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Artificial Intelligence Usage Intention for Sustainable Development: A Neo ESG Perspective Using Hybrid Methods

Vo Dinh Cao Nguyen[1)*], Huu Tam Do[2)]
[1,2)]Van Lang University, Vietnam
[1)]nguyen.vdc@vlu.edu.vn, [2)]tam.2273401200250@vanlanguni.vn

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Abstract This study finds that the rapid development of artificial intelligence, together with the growing pressure to implement environmental, social, and governance principles, has driven firms to search for new models of sustainable governance. However, prior research has lacked empirical evidence on the role of artificial intelligence usage intention within a dynamic environmental, social, and governance framework and its interplay with social and environmental dimensions. To address this gap, the study reconceptualizes environmental, social, and governance by representing governance through artificial intelligence, the social dimension through diversity, equity, and inclusion, and the environmental dimension through exploitative green innovation and exploratory green innovation. Based on survey data from 357 firms, a hybrid methodological approach employing partial least squares structural equation modeling, artificial neural networks, and fuzzy set qualitative comparative analysis is applied. The results reveal that diversity, equity, and inclusion has the strongest effect on sustainable development ($\beta = 0.533$; $t = 13.061$; $p < 0.001$), followed by artificial intelligence, while exploitative green innovation plays a supportive role and exploratory green innovation shows no significant impact. Artificial neural networks validate these findings with stable predictive accuracy, while fuzzy set qualitative comparative analysis identifies multiple alternative pathways to sustainability (equifinality). The study contributes by positioning artificial intelligence as a new governance mechanism within environmental, social, and governance and highlighting the central role of diversity, equity, and inclusion, while also offering strategic guidance for integrating technological and social factors to foster sustainable development.

Keywords Artificial Intelligence (AI); Neo-ESG; Diversity–Equity–Inclusion (DEI); Green Innovation; Sustainable Development

INTRODUCTION

Over the past decade, the dynamics of globalization combined with profound socio-economic shifts have placed enterprises under mounting pressure to reconcile economic growth with sustainable development. The United Nations, through its Sustainable Development Goals, has underscored the pivotal role of businesses in balancing economic interests with environmental and social responsibilities (Sharma & McLean, 2025). Against this backdrop, the environmental, social, and governance framework has emerged as a critical conceptual lens for assessing and guiding the degree of sustainability in corporate governance (Basah et al., n.d.). Environmental, social, and governance has moved beyond serving as a mere instrument of corporate social responsibility reporting; it has evolved into a strategic competitive advantage that directly shapes access to capital, attracts investment, enhances corporate reputation, and secures long-term viability (Pollman, 2019; Passas, 2024). In parallel, artificial intelligence is progressively reshaping the architecture of corporate governance and operations (Hilb, 2020). From big data analytics, process automation, and supply chain optimization to human resource management and marketing strategy, artificial intelligence not only

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improves operational efficiency but also enables innovative, more sustainable business models (Barbosa et al., 2018). The integration of artificial intelligence into corporate management is therefore regarded as transformative, with the potential to deliver a dual breakthrough: simultaneously enhancing economic performance while reducing environmental impact and strengthening social responsibility (Shkalenko & Nazarenko, 2024).

Nevertheless, despite its evident potential, the intention to adopt artificial intelligence in corporate management still faces significant barriers (Cubric, 2020). Enterprises, particularly in emerging economies, often lack clarity in strategies that integrate environmental, social, and governance with artificial intelligence, resulting in inconsistent implementation, limited effectiveness, and at times even counterproductive outcomes. Moreover, the existing body of research has largely concentrated on artificial intelligence's impact on operational efficiency or consumer behavior, while paying limited attention to the interactive relationship between environmental, social, and governance and artificial intelligence usage intention in the context of corporate governance for sustainable development. This omission represents a critical research gap (Rane et al., 2024).

Although recent studies have acknowledged the roles of artificial intelligence and environmental, social, and governance in sustainable management, their approaches remain constrained. First, Wang and Zhang (2025) demonstrate that artificial intelligence can enhance environmental, social, and governance performance and thereby improve sustainability, yet they treat environmental, social, and governance as a static composite index without unpacking its internal micro-mechanisms. Second, Babalola (2024) explores green artificial intelligence adoption through a TOE–TAM framework, but environmental, social, and governance is treated as an external backdrop rather than a central construct directly linked to artificial intelligence usage intention in governance. Third, Chen and Wang (2024) and Soomro et al. (2024) extend the methodological lens by applying hybrid approaches, yet both position environmental, social, and governance as an outcome or moderator, leaving unexplored the possibility of reconceptualizing environmental, social, and governance as generative mechanisms: governance through artificial intelligence usage intention, environment through exploitative and exploratory green innovation, and social through diversity, equity, and inclusion. Finally, Liu et al. (2025) emphasize that artificial intelligence's impact on environmental, social, and governance is contingent upon internal capabilities such as learning capacity and leadership, but environmental, social, and governance in their study remains a score rather than being examined as a dynamic driver of sustainable governance.

