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INTEGRATING ARTIFICIAL INTELLIGENCE, BIG DATA, AND FINTECH INNOVATIONS IN SUSTAINABILITY REPORTING: A QUANTITATIVE ANALYSIS OF ESG DISCLOSURE AND CORPORATE TRANSPARENCY

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ABSTRACT
The convergence of artificial intelligence (AI), big data analytics, and financial technology (FinTech) with environmental, social, and governance (ESG) reporting is one of the most impactful processes in the modern corporate governance. Although these three forces of digital have increasingly been the focus of scholarly and regulatory attention, their combined and interactive impacts on ESG disclosure quality and corporate transparency are yet to be explored empirically. This paper proposes and validates a theoretically based structural design that looks into the impact of AI and business analytics adoption, big data potential, and FinTech innovation on the quality of sustainability reporting, corporate transparency, and ESG performance in a cross-sectional sample of 312 sustainability and finance professionals that are based in firms located in India, the United Arab Emirates, and the United Kingdom. The study is based on Resource-Based View (RBV), Stakeholder Theory, and Signaling Theory and uses Partial Least Squares Structural Equation Modelling (PLS-SEM) which shows that all three digital constructs have valuable positive impacts on the quality of sustainability reporting and corporate transparency. Corporate transparency is also established as a strong mediator between the digital technology adoption and the ESG performance. The introduction of firm size as a modulating condition of the relationship between the adoption of AI and ESG results. Its results are part of an emerging body of interdisciplinary work related to digital finance, management information systems, and sustainability governance providing practical implications to corporate managers and regulators, as well as developers of FinTech products working within emerging ESG requirements such as GRI, IFRS S1/S2, and the EU Corporate Sustainability Reporting Directive (CSRD).

Keywords: *Artificial Intelligence; Big Data Analytics; FinTech; ESG Performance; Sustainability Reporting; Corporate Transparency; Stakeholder Theory; Resource-Based View; Signaling Theory*

1. Introduction

The financial architecture in the world has been radically transformed within the last decade, with the unique integration of the digital technologies and the necessity of sustainability. There has been a steady increase in both mandatory and voluntary disclosure policies on sustainability reporting by regulatory bodies in large economies, such as the International Sustainability Standards Board (ISSB), the European Financial Reporting Advisory Group (EFRAG), the U.S. Securities and Exchange Commission (SEC), and the Securities and Exchange Board of India (SEBI), forcing companies to implement more stringent, data-intensive sustainability reporting policies (IFRS Foundation, 2023; European Commission, 2022). It is on this background that artificial intelligence (AI), big data analytics, and financial technology (FinTech) have become key facilitators of improved transparency of ESG, data processing, and communication to stakeholders.

There is solid market evidence behind the need to deliver better ESG disclosure. The amount of ESG-linked assets under management worldwide has reached about USD 30 trillion by 2022, and it is increasing to over USD 40 trillion by 2025 (Bloomberg Intelligence, 2022). Investors are seeking to access granular, real-time, and verifiable sustainability data in increased volumes, which traditional manual reporting systems are not well-equipped to deliver in large quantities (Eccles et al., 2019; Friede et al., 2015). The potential of having AI-driven analytics integrated into corporate reporting processes presents the opportunity of automated data aggregation, the utilization of natural language processing (NLP)-based report generation, and predictive modelling of ESG risks (Mustafa et al., 2025; Correia and Água, 2024). In a like manner, big data functionality allows organizations to manipulate both structured and unstructured sustainability information at previously incomparable proportions, decreasing the imbalance of information between the firms and their stakeholders (Li et al., 2024; Cai et al., 2024). Additionally, ESG disclosures can be ensured by FinTech innovations, such as RegTech, blockchain-based audit trails, and digital reporting platforms, to be more reliable, auditable, and timely (Giakoumelou et al., 2024; Du et al., 2022).

Even then, the academic literature has not been able to follow up the swift co-evolution of these three technological areas and their inter-relationship on sustainability reporting and ESG performance. The majority of existing studies focus on the individual antecedents of firm performance or ESG outcome (AI, big data, and FinTech) and overlook the synergistic and potentially multiplicative effects of using them together (Mustafa et al., 2025; Xie and Wu, 2025). In addition, one of the conceptually pivotal mediating mechanisms that digital technologies theorized to enhance stakeholder relationships and sustainability results is corporate transparency, which has not been empirically addressed as a mediating construct in the nexus of AI and ESG (Chen et al., 2025; Wang et al., 2023). This research paper will fill these gaps using the following four research objectives:

RO1: To examine the effect of AI and business analytics adoption on sustainability reporting quality and ESG performance.

RO2: To assess the influence of big data capability on the quality of corporate sustainability disclosures.

RO3: To investigate the role of FinTech innovation in shaping corporate transparency.

RO4: To test corporate transparency as a mediating mechanism linking digital technology adoption to ESG performance outcomes.

