A Conceptual Model for Enhancing Environmental, Social, and Governance (ESG) Outcomes through Artificial Intelligence in Saudi Arabia

Khaleed Omair Alotaibi
College of Business, Imam Mohammad Ibn Saud Islamic University (IMSIU), Riyadh, Saudi Arabia
komalotaibi@imamu.edu.sa (corresponding author)

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ABSTRACT

This study developed a five-layer conceptual model for integrating Artificial Intelligence (AI) into Environmental, Social & Governance (ESG) management in Saudi Arabia. Guided by the Technology-Organization-Environment (TOE) framework and Institutional Theory, the model encompasses data infrastructure, AI analytics, governance mechanisms, stakeholder engagement, and outcome measurement, with four Saudi-specific cross-cutting enablers operating across all layers. A comparative analysis of four pioneering Saudi AI-ESG initiatives, including Sustain Insight, AhyaOS, SenseTime's AI Eco360, and the national SUSTAIN platform, was developed to validate the framework, assessing each model layer across diverse sustainability domains. The results demonstrated that AI substantially enhanced governance automation, accountability, social impact, and proactive environmental management, with Saudi Arabia's national AI infrastructure providing favorable enabling conditions. This is the first conceptual framework for AI-ESG integration in the Gulf region, providing insights for policymakers and practitioners, given that AI in the Gulf context has emerged as a challenge for social contract management aligned with Saudi Vision 2030.

Keywords-Artificial intelligence; ESG outcomes; Saudi Arabia; conceptual model; conceptual framework; sustainability; Vision 2030; technology governance; SDAIA; Gulf region

I. INTRODUCTION

The combination of Artificial Intelligence (AI) and Environmental, Social & Governance (ESG) performance has opened a new area for the development of sustainability management techniques. As regulators, investors, and the public force companies to provide evidence of ESG progress, AI can transform how organizations manage, perform, and report their ESG data. This is particularly valid for developing countries with a high rate of digital adoption and emerging AI sustainability frameworks.

Saudi Arabia is a representative example, through Vision 2030 [1], which seeks to diversify the national economy and advance both sustainability and AI. Saudi Data and AI Authority (SDAIA) has established national AI infrastructure aligned with the Saudi Green Initiative [2, 3], thereby enabling cross-institutional collaboration among government, industry, and civil society. For example, authors in [4] investigated the relationship between AI and ESG performance among Saudi companies over the period 2015-2024. The analysis revealed that the adoption of AI led to improvement of ESG scores, with the greatest development captured in the social and environmental aspects. However, such advancements are highly dependent on the prevalence of data governance, infrastructure, and readiness in the organization.

The 2026 World Economic Forum in referred to AI as a structural challenge for governance [5]. Specifically, the International Monetary Fund (IMF) reported that 40% of global employment faces AI exposure, which rises to 60% in advanced economies [5]. AI in the Gulf context constitutes a challenge for managing the social contract, balancing economic restructuring with social cohesion. SDAIA President Abdullah Alghamdi at the 2026 AI Impact Summit referred to this as a three-pronged approach: Building People's capabilities with the SamAI initiative (1.2 million trainees), developing AI infrastructure with specialized data centers of the new Humain entity (governance), and providing legislation aligned with international standards [6, 7].

AI and ESG are treated as separate domains in the existing literature. Present frameworks, including Technology Organization Environment (TOE)-based adoption studies and ESG compliance models, which often analyze AI capabilities in isolation from organizational governance and institutional context, or focus on ESG as a reporting compliance issue without addressing the mechanisms through which AI translates into tangible sustainability improvements. Consequently, no comprehensive model has yet captured the multi-layered, socio-technical dynamics of AI-ESG integration within a distinctive national context such as Saudi Arabia's. The present study directly addresses this gap by answering the following research questions:

- In what ways do AI technologies affect ESG outcomes, and what are the main processes that explain this effect?
- How do contextual elements in Saudi Arabia strengthen or limit the AI-ESG relationship?
- How can an integrative conceptual model of mechanisms and contextual elements, relevant with operational guidelines and frameworks, be constructed?

II. LITERATURE REVIEW AND THEORETICAL FOUNDATION

A. AI and ESG: The Emerging Evidence Base

A longitudinal study of Saudi-listed companies (2015-2024) was developed in [4], resulting in a novel examination of the effects of AI on ESG performance in the Gulf region. Using the Generalized Method of Moments (GMM) estimator and its metrics, the effect of AI adoption on ESG was estimated. It was concluded that AI has a positive and significant effect on ESG scores, with the greatest influence on the environmental and social dimensions. Unidirectional Granger causality tests, as confirmed in the [8] panel, exposed AI adoption as the primary independent driver of ESG, while a robust ESG performance could not instigate investment in AI. These findings support the claims that AI can process unstructured data, detect patterns that would otherwise remain unnoticed, and transform data to support sustainability initiatives in a proactive manner rather than a reactive one.