Building on these unresolved issues, this study addresses the identified research gap by advancing a general objective: to reconceptualize ESG as a dynamic system within corporate governance, where Governance is represented by AI usage intention, Environment by exploitative and exploratory green innovation, and Social by DEI. This reconceptualization enables a more comprehensive explanation of how firms construct sustainable development. More specifically, the study pursues three objectives:

(1) *To examine the direct and indirect effects of AI usage intention (Governance) on sustainable development through green innovation and DEI;*
(2) *To analyze the interactions and alternative configurations of dynamic ESG in shaping sustainable outcomes for enterprises.*
(3) *To propose and empirically validate a new ESG framework in which ESG is decomposed into Governance-Environment - Social, thereby moving beyond traditional index-based approaches.*

To achieve these objectives, the study is guided by the following research questions:

RQ1: In the context of corporate governance, how does AI usage intention, as a pillar of Governance, influence sustainable development when mediated by green innovation (exploitative and exploratory) and DEI (Social)?

RQ2: How do the three dynamic ESG components interact and complement one another in shaping alternative pathways toward sustainable development?

RQ3: Does reconceptualizing ESG as a dynamic system rather than a static index provide a more comprehensive and compelling theoretical framework for explaining the role of AI in sustainable governance?

To address these questions, the study employs a three-stage hybrid approach, combining PLS-SEM to test linear relationships and mediation effects, ANN to capture nonlinear relationships and variable importance, and fsQCA to identify alternative configurations leading to sustainable outcomes.

This research contributes to scholarship by reconceptualizing ESG as a dynamic system, where Governance is embodied by AI usage intention, Environment by exploitative and exploratory green innovation, and Social by DEI, thereby moving beyond traditional index-based approaches. This perspective allows for a more nuanced explanation of the micro-mechanisms through which firms achieve comprehensive sustainable development across financial, organizational, human, ethical, environmental, and societal dimensions. Furthermore, the study extends the theory of

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sustainable management by positioning AI usage intention at the core of Governance, demonstrating that AI should be viewed not merely as a technological tool but as a strategic governance driver. From a practical standpoint, the findings provide empirical evidence and actionable insights for enterprises particularly in emerging markets on embedding AI into ESG strategies to achieve sustainable development in a proactive and holistic manner.

The remainder of this article is organized as follows. Section 2 presents the theoretical foundations, reviews related literature, and develops the hypotheses alongside the proposed research model. Section 3 outlines the research methodology, including survey design, measurement scales, data collection procedures, and analytical techniques (PLS-SEM, ANN, and fsQCA). Section 4 reports the empirical findings and hypothesis testing results. Section 5 discusses the key insights, emphasizing academic and managerial contributions. Finally, Section 6 concludes the paper by highlighting limitations and directions for future research.

THEORETICAL FRAMEWORK AND HYPOTHESES

To establish a rigorous foundation for the proposed research model, this study grounds its hypotheses in four seminal theoretical perspectives that have shaped management, innovation, and sustainability research. First, the Technology Acceptance Model (Davis, 1989) provides the conceptual basis for understanding how managerial intention to use artificial intelligence as a governance mechanism translates into behavioral outcomes and organizational performance. Second, the Dynamic Capabilities Theory (Teece et al., 1997) explains how firms leverage exploitative and exploratory green innovation to adapt, reconfigure, and sustain competitive advantage under conditions of environmental change. Third, Stakeholder Theory (Freeman, 2010) offers the normative and instrumental justification for embedding diversity, equity, and inclusion into corporate strategies, emphasizing that firms must balance the interests of diverse stakeholders to achieve legitimacy and long-term success. Finally, the Triple Bottom Line framework (Elkington, 1997) provides the overarching lens through which sustainable development is conceptualized, positioning economic, social, and environmental outcomes as interdependent pillars of corporate sustainability. Collectively, these theoretical pillars not only justify the construction of the model but also enable the integration of artificial intelligence usage intention into environmental, social, and governance as a dynamic system for achieving sustainable development, as presented in Table 1.

Table 1. Theoretical Frameworks and Hypothesis Development

Variable	Hypotheses	Theoretical Basis	Sources
AI usage intention	H1 H2 H5 H6	Technology Acceptance Model (TAM)	Davis (1989)
Exploitative & Exploratory	H3 H4	Dynamic Capabilities Theory	Teece, Pisano, & Shuen (1997)
DEI	H7	Stakeholder Theory	Freeman (1984)
Sustainable Development	DV	Triple Bottom Line (TBL)	Elkington (1997)

Technology Acceptance Model (TAM)

The Technology Acceptance Model, originally proposed by Davis (1989), is one of the most influential frameworks for explaining the intention and behavior of technology adoption at both individual and organizational levels. At its core, the model posits that perceived usefulness and perceived ease of use shape users' attitudes toward technology, which in turn influence their behavioral intention and actual adoption. Over the past three decades, this model has been rigorously tested and extended across multiple domains, including electronic commerce, information systems, healthcare, and sustainable management (Venkatesh & Davis, 2000; King & He, 2006; Marangunić & Granić, 2015).

In the context of corporate governance, artificial intelligence usage intention can be interpreted as a strategic decision, reflecting managers' perceptions of its potential to enhance organizational effectiveness and mitigate operational risks. Governance mechanisms supported by artificial intelligence are increasingly perceived as both useful, such as improving efficiency, enabling data-driven decision making, and fostering innovation, and accessible,

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given the rapid advancement of user-friendly platforms (Shiau & Chau, 2016; Alsheibani et al., 2018; Dwivedi et al., 2022).