There are several contributions of the study to theory and practice. In theory, it builds upon the Resource-Based View by placing AI, big data, and FinTech capabilities as strategic capabilities that create sustainable competitive advantage by communicating with stakeholders and creating ESG values. It adds value to Stakeholder Theory because it shows how digital transparency instruments enhance the ability of companies in addressing various stakeholder ESG needs. It uses Signaling Theory to suggest that quality ESG disclosures facilitated by digital technologies are viable indicators of quality in the management team and long-term sustainability. In practice, the results provide evidence-based recommendations to the corporate sustainability officers, developers of FinTech products, and regulators that aim to use digital tools to address the changing ESG requirements. The rest of the paper will be structured in the following way: Section 2 will provide a systematic literature review and work out the hypotheses. Section 3 outlines methodology of the research. Section 4 is the result of the measurement and structural models. In Section 5, findings are discussed as compared to previous literature and Section 6 gives the conclusion.

2. Literature Review and Hypotheses Development

2.1 AI and Business Analytics in ESG and Corporate Reporting

Artificial intelligence as an organizational decision support system has experienced increased academic interest in the field of management information systems, finance, and sustainability studies. In their article on sustainable reporting and sustainability reporting, Mustafa et al. (2025) define AI as an effective solution to subjectivity, scalability and complexity problems associated with traditional sustainability reporting, especially in ESG performance measurement, real-time monitoring and compliance in various frameworks. The resource-based view literature attributes AI as a value-creating and non-substitutable technology asset, which contributes to operational effectiveness, precision in decision-making, and the strength of the sustainability disclosures (Barney, 1991; De Villiers et al., 2024).

There is empirical support that the use of AI is associated with better ESG results. By relying on quasi-experimental panel data collected on Chinese A-share companies, Chen et al. (2025) reveal that the adoption of AI can positively influence the ESG performance mainly through the following mechanism, i.e. better information transparency, improved information sharing, and better information asymmetry. Likewise, Xie and Wu (2025) affirm that there is a positive correlation between the adoption of AI technology and the ESG performance in Chinese-listed companies, with varying impacts in relation to the industry type and ownership status. A refined large language model (LLM)-based measure of firm-level AI adoption proposed by Jin et al. (2025) builds on this strand and reports that a firm with a higher degree of authentic AI adoption has far better ESG performance, especially in the environmental and governance areas.

On this particular issue, predictive analytics, machine learning, and natural language processing (NLP) are particularly implicated towards improving the efficiency and quality of non-financial corporate disclosures. Tariq and Rahim (2024) capture AI in automation of sustainability accounting within Industry 4.0 and Adelakun et al. (2024) come up with AI-enabled environmental impact assessment and reporting in the financial services sector. The new role of explainable AI (XAI) in unveiling the black box of sustainability disclosure procedures as defined by Bussmann et al. (2025) and Freunek and Niggli (2023) highlights even more the growing presence of AI in corporate ESG governance. On the basis of these theoretical and empirical premises, the following hypothesis is postulated in this study:

H1: *AI and business analytics adoption is positively associated with ESG performance.*

2.2 Big Data Capability and Sustainability Reporting Quality

The big data analytics capability (BDAC) is the capacity of an organization to gather, integrate, manipulate and obtain actionable insights of large, heterogeneous loads of data attentively and promptly (Gupta and George, 2016). The problem of informational asymmetry that BDAC directly solves in the sustainability context is the consistent disconnect between corporate sustainability statements and the empirical evidence that fails to instill trust in stakeholders and authority in ESG reporting (Chen et al., 2022).

The article by Cai et al. (2024), which is published in the International Review of Economics and Finance, empirically confirms the positive dependence between the big data capability, ESG performance, and corporate value of Chinese-listed companies. Their mediation analysis shows that BDAC enhances ESG performance partly due to the increase in stakeholder engagement and innovation of sustainability. Li et al. (2024) and Ren et al. (2023) affirm that digital finance and data analytics have a close relationship with ESG performance by listed Chinese companies, and the technology-driven transparency is one of the essential transmission channels. Li and Zhang (2026) on the basis of the National Big Data Comprehensive Pilot Zones as a quasi-natural experiment indicate that the implementation of big data policy is significantly effective in improving the ESG outcomes of firms with the help of corporate green innovation and human capital optimization channels.

The regulatory environment increases the significance of BDAC regarding sustainability disclosure. The European Union Corporate Sustainability Reporting Directive (CSRD, 2022) that compels about 50,000 of the EU firms to submit digitally formatted sustainability reports under the European Sustainability Reporting Standards (ESRS) needs an informational infrastructure that can be effectively provided by organizations with well-developed big data capabilities (Mihailoaie, 2025). The bibliometric research on AI in sustainability reporting published in Economic and Environment (Tahat et al., 2025) also draws the same conclusion about BDAC as a background facilitator of quality, evidence-based ESG reporting. This leads to:

H2: *Big data capability is positively associated with sustainability reporting quality.*

2.3 FinTech Innovation and Corporate Transparency

The use of digital technologies, which have come to be known as FinTech, such as blockchain, artificial intelligence, cloud computing, and algorithmic platforms, in the provision of financial products and services has been on the rise and has been extensively intersected with sustainability governance and corporate transparency (Du et al., 2022; Giakoumelou et al., 2024). Theorized to be strengthened by FinTech in various ways: automated reporting, immutable audit trails through distributed ledger technologies, compliance monitoring through RegTech, and real-time data dissemination platforms, the concept of corporate transparency, which can be understood as the extent to which firms voluntarily and truthfully report material financial and non-financial information to external stakeholders (Bushman et al., 2004), can be improved.