AI contributes differentially across the three ESG dimensions. Specifically, in the environmental domain, applications include emission forecasting, energy consumption optimization, and real-time ecosystem monitoring via satellite and sensor networks. As for the social domain, AI enables supply chain transparency analysis, community impact assessment, and worker welfare monitoring. Regarding the governance domain, AI supports algorithmic accountability, automated compliance checking, and ESG data verification; though in [9], it was indicated that governance AI may be adopted symbolically without substantive improvement if not accompanied by robust accountability frameworks. These concerns were reiterated during the 2026 Davos meetings, where PwC noted that AI would increase the global GDP by $15.7 trillion in 2030, and the balanced distribution of AI tools among all markets remains a governance challenge [5]. Studies in the Gulf context confirm these differentiated mechanisms and underscore the importance of national institutional enabling conditions [4, 10-11].

Beyond environmental applications, the social dimension of AI-ESG integration has gained attention. Specifically, AI-enabled supply chain transparency tools can identify labor rights violations, map subcontractor networks, and assess community impact through geospatial and social media analytics. In the governance domain, natural language processing supports automated compliance monitoring, board decision analysis, and ESG disclosure quality verification. In [11], applying the TOE framework to Saudi technology enterprises confirms that data quality is the moderating condition through which AI capabilities translate into measurable organizational performance improvements across all ESG dimensions. Authors in [12] documented persistent deficiencies in ESG verification and standardization in Saudi Arabia, identifying blockchain-integrated AI as a promising approach to remediation. These differentiated social and governance mechanisms underscore that a balanced AI-ESG framework should address all three pillars with equal analytical rigor rather than privileging environmental applications.

B. The Saudi Context and AI Ecosystem

Saudi Arabia's institutional environment for AI-enabled sustainability has evolved rapidly since the announcement of Vision 2030 [1]. SDAIA, established in 2019, oversees national AI strategy and infrastructure development [3]. At Davos 2026, Saudi Arabia unveiled the beta version of the SUSTAIN Platform [13, 14], an AI-powered matchmaking network for multi-sector sustainability collaboration, developed with the World Economic Forum and Bain & Company. Humain's specialized AI data centers [6, 7] and a SAR 4.5 billion strategic financing framework for hyperscale capacity [15] underscored the scale of national infrastructure commitment.

The Saudi regulatory landscape is undergoing a period of rapid formalization. The Saudi Exchange's ESG disclosure guidelines are increasingly treated as baseline expectations [16]. At the same time, the Capital Market Authority's (CMA's) sustainable finance frameworks and the National Center for Waste Management's (MWAN) implementing regulations create structured compliance environments [17] that strengthen demand for traceable, AI-generated sustainability data.

These regulatory outlines directly inform the model's architecture. Specifically, the Saudi exchange's ESG disclosure guidelines [16], aligned with Global Reporting Initiative (GRI) [18], Sustainability Accounting Standards Board (SASB) [19], and IFRS S1/S2 [20], and impose structured reporting requirements that strengthen demand for AI-generated sustainability data. The CMA's sustainable finance frameworks and MWAN's implementing regulations [17] create binding compliance environments that give organizational urgency to Layers 3 (Governance Mechanisms) and 4 (Stakeholder Engagement). The Saudi Vision 2030 and Green Initiative [1, 2] provide the main institutional mandate that drives cross-cutting enablers operating across all five layers. By grounding the model explicitly in these regulatory and strategic imperatives, the framework is directly applicable to organizations operating within the Saudi ESG compliance landscape.

C. Theoretical Foundations

Two complementary theoretical frameworks underpin the proposed model. First, the Technology-Organization-Environment (TOE) theory [21] suggests that technology adoption and impact are shaped by three contextual dimensions: technological context (AI capabilities and availability), organizational context (resources, governance, capabilities), and environmental context (industry structure, regulation, external support). In [10], TOE was applied to AI and blockchain in sustainability reporting in Saudi Arabia and the UAE, finding that metadata standardization enhances consistency and interoperability when sufficient digital governance maturity exists, a finding that directly informs the model's governance layer.

Second, institutional theory [22, 23] explains how regulatory, normative, and mimetic pressures drive AI-ESG adoption. Vision 2030 [1], SDAIA's national strategy [3], and evolving ESG regulations [16, 17] collectively create institutional pressure toward AI-enabled sustainability. Caution regarding unanticipated consequences of purposive action is operationally relevant: AI may be adopted symbolically without substantive ESG improvement, underscoring the necessity of robust governance mechanisms that ensure technological deployment, which translates into measurable outcomes [9]. Cooperatively, TOE theory provides the multi-level contextual factors (technological, organizational, and environmental) through which AI capabilities operate and interact, while institutional theory explains the external pressures, legitimacy-seeking behaviors, and constructive governance infrastructure that shape the adoption and governance of these technologies within the distinctive Saudi context.

Beyond these two frameworks, elements of Stakeholder Theory [24] are embedded in Layer 4 (Stakeholder Engagement), which posits that AI-generated insights must be designed and communicated with specific stakeholder information needs in mind-a direct operationalization of the principle that organizations are accountable to multiple stakeholder groups. The resource-based view is implicit in the model's treatment of data infrastructure and AI analytics capabilities as organizational resources that generate competitive ESG performance advantages, consistent with the RBV's emphasis on valuable, rare, inimitable, and non-substitutable capabilities.