Within a dynamic environmental, social, and governance framework, artificial intelligence usage intention is positioned under governance because it embodies managerial capacity and strategic foresight. While traditional governance emphasizes structures of control, transparency, and accountability, governance in the digital era also requires the ability to select, adopt, and direct emerging technologies. Artificial intelligence usage intention therefore reflects not only managerial attitudes toward technology but also the quality of governance decisions, the willingness to innovate, and the commitment to embedding advanced technologies into long-term strategies. In this sense, it represents a contemporary form of governance in which effectiveness is defined not only by institutional arrangements but also by technological capabilities (Hilb, 2020).

When managers perceive artificial intelligence adoption as strategically valuable, they are more likely to leverage it for both exploitative green innovation, focused on incremental improvements and resource optimization, and exploratory green innovation, aimed at developing disruptive solutions and sustainable business models. Recent literature further emphasizes that artificial intelligence adoption should be viewed primarily as a governance capability within the environmental, social, and governance framework, rather than solely as a technological or environmental factor. Empirical studies show that the implementation of artificial intelligence enhances environmental, social, and governance performance by improving decision-making quality, increasing transparency, and strengthening risk management processes (Papagiannidis et al., 2025; Tian et al., 2025; Xie et al., 2025; Shen et al., 2025).

In addition, Papagiannidis et al. (2025) characterize responsible artificial intelligence governance as an emerging dimension of corporate governance, emphasizing the need for oversight, accountability, and ethical control mechanisms. Similarly, Udupa and Modoor (2025) propose a framework integrating artificial intelligence with environmental, social, and governance objectives, highlighting its role in shaping sustainable governance structures. Collectively, these studies suggest that the decision to adopt artificial intelligence should be understood as a governance-level strategic choice, reflecting a commitment to data-driven, transparent, and responsible decision making. This orientation, in turn, supports environmental innovation and social inclusion, reinforcing the classification of artificial intelligence usage intention within the governance pillar of a neo environmental, social, and governance framework.

Empirical evidence also indicates that artificial intelligence usage intention influences both exploitative and exploratory innovation pathways (Rane et al., 2024). Accordingly, the Technology Acceptance Model (TAM)provides the theoretical foundation for linking artificial intelligence usage intention with green innovation (H1, H2).

***H1**: AI usage intention has a positive effect on exploitative green innovation.*

***H2:** AI usage intention has a positive effect on exploratory green innovation.*

Moreover, TAM has also been extended to the social dimension of governance. Recent studies indicate that AI adoption can strengthen diversity, equity, and inclusion (DEI) by reducing biases in decision making and enabling fairer and more transparent human resource practices (Shkalenko & Nazarenko, 2024). From the TAM perspective, AI usage intention is driven by the perception that technology can improve DEI outcomes, thereby reinforcing the social pillar of ESG. This theoretical grounding supports the hypotheses linking AI usage intention to DEI (H5, H6). Building on this foundation, the following hypotheses are proposed:

***H5**: AI usage intention has a positive direct effect on sustainable development.*

***H6:** AI usage intention has a positive effect on diversity, equity, and inclusion (DEI).*

1.1. Dynamic capbilities theory (DCT)

The Dynamic Capabilities Theory, originally articulated by Teece et al. (1997), explains how firms can integrate, build, and reconfigure internal and external competencies to address rapidly changing environments. Unlike the traditional resource-based view, which emphasizes the possession of valuable, rare, and inimitable resources, Dynamic Capabilities Theory highlights the ability of firms to continuously adapt through innovation, learning, and transformation. This perspective has become central to understanding how organizations maintain long-term competitiveness and sustainability in volatile markets (Eisenhardt & Martin, 2017).

Within the ESG framework, green innovation represents a key manifestation of dynamic capabilities. It is commonly divided into two complementary forms: exploitative innovation, which focuses on incremental improvements, efficiency gains, and resource optimization, and exploratory innovation, which emphasizes radical changes, experimentation, and the development of novel solutions (Benner & Tushman, 2003). By simultaneously pursuing both exploitative and exploratory green innovation, firms enhance their ability to respond to stakeholder pressures, regulatory requirements, and societal expectations, thereby securing sustainable competitive advantage (Bocken et al., 2014).

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In the context of this study, exploitative and exploratory green innovation are conceptualized as the environmental pillar of ESG (Chen, 2008). Dynamic Capabilities Theory provides the foundation to argue that these innovation capabilities are not merely outcomes of governance choices but active mechanisms through which firms translate strategic intentions, such as AI adoption, into sustainable development outcomes. Empirical research supports this view, showing that green innovation is a critical driver of corporate sustainability and mediates the relationship between managerial practices and long-term performance (Xue et al., 2019).