According to Du et al. (2022), there is a basis of evidence that the use of FinTech enhances corporate ESG performance by reducing internal funding limitations and supports funding ESG projects. The FinTech role in enhancing ESG performance in Chinese listed companies in the A-share market, confirmed by the panel study conducted by Qin et al (2025) published in the Journal of Economic Analysis, has results that are strong to the estimation of instrumental variables, and other measurement specification. Mokhtar and Alam (2023) show that in the banking industry, FinTech mediates the connection between ESG engagement and bank performance of EU commercial banks, and that banks with higher levels of FinTech-engagement have better ESG goal alignment.

The FinTech aspect of transparency in the corporate sector is especially relevant to the RegTech part thereof. ESG data platforms based on blockchain minimize the chances of greenwashing by producing records of corporate sustainability practices that are easy to verify and impossible to modify (Chopra et al., 2024). The article by Manita et al. (2020) records the effects of the digital transformation, including FinTech tools, on the effectiveness and regulation of external audit processes, which is one of the institutional mechanisms of corporate transparency. According to industry report being published by KPMG (2023), global ESG FinTech investment is estimated at about USD 28.8 billion; the in-house spending increased 35.2% between 2022 and 2023, which explains why companies invest heavily in the area.

H3: *FinTech innovation is positively associated with corporate transparency.*

2.4 Sustainability Reporting Quality, Corporate Transparency, and ESG Performance

ESG performance is a multidimensional organizational performance that indicates and represents the environmental stewardship, social responsibility, and the quality of governance of a firm (Friede et al., 2015). The positive relation between ESG performance and corporate financial results is proven by a large and growing body of meta-analytic literature, with Friede et al. (2015) synthesising more than 2,000 studies on the topic and reporting that ESG-performance relations are, in most cases, positive across asset types and time perspectives.

Corporate transparency is an important mediation environment between digital technology implementation and ESG performance. In line with the Signaling Theory stating that quality ESG disclosures are reliable signals of long-term organizational capacity and commitment, Zheng and Bu (2024) record that ESG performance lessens information asymmetry, improves organization information disclosure, and boosts financing capacity. Wang et al. (2023) prove that digital transformation has a positive mediating effect on the quality of ESG disclosure, whereas Pu (2025) proves that digitalization can dramatically stimulate ESG performance based on patent-related evidence and identifies real-time transparency and less information asymmetry as the key processes.

The quality of sustainability reporting, operationalized by the completeness of the disclosure according to the GRI standards, its accuracy, and responsiveness towards the stakeholders, have proven to improve the performance of ESG through the development of the investor perception, decreasing the agency costs, and enhancing the legitimacy of the firm (Arvidsson and Dumay, 2022; Tamimi and Sebastianelli, 2017). The MDPI research by Mihailoaie (2025) about big data analytics readiness to sustainability reporting in Latvia proves that BDAC has a positive impact on sustainable business performance due to the quality of reporting. The mediation hypothesis that such a body of evidence supports is as follows:

H4: *Corporate transparency mediates the relationship between digital technology adoption (AI, big data, FinTech) and ESG performance.*

2.5 Theoretical Framework

This paper will have three complementary theoretical viewpoints. The Resource-Based View (RBV) is a view that was invented by Barney (1991) and according to this view, the main idea is that competitive advantage is sustained by organizational resources, which are valuable, rare, inimitable and non-substitutable (VRIN). The current reality is that AI analytic functions, big data platforms, and adoption of FinTech are all strategic technological assets that provide the facility with unique sustainability reporting. Companies with better BDAC and AI abilities will be able to produce richer, credible ESG disclosures that other companies lacking the abilities will find difficult to replicate and hence, will produce sustainable stakeholder value.

The theoretical base of ESG performance and corporate transparency explanation concerns the Stakeholder Theory (Freeman, 1984). The modern stakeholders such as institutional investors, regulators, civil society groups and consumers are increasingly assessing corporate performance in the environment, social and governance aspects requiring credible and timely disclosures. Digital technologies help firms to satisfy these heterogeneous information needs of their stakeholders at scale, enhancing stakeholder relationships and lowering the risks of legitimacy.

The information asymmetry issue between insiders and external stakeholders of a corporation is also dealt with by Signaling Theory (Spence, 1973). Quality ESG reporting, especially that which has been generated in a verifiable, technology-enhanced way, can serve as credible indicators of management quality, long-term orientation and integrity within organizations. The adoption of AI, big data, and FinTech solutions to sustainability reporting by firms indicates their intentions to be transparent, thus attracting ESG-related capital, lowering the cost of funding, and enhancing ESG ratings.