D. Research Gap

Despite growing interest, no comprehensive model captures the multi-layered, socio-technical dynamics through which AI influences ESG outcomes in a distinctive national context. Authors in [4, 10] focused on technical AI capabilities in isolation or treated ESG as a reporting compliance issue, neglecting the organizational and institutional mechanisms. The Kingdom's hybrid governance model, rapid digital transformation, and position as an early adopter of national-scale AI sustainability infrastructure [13, 14, 25-27], create both the need and the opportunity for such a framework.

In the current study, the proposed model makes four explicit novel contributions that distinguish it from existing ESG-AI frameworks:

- It is a novel conceptual framework for AI-ESG integration in the Gulf region, addressing a significant geographic gap in the literature.
- It integrates TOE theory [21] and institutional theory [22, 23] within a unified five-layer sequential architecture, moving beyond single-theory approaches that dominate prior work [4, 10].
- It incorporates Saudi-specific cross-cutting enablers (national AI infrastructure, regulatory coherence, multi-sector collaboration, and talent development) as an explicit fourth analytical dimension, operationalizing the national institutional context as a moderating framework rather than treating it as background.
- It generates five testable propositions with a structured empirical testing agenda, enabling future quantitative and qualitative validation.

These contributions position the model as a foundational framework for AI-ESG research in emerging economies with centralized national AI strategies.

III. THE FIVE-LAYER CONCEPTUAL MODEL

The proposed model conceptualizes AI-enabled ESG enhancement as a sequential, feedback-driven process across five interdependent layers. Each layer transforms inputs from the preceding layer: Layer 1 (data infrastructure) supplies standardized multi-source data to Layer 2 (AI analytics), which generates actionable sustainability intelligence. Layer 3 (governance mechanisms) provides the accountability framework that determines whether AI-generated insights are credible and legitimate, enabling Layer 4 (stakeholder engagement) to translate those insights into organizational action. Layer 5 (outcome measurement) captures the resulting ESG performance data and feeds them back to all preceding layers, creating a self-reinforcing improvement cycle. Four Saudi-specific cross-cutting enablers (national AI infrastructure, regulatory coherence, multi-sector collaboration, and talent development) operate as moderating conditions across all five layers. This architecture reflects the core insight that AI adoption alone does not produce ESG improvement: it is the interplay of data quality, analytical capability, governance credibility, stakeholder operationalization, and measurement feedback that drives sustainable outcomes.

A. Layer 1: Data Infrastructure

Data infrastructure is the layer upon which all subsequent AI analytics depend. As the 'garbage in, garbage out' principle underscores, no algorithmic sophistication can compensate for poor-quality inputs. The ESG data ecosystem is rich but fragmented: environmental data may originate from IoT sensors, satellite imagery, corporate disclosures, and regulatory filings; social data encompass labor metrics and supply chain assessments; governance data include board composition, audit records, and compliance filings. In Saudi Arabia, rapid digital transformation has increased the volume of raw data without commensurate growth in integration capacity [10]. SDAIA's national data infrastructure [3] and Humain's AI data centers [6, 7] address this challenge, alleviating the pressure on individual organizations to build data infrastructure independently. In [11], the integration of the TOE framework into data from Saudi technology enterprises further confirmed that data quality is the critical moderating condition through which AI capabilities translate into measurable organizational performance improvements.

B. Layer 2: AI Analytics

Layer 2 transforms standardized data into actionable sustainability intelligence through three primary mechanisms. First, predictive analytics enable proactive sustainability management by forecasting emission trajectories, energy consumption patterns, and compliance risks (e.g., SUSTAIN's partner-matching algorithms [13, 14]). Second, detection and monitoring surface patterns imperceptible to human analysis: Sustain insight's OCR-based ESG extraction from unstructured project documents [25] and AI Eco360's monitoring of 50+ environmental parameters across atmospheric, terrestrial, and aquatic domains [26] illustrate this mechanism. Third, recommendations and optimization translate analytical insights into actionable decisions, optimizing resource allocation, proposing supply chain adjustments, and identifying governance weaknesses requiring board attention. These three mechanisms align with the empirical findings on the environmental and social channels through which AI improves ESG scores [4].

C. Layer 3: Governance Mechanisms

Governance is the mediating layer that determines whether AI capabilities translate into credible, accountable ESG improvements. Based on [10, 22], effective AI governance encompasses policies guiding AI development; accountability frameworks for system impacts; auditing mechanisms to verify algorithmic performance; and transparency protocols that enable stakeholders to evaluate and challenge AI-generated recommendations. SDAIA's AI ethics framework [3], the National Data Management Office's (NDMO) governance standards [27], the Saudi exchange's ESG disclosure guidelines [16], and the CMA's sustainable finance frameworks [17] constitute Saudi Arabia's governance infrastructure. The SUSTAIN Platform's 'trusted coalition formation' design [13, 14] exemplifies diverse approaches to AI governance credibility at the organizational level.