Thus, based on Dynamic Capabilities Theory, the following hypotheses are proposed:

H3: *Exploitative green innovation has a positive effect on sustainable development.*

H4: *Exploratory green innovation has a positive effect on sustainable development.*

1.2. Stakeholder Theory

Stakeholder Theory, introduced by Freeman (2010), has become one of the most influential theoretical foundations in modern management. The theory posits that the value of a firm is not created solely for shareholders but also for all stakeholders who influence or are influenced by the organization's activities, including employees, customers, suppliers, governments, and communities. This perspective broadens the scope of corporate responsibility beyond profit maximization to encompass social and environmental obligations, while underscoring the link between organizational legitimacy and long-term survival. Over the past three decades, Stakeholder Theory has been expanded across normative, instrumental, and descriptive dimensions (Jones, 1995). Normative studies emphasize the ethical responsibility of firms to serve the interests of all stakeholders, while instrumental research demonstrates that stakeholder-oriented governance enhances organizational performance, brand reputation, and long-term financial outcomes (Hyrynsalmi et al., 2025). Within the ESG discourse, Stakeholder Theory serves as a critical foundation, highlighting that firms must proactively embed social and environmental objectives into their strategies rather than focusing narrowly on short-term financial gains.

In this study, Stakeholder Theory is applied to explain the role of diversity, equity, and inclusion in sustainable management. Diversity, equity, and inclusion not only reflect corporate commitment to employees arguably the most critical stakeholder group but also signal an organization's dedication to building transparent, fair, and inclusive workplaces. Recent studies demonstrate that firms effectively implementing diversity, equity, and inclusion achieve higher levels of innovation, stronger employee engagement, and enhanced legitimacy in the eyes of customers and society (Wiyono et al., 2025). From a Stakeholder Theory perspective, advancing diversity, equity, and inclusion enables firms to meet societal expectations for fairness and human rights, while reinforcing legitimacy, cultivating trust, and laying the foundation for sustainable long-term growth. Thus, Stakeholder Theory provides a solid academic foundation for positioning diversity, equity, and inclusion as a bridge between governance and sustainable development.

H7: *Diversity, Equity, and Inclusion (DEI) has a positive effect on sustainable development.*

1.3. Triple Bottom Line (TBL)

The concept of the Triple Bottom Line, introduced by Elkington (1997), has become one of the most influential theoretical foundations in the study of sustainable development. It posits that corporate success must be assessed simultaneously across three pillars: profit, people, and planet. This perspective challenges the traditional view that focuses solely on financial returns by extending corporate responsibility to include social equity and environmental protection (Abraham, 2024). Over the past two decades, the Triple Bottom Line has evolved from a normative concept into a strategic management tool. Recent studies demonstrate that it is not merely a reporting metric but a foundational mechanism that integrates the pillars of ESG. Specifically, it establishes a tri-dimensional logic that compels firms implementing ESG to balance economic efficiency, social welfare, and environmental responsibility, rather than prioritizing one dimension at the expense of the others (Das et al., 2025).

In the context of this study, the Triple Bottom Line is employed to define and explain the essence of sustainable development, which serves as the central dependent variable in the proposed model. Unlike prior research that often restricts sustainable development to environmental outcomes, this study conceptualizes it as a multidimensional construct encompassing financial growth, competitive capability, employee engagement, ethical standards, social responsibility, and ecological stewardship. This reflects the comprehensive nature of the Triple Bottom Line and enables the framework to move beyond static, one-dimensional interpretations of ESG.

More specifically, artificial intelligence usage intention, representing the governance dimension, influences exploitative and exploratory green innovation, which constitute the environmental dimension, by optimizing existing operations while simultaneously enabling the development of sustainable business models. At the same time, artificial intelligence usage intention supports the creation of transparent and equitable workplaces, thereby advancing diversity, equity, and inclusion within the social dimension. These micro-level mechanisms converge at the macro level and are

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captured through the concept of sustainable development as articulated by the Triple Bottom Line. In this sense, sustainable development is conceptualized as an integrative outcome that reflects the combined value of economic prosperity, social justice, and environmental responsibility.

Based on these theoretical arguments, the conceptual research model is proposed to illustrate the dynamic relationships among artificial intelligence usage intention, green innovation, diversity, equity, and inclusion, and sustainable development, as presented in Figure 1.