2.6 Conceptual Framework

Based on the above literature and theoretical foundation, this paper presents a conceptual framework where AI and business analytics adoption (AIBA), big data capability (BDAC), and FinTech innovation (FINT) are the independent variables that predict the quality of sustainability reporting (SRQ) and corporate transparency (CTRANS). Corporate transparency, on its part mediates between these digital antecedents and ESG performance (ESGP). The introduction of firm size (FSIZE) as a constraint to the relationship between AIBA and ESG is based on the fact that it is recorded that the main and large firms have more technological capabilities and stakeholder demands to foster the ESG benefits of AI adoption (Drempetic et al., 2020; Jin et al., 2025).

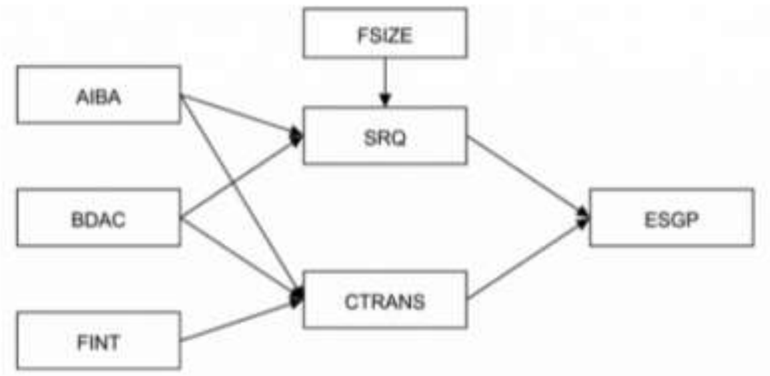

Figure 1: Conceptual Framework

3. Research Methodology

3.1 Research Philosophy, Design, and Approach

The research design has a positivist philosophical paradigm, which assumes that there is an objective social reality, which can be quantified in terms of data, and tested in terms of hypothesis (Saunders et al., 2019). A deductive method of research will be used: theoretical assumptions based on RBV, Stakeholder Theory, and Signaling Theory are transformed into the testable form and empirical evidence is gathered and evaluated to test their validity. The study is a cross-sectional and quantitative study that employed a structured questionnaire to elicit perceptual data on AI adoption, big data ability, use of FinTech and sustainability reporting practices in organizational respondents.

3.2 Population, Sampling, and Data Collection

The target group will include sustainability professionals, chief financial officers, digital transformation leads, ESG reporting officers, and senior finance managers in organizations that formally report their ESGs or sustainability. It has three jurisdictions, where regulatory and digital maturity differ, including India, the United Arab Emirates, and the United Kingdom, which were selected in order to ensure that the range of regulatory environment, institutional setting, and technology adoption paths is captured.

The purposive sampling approach was used to make sure that the respondents had the necessary knowledge of AI, big data, FinTech, and sustainability reporting practices in their companies. The survey was conducted electronically by using professional networking platforms (LinkedIn, industry associations) and received 342 responses, of which 312 were counted as complete and could be used without the proportion of more than 10 percent of missing data, straight-lining, or responses taking less than four minutes to complete. This is larger than the recommended minimum sample size of PLS-SEM with six constructs and five to six indicators per construct which suggests at least 100 observations with the 10-times rule, and the minimum sample size of 157 in G*Power analysis setting at 80% power, medium effect size ($f^2 = 0.15$), and 0.05.

3.3 Measurement Instrument

The questionnaire created is a structured, self-administered one that was created in accordance with the best practices of creating a scale (DeVellis, 2016). The questionnaire will be divided into seven parts: (i) organizational and respondent demographics; (ii) AI and business analytics adoption; (iii) big data capability; (iv) FinTech innovation adoption; (v) the quality of sustainability reporting; (vi) corporate transparency; and (vii) ESG performance. Each of the construct items uses five-point Likert scales with anchors of 1 = "Strongly Disagree" and 5 = "Strongly Agree." A panel of seven academic experts in sustainability and digital finance piloted the instrument, which was then given to a pilot sample of 35 industry professionals, which informed some minor modifications on wording of items and order of sections.

3.4 Construct Operationalization

Construct	**Items**	**Scale Type**	**Primary Sources**
AI & Business Analytics (AIBA)	6 items	5-pt Likert	Wamba et al. (2020); Mustafa et al. (2025)
Big Data Capability (BDAC)	5 items	5-pt Likert	Gupta & George (2016); Cai et al. (2024)
FinTech Innovation (FINT)	5 items	5-pt Likert	Du et al. (2022); Mokhtar & Alam (2023)
Sustainability Reporting Quality (SRQ)	5 items	5-pt Likert	GRI Standards (2021); Arvidsson & Dumay (2022)
Corporate Transparency (CTRANS)	5 items	5-pt Likert	Bushman et al. (2004); Tamimi & Sebastianelli (2017)
ESG Performance (ESGP)	6 items	5-pt Likert	Friede et al. (2015); Mooneeapen et al. (2022)