D. Layer 4: Stakeholder Engagement

AI-enhanced ESG outcomes depend not only on technical capabilities but also on how AI-generated insights are communicated to and operationalized by stakeholders. Internal stakeholders, boards, operational managers, and employees require understandings formatted for strategic decision-making and workflow integration. Conversely, external stakeholders, investors, regulators, supply chain partners, and civil society demand reliable, comparable, and contextually interpretable ESG data. Communication mechanisms range from Sustain Insight's real-time dashboards for construction executives [25] and Ahya's audit-grade reports for enterprise and government clients [26] to AI Eco360's ecosystem management platforms for Red Sea decision-makers [27] and SUSTAIN's cross-sector coordination mechanisms [13, 14]. In Saudi Arabia, this layer operates within Vision 2030's distinctive governance model, emphasizing coordinated action among government, private sector, and civil society [1, 28].

The social dimension of ESG deserves explicit elaboration within the stakeholder engagement layer. AI-enabled social impact assessment tools allow organizations to monitor labor conditions across multi-tier supply chains, quantify community development contributions, and track worker welfare indicators in real time. In Saudi Arabia's Vision 2030 context, where labor market nationalization (Saudization) and workforce development are central social policy objectives [1], AI-powered social analytics can provide organizations with granular data on national workforce participation rates, training program effectiveness, and community investment outcomes. These social metrics are increasingly demanded by institutional investors applying ESG screens and by the CMA's evolving disclosure expectations. Stakeholder engagement in the social dimension therefore, requires not only reporting AI-generated social data but co-designing the metrics themselves with community representatives, labor regulators, and civil society organizations to ensure that the data collected reflect material social concerns rather than organizationally convenient proxies.

E. Layer 5: Outcome Measurement

Outcome measurement is the layer through which AI investment is evaluated and through which feedback drives continuous improvement across all preceding layers. Credible ESG metrics should satisfy the criteria of reliability, relevance, and comparability. The Saudi ESG disclosure guidelines [16], aligned with GRI [18], SASB [19], and IFRS S1/S2 [20], provide a foundation; however, in [12], persistent deficiencies were noted in verification, standardization, and risk transparency. The 2026 regulatory tightening of MWAN's extended producer responsibility requirements [17], RVCMC's carbon credit exchange delivering over 2.2 million metric tons in transactions [17], and the imminent shift from voluntary to mandatory ESG disclosure increase the stakes for credible baseline measurement and defensible inventory data. Feedback loops from Layer 5 to Layers 1 through 4 ensure that outcome data inform algorithm refinement, governance adaptation, and improved stakeholder communication. To illustrate this, Ahya's carbon credit data from RVCMC transactions [17] provide verified outcome signals that flow back to Layer 2, informing recalibration of AhyaAI's climate intelligence engine and emission forecasting algorithms - a concrete example of how Layer 5 feedback refines upstream analytical mechanisms and strengthens the self-reinforcing improvement cycle described in Proposition P5. Within the TOE framework [11], Layer 5 functions as the environmental feedback mechanism through which organizational learning occurs: outcome data reveal gaps in data infrastructure (L1), analytical capability (L2), and governance effectiveness (L3) that drive subsequent adaptation. Within institutional theory [22, 23], outcome measurement serves a dual function: it fulfills the legitimacy-signaling requirements imposed by regulatory coercion (mandatory ESG disclosure [16, 17]) and normative pressure (international reporting standards [18-20]), while also generating credibility signals that enable mimetic isomorphism, allowing other organizations to benchmark and adopt proven AI-ESG practices. Thus, Layer 5 is simultaneously a technical assessment mechanism, an organizational learning driver, and an institutional legitimacy instrument.

F. Cross-Cutting Saudi-Specific Enablers

Four cross-cutting enablers operate across all five model layers, constituting the Saudi-specific moderating context:

- National AI Infrastructure: SDAIA's data platforms [3], Humain's specialized data centers [6, 7], and the SAR 4.5B hyperscale financing framework [15] create significant resources that individual organizations could not independently access.
- Regulatory Coherence: The alignment of Vision 2030 [1], the Saudi Green Initiative [2], national ESG guidelines [16], and MWAN's waste regulations [17] provides consistent policy signals, reducing investment uncertainty.
- Multi-Sector Collaboration Frameworks: SUSTAIN [13, 14] enables collective action that transcends what any single actor could achieve.
- Talent Development: SamAI initiative (1.2 million trainees) [6, 7], the National Technology Development Program [27], and the Financial Academy's 'Innovating Exchanges' program [28] build the human capabilities required for AI-ESG system operation.

Each of the five layers is defined as:

- Layer 1 (Data Infrastructure): Refers to the systems, standards, and processes for collecting, standardizing, and integrating multi-source ESG data.
- Layer 2 (AI Analytics): Refers to the predictive, detection, and optimization algorithms that transform standardized data into sustainability intelligence.
- Layer 3 (Governance Mechanisms): States the policies, accountability frameworks, audit mechanisms, and transparency protocols that ensure that AI deployment is credible and accountable.
- Layer 4 (Stakeholder Engagement): Mentions the communication systems and co-design processes through which AI insights are translated into stakeholder action.
- Layer 5 (Outcome Measurement): Refers to the metric systems and feedback mechanisms through which ESG performance is evaluated and improvement cycles are initiated.