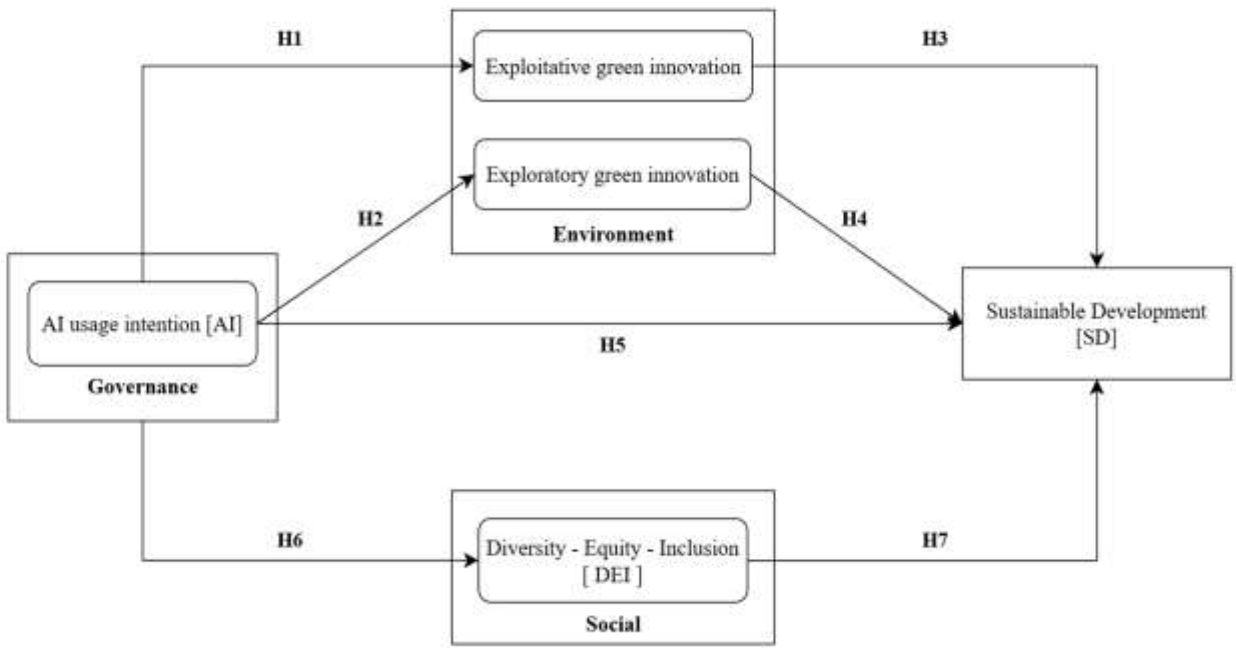

Figure 1. Research model

METHODOLOGY

Research Design

In this study, we adopt a hybrid, multi-phase research design that integrates partial least squares structural equation modeling, artificial neural networks, and fuzzy-set qualitative comparative analysis to capture both the linear and non-linear dynamics of ESG–AI interactions in the context of sustainable development (Hair, 2014). A single-method approach may oversimplify the complexity of governance, innovation, and social inclusion; therefore, a triangulated methodological framework is employed (Wang et al., 2024).

First, data were collected through a structured survey, following rigorous scale development and validation procedures to ensure content validity and reliability. Second, partial least squares structural equation modeling was conducted using SmartPLS 4 to evaluate both the measurement model, including indicator reliability, convergent validity, and discriminant validity, and the structural model, including path coefficients, R^2 values, and model fit indices. After testing the hypothesized direct and mediating effects, the algorithm results were exported, and latent variable scores were used as inputs for artificial neural network analysis.

Third, artificial neural networks were implemented using SPSS for data preprocessing and RapidMiner for model training and validation. This approach allows for the exploration of non-linear relationships and the identification of the relative importance of predictors, thereby enhancing robustness and predictive accuracy beyond structural equation modeling results. Finally, the original dataset was standardized and reformatted for analysis using fuzzy-set qualitative comparative analysis, enabling the identification of configurational causality and multiple sufficient pathways through which firms can achieve sustainable development (Kraus et al., 2018).

This integrated design enables both theory testing through structural equation modeling and theory building through artificial neural networks and fuzzy-set qualitative comparative analysis, aligning with recent calls for methodological pluralism in management research (Aguinis et al., 2018). The overall procedure is summarized in Figure 2.

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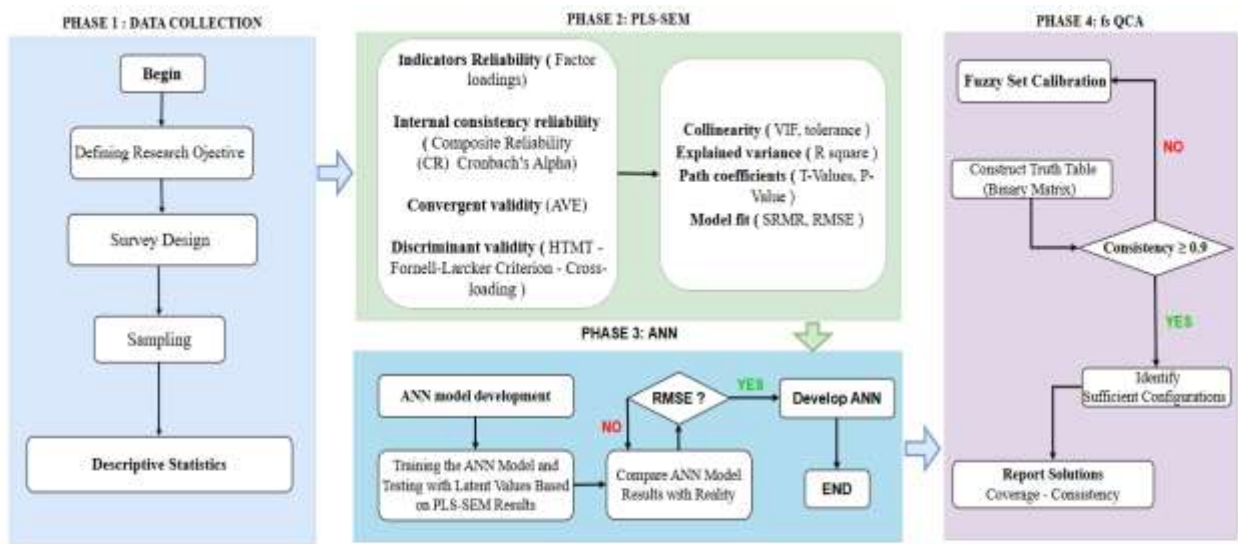