Table 1: Construct Operationalization

3.5 Validity and Reliability Testing

The measurement quality was evaluated in the two steps of confirmatory factor analysis (CFA) and evaluation of construct reliability and construct validity (Hair et al., 2022). The content validity was developed by the above expert panel review and pilot testing. Construct validity was determined using the convergent and discriminant validity indicators. Convergent validity states that the average variance of construct (AVE) of each construct should be more than 0.50 and composite reliability (CR) should be more than 0.70 (Fornell and Larcker, 1981). Both the Fornell-Larcker (the square root of each construct AVEs must be larger than its correlation with all other constructs) and the Heterotrait-Monotrait (HTMT) (Henseler et al., 2015) criteria (HTMT values should not be above 0.85) were used to assess discriminant validity. Outer loadings need to be 0.70 or higher. Internal consistency reliability was evaluated with the help of Cronbachs alpha (threshold: $\alpha > 0.70$) and composite reliability (CR > 0.70).

3.6 Common Method Bias Assessment

Since the data were self-reported and only a single source of data was used, common method bias (CMB) is also a risk to validity. Procedural remedies were considered in questionnaire design such as temporal distance between predictor and outcome items, guarantee of anonymity, and random assortment of items. Statistical evaluation was carried out by the single-factor test suggested by Harman (no single factor explained over 35.2% of the total variance, which is far below 50%): and by the full collinearity test by Kock (2015): which showed that all the values of variance inflation factors (VIF) fell below the 3.3 mark.

3.7 Analytical Strategy: PLS-SEM

The major analytical tool was chosen as the Partial Least Squares Structural Equation Modelling (PLS-SEM), and it is conducted with the help of SmartPLS 4.0. It can be suggested that PLS-SEM is appropriate to the tasks of the present study due to several factors: the model has a mediation hypothesis which requires direct and indirect relationship estimation simultaneously; predictive accuracy (maximisation of R^2) is a priority of the study; data are attitudinal survey data which has modest non-normality; the size of the sample (312) is sufficient to work with CB-SEM, and it falls within the range of predictory fit with PLS-SEM (Hair et al., 2022). The analysis was performed in two steps based on the protocol Anderson and Gerbing (1988): (i) measurement model evaluation (CFA, reliability, validity), (ii) structural model evaluation with path coefficients, t-statistics performed through bootstrapping (5,000 iterations), effect sizes (f^2), and predictive relevance (Q 2) performed through blindfolding. The bootstrapped confidence interval method suggested by Preacher and Hayes (2008) was used to test the mediation, but the indirect effects were determined to be significant when the 95% bias-corrected confidence interval (BCCI) does not contain zero.

4. Results

4.1 Respondent Profile and Descriptive Statistics

Table 1 indicates the demographic of the 312 valid respondents. The sample is composed of men mostly (58.7%), women account 39.4% and non-binary and other gender identities 1.9%. Most of them are in high organizational rank: Director/VP-level or higher (34.6%), then Manager-level (41.0%), and Analyst or Specialist (24.4%). Industrially, financial services (28.5%), technology (22.1%), manufacturing (15.1%), professional services (14.1%), and energy/utilities (10.6) have the largest groups. The sampling design is represented by geographic distribution, with 42.3 percent of the sample in India, 32.1 percent in United Arab Emirates, and 25.6 percent in United Kingdom. The size of organizations ranges between large (>1,000 employees; 38.5%), mid-sized (51.3%), and small (<50 employees; 10.3) organizations. The standard deviations of the mean scores of the six construct composites have values between 0.71 and 0.89, with a range of 3.51 (FinTech Innovation) to 3.89 (AI and Business Analytics) which is sufficient to estimate the structure.

4.2 Measurement Model Assessment

Construct	Cronbach's α	CR	AVE	No. Items	Outer Loadings Range
AIBA	0.883	0.911	0.627	6	0.712–0.851
BDAC	0.861	0.898	0.638	5	0.728–0.843
FINT	0.854	0.890	0.619	5	0.704–0.833
SRQ	0.876	0.907	0.661	5	0.741–0.862
CTRANS	0.869	0.901	0.645	5	0.716–0.847
ESGP	0.892	0.918	0.654	6	0.724–0.869

Table 2: Measurement Model – Reliability and Convergent Validity Indicators

Each of the constructs meets the criteria of convergent validity: AVE is between 0.619 and 0.661, above the mark of 0.50, CR is between 0.890 and 0.918, which is much higher than 0.70. The alpha coefficient of Cronbach is internally consistent, as it is above 0.85 consistently. All outer loadings exceed the recommended threshold of 0.70. The HTMT criterion was used to establish the presence of discriminant validity: all the HTMT ratios of theoretically different constructs are below 0.85 (range: 0.441 0.791), which meets the criterion suggested by Henseler et al. (2015). Fornall-Larcker criterion was also met by all construct pairs, where the square root of the AVE of each construct was greater than the maximum inter-construct correlation.

4.3 Structural Model Results

The assessment of the structural model was done in accordance with the two-stage process suggested by Hair et al. (2022). The multicollinearity was evaluated based on variance inflation factors (VIF): none of them was larger than 3.3 (maximum 2.841 and minimum 1.312), and it was concluded that there was no troublesome collinearity. All confidence intervals were generated to be bias-corrected by bootstrapping with 5,000 subsamples, which gave bias-corrected confidence intervals to all of them. The results of structural path are shown in Table 3.