IV. MODEL ILLUSTRATION AND APPLICATION

A. Illustration Approach

The five-layer model is illustrated through structured analysis of four Saudi AI-ESG initiatives: SustainInsight [25], AhyaOS/AhyaAI [26], SenseTime's AI Eco360 [27], and the SUSTAIN Platform [13, 14] - assessing the presence and operation of each model layer and the alignment of observed mechanisms with the model's propositions. The illustration draws on publicly available platform documentation, official regulatory filings, validated academic sources, and reputable news coverage of national AI and ESG initiatives. This approach is appropriate for the initial illustration of a conceptual model and sets the stage for future primary data collection through case studies and interviews. Initiatives represent diverse sustainability domains (construction ESG reporting, carbon management, ecosystem monitoring, and cross-sector collaboration) and different stages of deployment (pilot to operational).

The model development followed a three-stage process. Stage 1 (systematic literature synthesis) involved a structured review of peer-reviewed studies published between 2012 and 2026 on AI adoption, ESG management, sustainability reporting, and technology governance in the Gulf region and comparable emerging economies. The research was based on databases, such as Scopus, Web of Science, and Google Scholar, using search terms combining 'artificial intelligence', 'ESG', 'sustainability', 'Saudi Arabia', 'Gulf', and 'TOE framework'. Stage 2 included theoretical integration: two complementary theoretical frameworks (TOE theory [21] and Institutional Theory [22, 23]) were selected based on their demonstrated applicability to technology adoption in institutional contexts, and their propositions were mapped onto a five-layer sequential architecture that reflects the empirical mechanisms identified in the literature review. Stage 3 contained illustrative validation where the model was applied to four pioneering Saudi AI-ESG initiatives (SustainInsight [25], AhyaOS/AhyaAI [26], AI Eco360 [27], and SUSTAIN [13, 14]) using structured analysis of publicly available platform documentation, official regulatory filings, and validated academic and news sources.

This three-stage approach is consistent with established methodologies for conceptual model development in information systems and sustainability management research.

B. Validation Findings by Layer

The four initiatives examined represent distinct sustainability domains: SustainInsight (construction ESG reporting), AhyaOS/AhyaAI (carbon management), AI Eco360 (ecosystem monitoring), and SUSTAIN (cross-sector collaboration), spanning pilot to fully operational stages of deployment. Table I presents model illustration findings across all four initiatives, examining each model layer in turn.

Layer 1 validation confirms that data infrastructure needs differ substantially across application domains. SustainInsight [25] addresses unstructured construction data through OCR-based extraction; Ahya [26] resolves the Middle East's inconsistent emission data problem through global-regional standard integration; AI Eco360 [27] constructs a bespoke real-time environmental monitoring infrastructure; and SUSTAIN [13, 14] aggregates partnership and initiative data across institutions and sectors. Layer 2 validation demonstrates all three AI analytics mechanisms across the initiatives. Layer 3 reveals diverse governance approaches from supplier rating models and external audit validation to national governance indices, confirming that governance must be calibrated to specific risk profiles and stakeholder expectations rather than applying uniform solutions. Layers 4 and 5 confirm stakeholder engagement and outcome measurement as essential operational layers, with feedback loops providing iterative improvement capacity.

C. Propositions: Validation Evidence and Testing Agenda

Table II presents the five model propositions, along with validation evidence and directions for empirical testing. P1 states that AI analytics positively influence ESG outcomes through predictive, detection, and optimization mechanisms - supported by all four initiatives and panel data of [4], confirming unidirectional Granger causality. P2 states that governance structures moderate the positive effect of AI on ESG outcomes - supported by the diversity of governance approaches observed. P3 says that stakeholder engagement mediates the translation of AI-driven insights into ESG performance improvements, supported by initiatives that integrate multi-tier stakeholders. P4 expresses that Saudi-specific enablers positively moderate the AI-ESG relationship - supported by SDAIA infrastructure, Human data centers, and multi-sector platforms. P5 reveals that outcome measurement feedback loops create self-reinforcing improvement cycles - preliminary evidence from Ahya's iterative platform development.