Figure 2. Flowchart

Sampling and Data Collection

To empirically validate the proposed model, this study employed a purposive sampling strategy, targeting large domestic enterprises and multinational corporations operating in Vietnam, particularly firms actively engaged in ESG-oriented management practices and AI adoption. This approach ensured the representation of organizations that are actively engaging with ESG-driven management practices and AI adoption in their operations. Data were collected from 357 valid respondents, consisting of both business representatives (managers, executives) and individual employees, thereby capturing multiple stakeholder perspectives within organizational governance. All constructs in the study were measured using a seven-point Likert scale, ranging from 1 (“strongly disagree”) to 7 (“strongly agree”), which is widely recognized in management and sustainability research for its robustness and ability to capture nuanced attitudes. The use of a 7-point scale increases measurement sensitivity, particularly when dealing with abstract constructs such as AI usage intention, green innovation, DEI, and sustainable development.

Table 2 presents the demographic profile of the respondents. The results show a balanced distribution across gender and age groups, with the majority of participants holding at least an undergraduate degree. Importantly, the sample exhibits an international orientation, as over half of the respondents are employed in large-scale enterprises (over 1000 employees), and nearly three-quarters report monthly incomes above 21 million VND, indicating the predominance of higher-income, innovation-driven firms. This distribution supports the credibility of the dataset in reflecting organizational practices aligned with sustainability and digital transformation trends.

Table 2. Descriptive Analysis (N=357)

Variable	Category	Frequency	Percentage (%)
Gender	Male	192	53.8
	Female	165	46.2
Age	18 – 24	48	13.4
	25 – 34	112	31.4
	35 – 44	115	32.2
	45 – 54	55	15.4
	Above 55	27	7.6
Education Level	High school	122	34.2
	Undergraduate	128	35.9
	Post-graduate	107	29.9
Income Level (mil. VND)	10 – 20	102	28.6
	21 – 32	118	33.1
	Above 32	137	38.3

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Business Size	<500 employees	46	12.8
	501 – 1000 employees	114	32.0
	>1000 employees	197	55.2
Respondent Type	Individual employees	171	47.9
	Business representatives	186	52.1
Region	Ho Chi Minh City	127	35.6
	Ha Noi	92	25.8
	Other provinces (Vietnam)	138	38.6

1.4. Measurement Intruments

To operationalize the proposed constructs, this study employed well-established measurement scales adapted from prior literature. All items were assessed on a seven-point Likert scale ranging from 1 (“strongly disagree”) to 7 (“strongly agree”), with wording carefully refined to fit the context of business management and sustainable development. A back-translation procedure was applied to ensure linguistic equivalence and conceptual clarity. The constructs and their measurement sources are described in table 3:

Table 3. Data collection instruments

Construct	**No.of items**	**Sources**
AI Usage Intention [AI]	6	Davis (1989); Juranek & Pochwatko (2024); McGrath et al. (2025)
Exploitative Green Innovation [EGI]	4	Teece et al. (1997); Liu et al. (2025);
Exploratory green innovation [EIG]	4	Sarfo et al. (2025)
Diversity, Equity, and Inclusion [DEI]	9	Freeman (2010); Hassan (2025)
Sustainable Development [SD]	7	Calik (2023); Li et al. (2022)

AI Usage Intention (Governance): This construct was measured with six items adapted from the Technology Acceptance Model developed by Davis (1989) and extended by subsequent studies on artificial intelligence adoption and intention to use technology (Juranek & Pochwatko, 2024; McGrath et al., 2025). The items capture managerial perceptions of usefulness, ease of use, and strategic intention to employ artificial intelligence in governance and decision making.

Exploitative Green Innovation and Exploratory Green Innovation (Environment): These constructs were measured using items adapted from prior research on dynamic capabilities and environmental innovation. Exploitative green innovation was measured with three items reflecting a firm’s ability to improve existing processes, optimize resources, and enhance operational efficiency with an environmental orientation (Liu et al., 2025). Exploratory green innovation was measured with three items capturing the firm’s pursuit of novel and breakthrough innovations aimed at sustainable transformation and long-term environmental competitiveness (Sarfo et al., 2025).

Diversity, Equity, and Inclusion (Social): Diversity, equity, and inclusion was measured with nine items adapted from organizational research on fairness and inclusivity (Hassan, 2025). The items cover diversity management practices, equitable decision making, and an inclusive organizational culture in which employees feel respected and valued.

Sustainable Development (Dependent Variable): The dependent construct was assessed with seven items grounded in the Triple Bottom Line framework. The items capture the extent to which firms balance financial growth, social welfare, and environmental responsibility. Measurement items were adapted from validated sustainability performance scales (Calik, 2023; Li et al., 2022). By integrating these scales, the study ensures both theoretical rigor and empirical robustness while maintaining consistency with prior literature.