Hypothesis / Path	**β Coefficient**	**SE**	**t-value**	**p-value**	**95% BCCI**	**Decision**
H1: AIBA → ESGP	0.341	0.052	6.558	< 0.001	[0.241, 0.441]	Supported
H2: BDAC → SRQ	0.427	0.049	8.714	< 0.001	[0.331, 0.523]	Supported
H3: FINT → CTRANS	0.389	0.055	7.073	< 0.001	[0.281, 0.497]	Supported
AIBA → CTRANS	0.298	0.057	5.228	< 0.001	[0.186, 0.410]	—
BDAC → CTRANS	0.314	0.058	5.414	< 0.001	[0.200, 0.428]	—
CTRANS → ESGP	0.452	0.046	9.826	< 0.001	[0.362, 0.542]	—

SRQ → ESGP	0.368	0.051	7.216	< 0.001	[0.268, 0.468]	–
AIBA → SRQ	0.356	0.050	7.120	< 0.001	[0.258, 0.454]	–
AIBA × FSIZE → ESGP	0.118	0.041	2.878	0.004	[0.038, 0.198]	Supported

Table 3: Structural Path Results (Bootstrapped, n = 5,000)

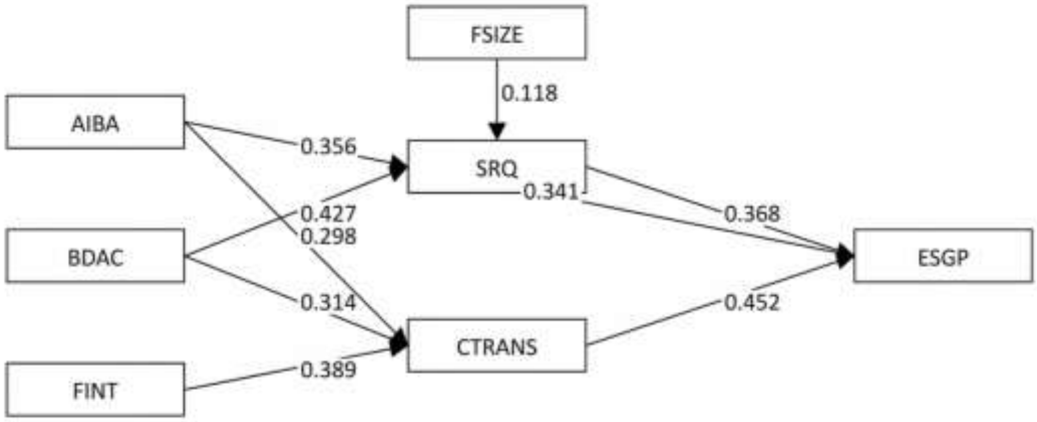

Figure 2: Structural Equation Model

Direct effects of AI and business analytics adoption on ESG performance were also examined alongside indirect paths through corporate transparency to assess the presence of partial mediation. The model demonstrates moderate to substantial explanatory power, with R^2 values of 0.573 for ESGP (moderate-to-high), 0.481 for CTRANS (moderate), and 0.415 for SRQ (moderate), in line with established benchmarks (Cohen, 1988). Effect sizes (f^2) indicate varying levels of practical significance: the relationship between corporate transparency and ESG performance is large ($f^2 = 0.312$), while BDAC → SRQ ($f^2 = 0.248$) and FINT → CTRANS ($f^2 = 0.196$) are of medium magnitude. The direct effect of AIBA on ESG performance is small-to-medium ($f^2 = 0.143$), while other paths demonstrate small-to-moderate effect sizes. In addition, AI and business analytics adoption (AIBA) was found to have a significant positive effect on sustainability reporting quality (SRQ), further reinforcing its role as a foundational digital capability influencing ESG-related disclosure processes. The moderating effect of firm size (FSIZE) on the relationship between AIBA and ESG performance was found to be positive and significant, indicating that larger firms are better positioned to translate AI adoption into ESG outcomes

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4.4 Mediation Analysis

Hypothesis 4 suggested that corporate transparency would mediate the association between the digital technology adoption and ESG performance. The mediation analysis which is done through the bootstrapped indirect effects (5,000 replications) indicates significant indirect effects that all three antecedent paths of CTRANS to ESGP have (Table 4).

