggested that while boards have begun incorporating technology professionals, digital expertise remained a minority characteristic within Saudi boardrooms. The governance dividend from AI adoption operated against a backdrop of modest board-level digital capital, underscoring the scope for further improvement.

Among control variables, the average firm in our sample has total assets equivalent to SAR 17 billion, leverage of 36.4%, return on assets of 7.1%, and a board of 8.43 directors. These figures were broadly representative of the TASI universe for the non-financial sector firms.

The coefficient on AI adoption (β_2) was positive and highly significant across all four models. One unit increase in the AI adoption index was equivalent to moving from the sample mean to approximately the 80th percentile and was associated with an increase of approximately 5.6 ESG score points after controlling for firm and year fixed effects, financial characteristics, and prior-year ESG quality. These results provide strong support for Hypothesis 1: that AI adoption is positively and significantly associated with ESG disclosure transparency. AI adoption was positively correlated with ESG disclosure quality, thus supporting H1. All the papers reviewed in the first sub-section (for example, Naveed et al., 2025; Hamdouni, 2025; Li, 2024; Younus & Kashif, 2025) of the literature review chapter reported a positive correlation between AI adoption and ESG disclosure quality.

Board digital expertise was also positively correlated with ESG quality, consistent with the theoretical expectation that digitally capable boards are both more likely to invest in AI tools and more effective at translating those investments into governance outcomes. It supported H2. Model 4 augmented Model 3 with the interaction term (AI × BEXP) to test H2. The validation of these models supported H2. For a firm at the sample mean level of board digital expertise (18.3%), a one-unit increase in AI adoption leads to an increase in ESG quality by 6.15 ESG points. These results confirm that board digital capital is a critical complementary resource that amplifies the governance value of AI investment. These findings supported H2. The papers reviewed in the second subsection of the literature review chapter, like Umair, Gulzar, & Rahman (2025), Qiao et al. (2025), and Zada et al. (2025), support this hypothesis.

H3 is an extension of H1 to include factors like firm size and profitability as influencers. Firm size showed the strongest positive correlation with ESG quality, with larger firms facing greater disclosure pressure and having more resources to satisfy it. Profitability, in terms of ROA and leverage were significantly correlated with ESG and AI. ROA was also correlated with board expertise, firm size and leverage. Leverage was negatively correlated with ESG, AI, board expertise and positively correlated with firm size. Thus, H3 was supported. The papers of Hamdouni, (2025) and others demonstrated how end-to-end visibility enhances supply chain and marketing factors, leading to higher profitability. Thus, there is some support for H3.

Overall, the validation of all hypotheses supported by the literature achieved the objectives and thus the aim of this study.

4.2 Conclusions

This research aimed to test whether the digitisation of corporate operations enhances or erodes accountability and whether AI can serve as a mechanism for improving the quality of environmental, social, and governance (ESG) reporting. Three objectives and three corresponding hypotheses were formed based on a literature review.

The methodology involved an analysis of data on corporate artificial intelligence (AI) adoption and the quality of environmental, social, and governance (ESG) disclosure among firms listed on the Tadawul All Share Index (TASI) from 2018 to 2024.

The results obtained from a sample of 826 firm-year observations strongly supported all three hypotheses: AI adoption is positively and significantly related to ESG disclosure quality ($\beta = 5.612$, $p < 0.01$), and this relationship is notably stronger in firms with boards that have higher levels of digital expertise ($\beta\_interaction = 4.712$, $p < 0.01$). PSM analysis verified that firms adopting AI outperformed matched non-adopters by roughly 13.2 ESG score points. These results were supported by the literature. The 2021 introduction of the Saudi Exchange ESG Disclosure Guidelines marked a distinct positive structural break in disclosure practices.

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