To assess potential common method bias, Harman's single-factor test was conducted. The analysis revealed that the first unrotated factor accounted for 47.28% of the total variance, which is below the 50% threshold, suggesting that common method bias is not a serious concern. In addition, the Kaiser–Meyer–Olkin measure yielded a value of 0.712, and Bartlett's test of sphericity was statistically significant ($p < 0.001$), confirming the adequacy of the data for factor analysis (Shrestha, 2021). Taken together, these results provide evidence of the dataset's appropriateness for subsequent analyses using partial least squares structural equation modeling and artificial neural networks.

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Table 4. Common Method Bias

Statistical Indicator	Value
Total number of survey variables	30
SS loadings	22.012
Variance explained by a single factor	47.28%

RESULT AND ANALYSIS

Measurement Model Assessment

The PLS Algorithm was employed as the first step to assess the reliability and validity of the measurement model. As presented in Table 5, most outer loadings exceeded the recommended threshold of 0.70 (Hair et al., 2020), ranging from 0.706 (SD1) to 0.866 (EIG3), thus confirming acceptable indicator reliability. However, a few items such as AI5 (0.518), AI6 (0.517), EGI2 (0.687), DEI1 (0.696), DEI9 (0.633), and SD4 (0.575) loaded below 0.70, which slightly reduced the Average Variance Extracted (AVE) for AI (0.473). Despite this, the construct still meets the minimum convergent validity criterion when considering composite reliability and theoretical justification. The AVE values of the remaining constructs fall between 0.530 and 0.713, all above the 0.50 benchmark, confirming that latent variables capture sufficient variance from their indicators and are appropriate for further structural testing.

$$AVE = \frac{\sum_{i=1}^{M} \lambda_i^2}{M} \tag{1}$$

With: λ_i^2: Standardized external loadings of the indicators. M: Number of indicators in a factor.

To further evaluate construct reliability, Table 5 reports the Cronbach's Alpha values for the five latent constructs, ranging from 0.725 (EGI) to 0.889 (DEI), all exceeding the threshold of 0.70.

$$\alpha = \frac{K}{K-1} \times \left(1 - \frac{\sum_{i=1}^{K} \sigma_{Y_i}^2}{\sigma_X^2}\right) \tag{2}$$

With: K: Number of indicators in a scale. $\sigma_{Y_i}^2$: Variance of a particular indicator Y_i. σ_X^2: Total variance of all indicators.

The Rho_A coefficient (Khoi, 2021) ranged from 0.739 to 0.889, confirming internal consistency across all constructs. Similarly, the Composite Reliability (CR) values ranged from 0.827 (EGI) to 0.910 (DEI), all above the 0.70 threshold, indicating high construct reliability.

$$CR = \frac{\left(\sum_{j=1}^{k} \lambda_j\right)^2}{\left(\sum_{j=1}^{k} \lambda_j\right)^2 + \sum_{j=1}^{k} \sigma_j^2} \tag{3}$$

With: λ_j: The standardized external loading factor of the jth indicator in a measurement model. σ_j^2: Variance of measurement error of the jth indicator.

Taken together, the results confirm that all constructs exhibit adequate reliability and convergent validity, with the minor exception of AI's AVE slightly below 0.50 due to two weaker items. This is considered acceptable given strong CR and Cronbach's Alpha scores. Discriminant validity was further assessed using cross-loadings, Fornell–Larcker criterion, and HTMT ratios, all of which support the distinctiveness of the latent constructs.

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Table 5. Items Loadings and Reliability Measures

Latent Variable	Obs. Var	Out. Load	Cronbach's Alpha	Rho_A	CR	AVE
AI Usage Intention	AI1	0.725	0.767	0.784	0.840	**0.473**
	AI2	0.800				
	AI3	0.790				
	AI4	0.717				
	AI5	0.518				
	AI6	0.517				
Diversity, Equity & Inclusion	DEI1	0.696	0.889	0.889	0.910	0.531
	DEI2	0.729				
	DEI3	0.728				
	DEI4	0.791				
	DEI5	0.789				
	DEI6	0.714				
	DEI7	0.744				
	DEI8	0.720				
	DEI9	0.633				
Exploitative Green Innovation	EGI1	0.703	0.725	0.739	0.827	0.546
	EGI2	0.687				
	EGI3	0.743				
	EGI4	0.816				
Exploratory Green Innovation	EIG1	0.813	0.867	0.879	0.909	0.713
	EIG2	0.835				
	EIG3	0.866				
	EIG4	0.863				
Sustainable Development	SD1	0.706	0.851	0.859	0.887	0.530
	SD2	0.775				
	SD3	0.765				
	SD4	0.575				
	SD5	0.756				
	SD6	0.753				
	SD7	0.745				

The results presented in Table 5 provide strong evidence of the reliability and validity of the measurement model. Although some items such as AI5, AI6, DEI1, DEI9, EGI2, and SD4 exhibit outer loadings slightly below the 0.7 threshold, the constructs overall demonstrate acceptable psychometric properties. All Cronbach's Alpha and rho_A values surpass 0.70, confirming internal consistency. Composite Reliability (CR) values also exceed the recommended cut-off, with DEI (CR = 0.910) and Exploratory Green Innovation (CR = 0.909) standing out as the most robust constructs. The relatively lower AVE for AI Usage Intention (0.473) suggests a broader and more heterogeneous conceptualization of governance-oriented AI adoption, reflecting the diverse perceptions of managers toward AI usefulness and ease of use. Conversely, the high AVE values for exploratory innovation (0.713) indicate that this construct effectively captures the essence of radical innovation dynamics. Taken together, these results highlight a reliable and theoretically coherent measurement model, providing a solid foundation for subsequent structural analysis. The next section presents the cross-loadings in Table 6.