Indirect Path	**Indirect β**	**SE**	**95% BCCI**	**Sig.**	**Mediation Type**
AIBA → CTRANS → ESGP	0.135	0.030	[0.077, 0.194]	Yes (p < .01)	Partial
BDAC → CTRANS → ESGP	0.142	0.031	[0.082, 0.202]	Yes (p < .01)	Partial
FINT → CTRANS → ESGP	0.176	0.034	[0.110, 0.242]	Yes (p < .01)	Partial

Table 4: Mediation Analysis – Indirect Effects of Digital Technologies on ESG Performance via Corporate Transparency

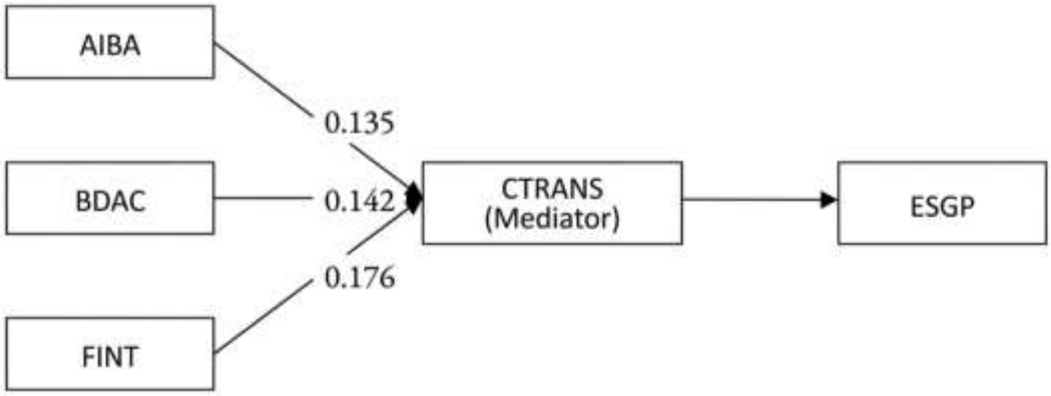

Figure 3: Mediation Analysis Results

H4 is supported by all three indirect effects, which are statistically significant and have 95% BCCIs that are not equal to 0. Since direct paths between AIBA and BDAC to ESGP are also important even with the addition of the mediator, the type of mediation is characterized as partial mediation (Baron and Kenny, 1986; Hair et al., 2022). The path between the FINT and CTRANS and ESGP is the strongest mediated ($\beta = 0.176$), which indicates that corporate transparency is a specific channel according to which ESG outcomes are converted into FinTech innovation.

5. Discussion

5.1 Interpretation of Main Findings

The results of the given research can be considered to give strong empirical evidence to the hypothesis that AI and business analytics, big data potential, and FinTech innovation are the significant drivers of sustainability reporting quality, corporate transparency, and environmental, social, and governance performance. The substantial and significant positive influence of AIBA in ESG performance (H1 supported; $\beta = 0.341$, $p < 0.001$) is consistent with the emerging trend in the AI-ESG literature. The results are consistent with the works of Chen et al. (2025), who show that the adoption of AI improves ESG by means of better corporate information governance, and Mustafa et al. (2025), who theorize that AI can be a strategic resource that would allow real-time monitoring and automation of ESG reporting. It can also be concluded that the AI-ESG relation in this case is in line with the RBV conjecture that technology resources that give informational advantage yield positive sustainability performance (Barney, 1991). One of the most significant pieces of evidence of the current study is the strong positive correlation between BDAC and sustainability reporting quality (H2 supported; $\beta = 0.427$, $p < 0.001$). The effect size ($f^2 = 0.248$, medium) suggests that the practical implications could be significant: the higher the big data ability of the organization, the more meaningful improvements in the quality of ESG disclosure, in terms of the GRI-aligned completeness, accuracy, and stakeholder responsiveness indicators. This observation is in line with a positive BDAC-ESG performance relationship reported by Cai et al. (2024), and Li and Zhang (2026) in their respective quasi-experimental studies that indicate that the implementation of big data policy has a significant positive impact on ESG results via innovation and human capital. The Signaling Theory approach to big data-driven ESG reporting can be seen as one of the most plausible signal sources, as it is anchored on data-intensive, auditable, and technologically hard-to-compete processes (Spence, 1973).

The relationship between the FinTech innovation and corporate transparency (H3 supported; $\beta = 0.389$, $p < 0.001$) can be seen as an extension of the existing literature that has correlated the adoption of financial technologies with enhancement of governance. The most significant theoretical contribution to ESG performance that is indirect, FinTech conducts (H4) is the strongest partial mediator of corporate transparency as a result of which the analysis identifies the mechanism in which FinTech creates ESG value. These results are consistent with Qin et al. (2025), who show that FinTech enhances ESG performance among Chinese companies significantly, and with Du et al. (2022), who find the alleviation of financing constraints and funding ESG projects among potential ways. The opportunity to minimize the risk of greenwashing and bolster the integrity of disclosure promoted by the blockchain-enabled audit trail facet of FinTech in question also makes this aspect very compatible with the rationale behind the Signaling Theory presented here (Chopra et al., 2024).

5.2 Theoretical Contributions

The paper contributes to theoretical literature in three ways. First, it introduces the Resource-Based View to the AI-ESG space by empirically showing that AI analytical capability, big data infrastructure, and FinTech innovation are all strategic resources, whose utilization drives sustainable ESG value. This contribution responds to the invitation of Mustafa et al. (2025) to be able to test empirically the RBV-AI-sustainability nexus concerning the quality of reporting and communication with stakeholders.