TABLE I. MODEL VALIDATION: FIVE LAYERS ACROSS FOUR SAUDI AI-ESG INITIATIVES

Layer	SustainInsight [25]	AhyaOS/AhyaAI [26]	AI Eco360 [27]	SUSTAIN Platform [13, 14]
L1 (data Infrastructure)	OCR-based extraction from unstructured construction documents; multi-format data ingestion.	Global-regional emission standard integration; resolves ME data inconsistency.	Bespoke real-time multi-sensor infrastructure; 50+ environmental parameters.	Cross-institutional partnership and initiative data aggregation across sectors.
L2 (AI analytics)	Predictive project-level ESG benchmarking; automated disclosure generation.	AhyaAI climate intelligence engine; scope 1-3 emission forecasting; Tawazun marketplace optimization.	Atmospheric, terrestrial, and aquatic monitoring; anomaly detection; ecosystem trend forecasting.	Partner-matching algorithms; collective-action opportunity identification; initiative scoring.
L3 (Governance)	Supplier rating and ESG scoring transparency; audit trail generation.	EY- and KPMG-validated reporting; ISSB/GRI alignment; blockchain provenance.	National governance index integration; environmental compliance tracking; multi-agency data sharing.	Trusted coalition formation design; WEF and Bain & Company governance oversight.
L4 (stakeholder engagement)	Real-time dashboards for construction executives; regulatory-grade disclosures.	Audit-grade reports for enterprise and government clients; investor-facing analytics.	Red Sea ecosystem management platform; multi-agency decision-maker access.	Cross-sector coordination mechanisms; bilateral and multilateral partner onboarding.
L5 (outcome measurement)	Project-level ESG score improvement tracking; GRI/SASB comparability.	Verified carbon credit generation; scope reduction trajectory monitoring; RVCMC exchange compatibility.	Ecosystem health indices; biodiversity and water-quality trend metrics; longitudinal baseline tracking.	Collaboration effectiveness metrics; sustainability initiative impact aggregation; SDG alignment reporting.

TABLE II. MODEL PROPOSITIONS: VALIDATION EVIDENCE AND PROPOSED EMPIRICAL TESTS

P #	Proposition statement	Validation Evidence	Proposed empirical tests
P1	AI analytics (predictive, detection, optimization) positively influence ESG outcomes.	Confirmed across all four initiatives; Panel data by [4] confirm unidirectional Granger causality (AI → ESG) with the largest effects in environmental and social dimensions.	Structural equation modeling with AI adoption as antecedent; ESG score improvements as outcome; analytics mechanism as mediator.
P2	Governance structures moderate the positive effect of AI on ESG outcomes.	Diverse governance approaches observed (supplier ratings [25], external audit [26], national indices [27], coalition design [13, 14]). In [9], it was cautioned that weak governance may produce symbolic adoption without substantive improvement.	Multi-group moderated regression: governance maturity (operationalized using the COBIT or ISO/IEC 38500 corporate governance of IT maturity scale) as moderator of AI → ESG path; compare strong- vs. weak-governance sub-samples.
P3	Stakeholder engagement mediates the translation of AI-driven insights into ESG performance improvements.	Multi-tier stakeholder integration demonstrated across all four initiatives; co-design of output formats with target stakeholders improves utilization.	Mediation analysis: AI analytics → stakeholder engagement → ESG outcomes; Baron and Kenny or bootstrapped Preacher-Hayes approach.
P4	Saudi-specific institutional enablers positively moderate the AI-ESG relationship.	SDAIA infrastructure [3], Humain data centers [6, 7], SAR 4.5B financing [15], SamAI initiative [6, 7], and SUSTAIN platforms [13, 14] create enabling conditions unavailable to organizations operating without national support.	Cross-country comparative study: Saudi vs. GCC peers ([30], UAE) vs. non-GCC emerging economies; test interaction of national AI index and AI → ESG path coefficient.
P5	Outcome measurement feedback loops create self-reinforcing ESG improvement cycles.	Preliminary evidence from Ahya's iterative platform development [26] and RVCMC carbon credit data (over 2.2 million metric tons in verified transactions [17]) create continuous performance signals; regulatory tightening [17] increases feedback loop intensity.	Longitudinal panel study across multiple reporting cycles; test whether prior ESG measurement quality predicts subsequent ESG improvement rates.

P = Proposition, Validation evidence draws on initiatives in Table I and cited studies.

V. DISCUSSION

A. Theoretical Contributions

This research contributes to theory at the intersection of AI, ESG, and sustainability management. By integrating TOE theory [21] and institutional theory [22, 23] within a five-layer conceptual architecture, a detailed account of how technological capabilities interact with organizational and institutional dimensions to shape sustainability outcomes is provided. The findings advance TOE theory by specifying how technological context (AI capabilities) operates through data infrastructure and analytics; how organizational context (governance and stakeholder engagement) mediates technology-to-outcome translation; and how environmental context (Saudi-specific enablers) moderates the relationship across all layers, extending [10, 21].

Additionally, the model advances institutional theory by demonstrating how Saudi Arabia's institutional framework shapes AI-ESG integration not only through regulatory coercion [1, 2, 16, 17] but also through constructive institutional infrastructure and coordination mechanisms that reduce transaction costs and enable collective action. This suggests that the mechanisms of regulatory, normative, and mimetic isomorphism of [22] should be complemented by recognition of constructive institutional frameworks that proactively support sustainability-oriented technological adoption, while remaining attentive to [9] caution regarding unanticipated consequences. The self-reinforcing nature of outcome measurement feedback loops (P5) is explained by the interaction of organizational learning and institutional dynamics: credible ESG outcome data (L5) simultaneously improve the quality of data inputs (L1) through refined sensor calibration and reporting protocols, enhance algorithmic accuracy (L2) through training data enrichment, strengthen governance legitimacy (L3) through verified performance evidence, and deepen stakeholder confidence (L4) through demonstrated accountability. As demonstrated in [31], organizations with stronger sustainability measurement systems achieve superior long-term performance, creating a virtuous cycle in which measurement investment generates returns that justify further investment.

While the model is grounded in and validated within Saudi Arabia's institutional context, its core architecture has relevance beyond the Gulf region. The five-layer logic-data infrastructure enabling AI analytics, mediated by governance and stakeholder engagement, and evaluated through outcome measurement, is applicable wherever organizations seek to integrate AI into sustainability management systems. The Saudi-specific enablers serve as a template for the enabling conditions that governments in other emerging economies may seek to establish. Comparative application of this model in contexts, such as Southeast Asia's varied regulatory environments or Sub-Saharan Africa's emerging sustainability frameworks, would both test the model's generalizability and illuminate which components are context-specific versus universally applicable.

B. *Policy Implications*

The framework identifies five strategic priorities for Saudi policymakers. While all these properties are interdependent, a sequential investment logic is proposed: data infrastructure (P1) should precede AI analytics deployment; regulatory frameworks (P2) should be established concurrently with infrastructure to ensure accountability; multi-sector collaboration platforms (P3) can then be scaled on this foundation; human capability development (P4) should be initiated early and sustained throughout; and outcome measurement credibility (P5) can be institutionalized as systems mature.

First, a continuous investment in national AI infrastructure, such as SDAIA's data platforms [3], Humain's data centers [6, 7], and the hyperscale financing framework [15], reduces organizational barriers to AI-ESG adoption. Second, ongoing regulatory adaptation is required as ESG disclosure standards shift from voluntary guidance to mandatory requirements; collaboration among SDAIA, the CMA, and MWAN is essential for coherent cross-sector governance [17]. In particular, SDAIA and the CMA should develop joint standards for the independent verification of AI-generated ESG data to directly address the verification and standardization deficiencies identified in [12]. Third, multi-sector collaboration platforms such as SUSTAIN [13, 14] should be scaled and sustained as institutional infrastructure to enable collective action on persistent sustainability challenges. Fourth, human capability development at the AI-sustainability intersection, through the SamAI initiative [6, 7], and the Financial Academy [28], is crucial for the model's operationalization. Fifth, outcome measurement credibility requires investment in third-party verification, regulatory oversight of AI-generated ESG reporting, and market infrastructure such as RVCMC's carbon credit exchange [17].

Taken together, these institutional, regulatory, and infrastructural developments position Saudi Arabia as an exceptionally well-resourced national context for AI-ESG integration. The combination of centralized national AI infrastructure (SDAIA, Humain), cross-sector collaboration platforms (SUSTAIN), maturing ESG disclosure requirements (Saudi Exchange [16], CMA), and large-scale talent development programs (SamAI) constitutes a distinctive enabling environment that directly informs the Saudi-specific cross-cutting enablers incorporated in the model.

C. *Managerial Implications*

For organizational leaders, the model offers five practical directives. Organizations should prioritize data standardization before deploying advanced analytics, leveraging national infrastructure, including Humain's data centers [6, 7]. Governance structures should be calibrated to specific risk profiles: the diverse approaches observed from supplier rating models [25] to external audit validation [26] confirm that context-sensitive governance outperforms generic compliance approaches. Stakeholder engagement should be designed from the outset, with co-design of AI system parameters and output formats with key internal and external stakeholders. Organizations should actively engage with SDAIA initiatives [3], SUSTAIN [13, 14], and MWAN's compliance frameworks [17] rather than building isolated in-house systems. Finally, feedback loops from Layer 5 to earlier layers should be formally institutionalized, as the enduring value of AI-ESG systems lies in iterative improvement rather than one-time insight generation.

At the organizational level, AI-ESG integration should be pursued as a structured, phased program:

- Phase 1 (Foundation): Involves data infrastructure audit and standardization, leveraging national platforms where available.

- Phase 2 (Analytics): Refers to the deployment of predictive and monitoring AI tools calibrated to sector-specific ESG materiality.
- Phase 3 (Governance): Contains the establishment of AI ethics policies, audit protocols, and third-party verification arrangements.
- Phase 4 (Engagement): Comprises the co-design of AI output formats with key internal and external stakeholders.
- Phase 5 (Measurement): Involves implementation of credible outcome metrics with formal feedback loop institutionalization.

This phased approach aligns with the model's sequential architecture and directly supports compliance with Saudi Exchange ESG disclosure requirements [16].