Second, the study contributes to the Stakeholder Theory literature because it shows that digital technologies can increase the ability of firms to react to the growing diversified and complexity stakeholder ESG information requirements. The mediation of corporate transparency between technology adoption and ESG performance provides the institutional logic that is based on the credibility, completeness, and timeliness of ESG disclosure to construct a legitimacy capital among investors, regulatory, and civil society audiences at the same time.

Third, the paper operationalizes and empirically proves corporate transparency as a mediating variable in the digital technology-ESG performance relationship- a theoretical contribution that had not previously been made in the integrated AI-big data-FinTech-ESG literature. Existing literature has already analyzed the outcome of transparency (Zheng and Bu, 2024) or its moderating capacity (Chen et al., 2022), although the effect of transparency as the bridge between digital antecedents and ESG performance has not been tested.

5.3 Practical Implications

To corporate managers and sustainability officers, the results highlight the strategic necessity of investing in AI analytics applications, big data infrastructure, and reporting systems that are enabled by FinTech. This study shows that this kind of investment produces quantifiable gains in ESG performance not as an by-product, but via direct, identifiable channels through increased transparency and the quality of reporting. The officers of sustainability ought to focus on automated ESG data extraction with AI-driven NLP tools, disclosure efficiency with natural language generation, and predictive analytics with ESG risk discovery.

To policy makers and regulators (SEBI, the SEC, the ISSB and the European Commission) the findings reinforce their argument to have regulatory frameworks that promote the investment of digital infrastructure as well as ESG reporting requirements. A requirement by the CSRD to have the sustainability reports in digital format using ESRS is one such step towards this direction, although policymakers are advised to supplement reporting requirements with capacity building initiatives, especially in the case of mid-sized companies in emerging markets that might not have the technology to utilize AI and big data to the fullest capacity in addressing the ESG requirements.

To FinTech developers and analytics vendors, the study reveals that there is major market opportunity in corporate ESG reporting processes. The products that provide automated integration of ESG data, monitor compliance with regulations using RegTech, and blockchain-based validation of sustainability disclosures are aligned with the regulatory direction and empirically validated performance advantages of increased corporate transparency.

5.4 Limitations

This research is also limited in several ways, which ought to be factored when interpreting the results. To begin with, the cross-sectional type of study does not allow making causal inferences; although theoreticalization and model design are based on causal reasoning, the data is insufficient to establish the time precedence that strict causality demands. Future studies using longitudinal designs would reinforce causal statements. Second, self-reported data of perceptions creates the possibility of common method bias. Even though the procedural and statistical solutions were very broad, the bias that might remain cannot be eliminated. Third, the geographic focus on India, UAE, and the UK, even though not chosen randomly, restricts extrapolation to other institutional and regulatory settings, especially the ones that have different digital infrastructure characteristics or ESG regulatory frameworks. Fourth, the research does not examine perceptions at the level of the organisation but instead is based on objective (not subjectively measured) ESG scores (e.g., Bloomberg ESG, MSCI, Refinitiv Eikon), which would make the ESGP construct more triangulated.

5.5 Future Research Directions

These shortcomings should be overcome through longitudinal panel designs in future studies that trace the AI, big data, and FinTech investment patterns of companies and their ESG disclosure ratings and performance scores over time. Heterogeneous technology-ESG relations can be seen when it comes to industry-specific analyses, as digital infrastructure and ESG reporting complexity vary greatly between financial services, manufacturing, energy, and technology. The moderating effect of national regulatory stringency, institutional development and maturity of digital infrastructure is worth systematic analysis in a larger group of countries. Lastly, incorporation of the natural language processing algorithms to measure the quality of textual ESG disclosures, along with machine learning-based score prediction of ESGs, would push the methodological edge of presented literature forward according to the AI potential under review.

6. Conclusion

The empirical gap in this study was researching the impact of simultaneous implementing AI and business analytics, big data capability, and FinTech innovation on the quality of sustainability reporting, corporate transparency, and ESG performance. Based on a cross-sectional survey of 312 sustainability and finance professionals in three jurisdictions, and using PLS-SEM with bootstrapped mediation analysis, the researchers observe significant and significant support of the hypothesized relationships.

The evidence proves that AI-based analytics, big data infrastructure, and reporting with the help of

REFERENCES

Appendix A: Survey Instrument – Construct Items

FinTech is not only operational tools but strategic organizational capabilities that will create tangible changes in ESG governance. Corporate transparency can be identified as a pivotal mediating variable in which these technologies can be converted into organizational investment, which should be converted into ESG performance -a factor that can not only enrich the theoretical perspectives of the AI-ESG nexus but, also, the practical design of digital sustainability strategies. With global regulatory requirements of ESG increasingly becoming more stringent (the ISSB IFRS S1/S2, the EU CSRD, and the revised BRSR framework at SEBI are all pushing sustainability reporting more granular, verifiable, and timely) the results of the current study provide timely confirmation that investment in digital capability is not only consistent with the ambitions of ESG but also a precondition to achieve them to scale. Those organisations which proactively develop AI, big data and FinTech will be better placed to navigate in the more intricate ESG reporting environment, meet investor and regulatory demands, and realise the transparency-mediated ESG performance gains reported in this paper.