Organizations implementing this framework should anticipate three principal challenges:

- Data standardization: ESG data in Saudi Arabia remain fragmented across government agencies, third-party providers, and internal systems; organizations should leverage SDAIA's national data infrastructure [3] and the Digital Government Authority's standardization framework [20] to reduce integration costs.
- Governance calibration: AI-generated ESG data must meet the verification standards embedded in the Saudi Exchange's ESG Disclosure Guidelines [16] and the emerging mandatory disclosure environment [17]; organizations should establish third-party audit arrangements early, drawing on the precedent set by Ahya's EY- and KPMG-validated reporting [26].
- Talent readiness: The successful operation of AI-ESG systems requires personnel with hybrid competencies spanning data science, sustainability management, and regulatory compliance; organizations should engage with the SamAI initiative [6, 7] and the Financial Academy's AI and Sustainability program [29] to build internal capability.

Addressing these challenges proactively, rather than treating them as implementation barriers, is significant for realizing the full potential of AI-ESG integration.

VI. LIMITATIONS AND FUTURE RESEARCH

This research includes four main limitations. First, model validation relies on publicly available documentation rather than primary data. Future studies should conduct in-depth case studies, using interviews and observational data to rigorously test the model's propositions. Second, the rapid evolution of both AI technologies and Saudi regulatory policy may necessitate model adaptation; longitudinal research tracking AI-ESG integration across multiple time points, building on the panel approach and SDAIA's National AI Index [4], would reveal how model components evolve in response to technological and institutional change. Third, the Saudi focus constrains generalizability; comparative research across GCC states, including Bahrain's emerging AI-sustainability initiatives [28] and between Saudi Arabia and other emerging and advanced economies, would help determine which model components are context-specific and which are universally applicable. Fourth, the model's governance dimension could be elaborated to address specific challenges of algorithmic bias, data privacy, and AI's carbon footprint, the last of which represents a direct ESG cost of AI deployment that the current model treats as exogenous.

Future empirical validation of the model should prioritize three methodological pathways:

- Survey-based Structural Equation Modeling (SEM) using established AI adoption indicators (e.g., SDAIA's National AI Index scores, AI investment metrics) as antecedents and verified ESG disclosure scores as outcomes, with governance maturity and stakeholder engagement indices as mediating and moderating variables.
- Longitudinal case study research using semi-structured interviews and archival analysis with firms operating within the four initiative platforms (SustainInsight, AhyaOS, AI Eco360, SUSTAIN), following a multiple case embedded design.
- Cross-national comparative analysis contrasting Saudi Arabia with GCC peers (UAE, Bahrain) and non-GCC emerging economies to test the generalizability of the model and identify which components are context-specific.

Several explicit assumptions underpin this framework and should be acknowledged. Initially, the model assumes that organizations have baseline digital infrastructure capable of supporting AI deployment. In practice, significant heterogeneity exists across Saudi firms, particularly between large, listed companies and SMEs. Additionally, it adopts regulatory coherence and institutional alignment as enabling conditions, whereas regulatory fragmentation or enforcement gaps could significantly reduce the effectiveness of Layers 3 and 5. The model also treats AI capabilities as improving over time, consistent with observed trajectories; however, capability plateaus or AI system failures could disrupt the self-reinforcing improvement cycles described in Proposition 5. Finally, the framework assumes stakeholder willingness to engage with AI-generated ESG data; in contexts where trust in algorithmic outputs is low, stakeholder adoption may be more limited than the framework suggests.

These assumptions delineate the boundary conditions within which the model's propositions are expected to hold, and their relaxation contributes to future theoretical and empirical work. Data constraints also represent a significant practical limitation: the current absence of longitudinal, firm-level AI adoption and ESG performance data in Saudi Arabia means that full empirical validation of the five propositions must await data infrastructure development, potentially through SDAIA's National AI Index expansion [6, 7].

VII. CONCLUSION

This paper constructed and validated a five-layered conceptual model portraying how Artificial Intelligence (AI) implementation can improve Environmental, Social & Governance (ESG) factors in Saudi Arabia. The model, which includes data infrastructure, AI analytics, governance, stakeholder engagement, and outcome measurement, offers a first-of-its-kind conceptual framework for AI-ESG integration for the Gulf region. Its validation using four initiatives confirms the model's explanation and application across various sustainability domains and different deployment settings. The uniqueness of combining the Technology-Organization-Environment (TOE) and the institutional perspective provides a novel contribution through a multi-layered framework that integrates the various processes, mediators, moderators, and enablers of AI-ESG integration. The key focus areas for investment are also outlined from a policy standpoint: AI national infrastructure, regulatory alignment, cross-sector partnership, and people-centered approaches to capability building, which are in synergy with the aspirations of Saudi Arabia's Vision 2030.

As AI capabilities and sustainability imperatives continue to evolve in tandem, the conceptual model presented in this paper provides a structured foundation for future empirical investigations, including longitudinal panel studies, cross-GCC comparative research, and primary data case studies, offering a practical implementation roadmap for organizations and policymakers.

DECLARATION OF COMPETING INTERESTS

The author declares no competing interests.

DATA AVAILABILITY

This study is a conceptual paper and does not involve the generation or analysis of primary datasets. All sources used in developing and illustrating the model are publicly available and cited in the Reference section.

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DECLARATION OF GENERATIVE AI USE

The author did not use any Generative AI tools in the writing of this manuscript.

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