Table 6. Cross-loadings of Measurement Items

Items	AI	DEI	EGI	EIG	SD
AI1	**0.725**	0.294	0.338	0.358	0.364
AI2	**0.800**	0.304	0.389	0.287	0.432
AI3	**0.790**	0.286	0.331	0.278	0.374
AI4	**0.717**	0.243	0.283	0.322	0.373
AI5	**0.680**	0.249	0.351	0.309	0.379
AI6	**0.670**	0.374	0.304	0.300	0.374

*name of corresponding author

DEI1	0.340	**0.696**	0.443	0.496	0.469
DEI2	0.310	**0.729**	0.370	0.367	0.472
DEI3	0.319	**0.728**	0.445	0.372	0.450
DEI4	0.358	**0.791**	0.475	0.388	0.494
DEI5	0.421	**0.789**	0.446	0.322	0.492
DEI6	0.380	**0.714**	0.479	0.460	0.518
DEI7	0.430	**0.744**	0.452	0.427	0.530
DEI8	0.334	**0.720**	0.355	0.516	0.602
DEI9	0.299	**0.680**	0.418	0.278	0.545
EGI1	0.391	0.390	**0.703**	0.476	0.398
EGI2	0.326	0.318	**0.700**	0.371	0.426
EGI3	0.305	0.493	**0.743**	0.577	0.430
EGI4	0.398	0.515	**0.816**	0.506	0.491
EIG1	0.346	0.443	0.532	**0.813**	0.344
EIG2	0.267	0.354	0.456	**0.835**	0.275
EIG3	0.320	0.373	0.442	**0.866**	0.251
EIG4	0.339	0.423	0.423	**0.863**	0.327
SD1	0.331	0.579	0.403	0.225	**0.706**
SD2	0.433	0.551	0.466	0.338	**0.775**
SD3	0.370	0.566	0.449	0.279	**0.765**
SD4	0.360	0.497	0.278	0.301	**0.650**
SD5	0.428	0.460	0.346	0.387	**0.756**
SD6	0.424	0.461	0.398	0.276	**0.753**
SD7	0.332	0.506	0.382	0.277	**0.745**

The cross-sectional analysis results provide significant evidence for assessing the discriminant validity of the measurement model. According to the criteria of Fornell and Larcker (1981) and Hair et al. (2020), each indicator should exhibit the highest discriminant coefficient on the construct to which it is assigned, while the discriminant coefficient on other constructs should be significantly lower. The findings indicate that:

The AI Intention to Use indicators (AI1–AI6) have high discriminant coefficients on their intended constructs, with values ranging from 0.67 to 0.80, all of which are higher than the discriminant coefficients on other constructs. This demonstrates that this scale adequately reflects management perceptions of AI adoption and intention to use. The Diversity, Equity, and Inclusion (DEI) measurement items (DEI1–DEI9) had discriminant coefficients ranging from 0.68 to 0.79, consistently higher on the DEI construct than on the other constructs, confirming its discriminant validity as a standalone ESG dimension. The indicators of Exploitative Green Innovation (EGI) ranged from 0.70 to 0.82, while Exploratory Green Innovation (EIG) achieved particularly high factor loadings ranging from 0.81 to 0.87. These results confirm the conceptual distinction between exploitative and exploratory forms of green innovation, supporting their mediating role in the proposed framework. Sustainable Development (SD) exhibits factor loadings ranging from 0.65 to 0.77, all above the recommended threshold, confirming its robustness as a multidimensional outcome construct integrating financial, social, and environmental dimensions. The results meet the cross-loading criterion, with each indicator exhibiting higher factor loadings on its intended construct than any alternative construct.

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Table 7. Fornell-Larcker Criterion

Construct	AI	DEI	EGI	EIG	SD
AI	**0.688**				
DEI	0.422	**0.728**			
EGI	0.483	0.592	**0.739**		
EIG	0.355	0.478	0.553	**0.845**	
SD	0.516	0.690	0.541	0.362	**0.728**

The Fornell–Larcker criterion was employed to assess discriminant validity, and the results confirm the robustness of the measurement model. As shown in Table 7, the square roots of AVE (diagonal values) consistently exceed the inter-construct correlations, indicating that each construct explains more variance in its own indicators than in those of others. For instance, AI Usage Intention (0.688) is well above its correlations with DEI (0.422), EGI (0.483),

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EIG (0.355), and SD (0.516), underscoring its conceptual distinctiveness. Likewise, EIG (0.845) demonstrates strong separation from related constructs, validating the independence of exploitative versus exploratory innovation pathways. Notably, the relatively higher correlation between DEI (0.728) and SD (0.690) suggests a substantive theoretical link, where inclusive practices constitute a central driver of sustainable development outcomes. This balance between discriminant validity and meaningful theoretical proximity strengthens the empirical soundness of the model while also highlighting the integrative nature of ESG dimensions. Figure 3 illustrates the PLS-SEM structural model with path coefficients,

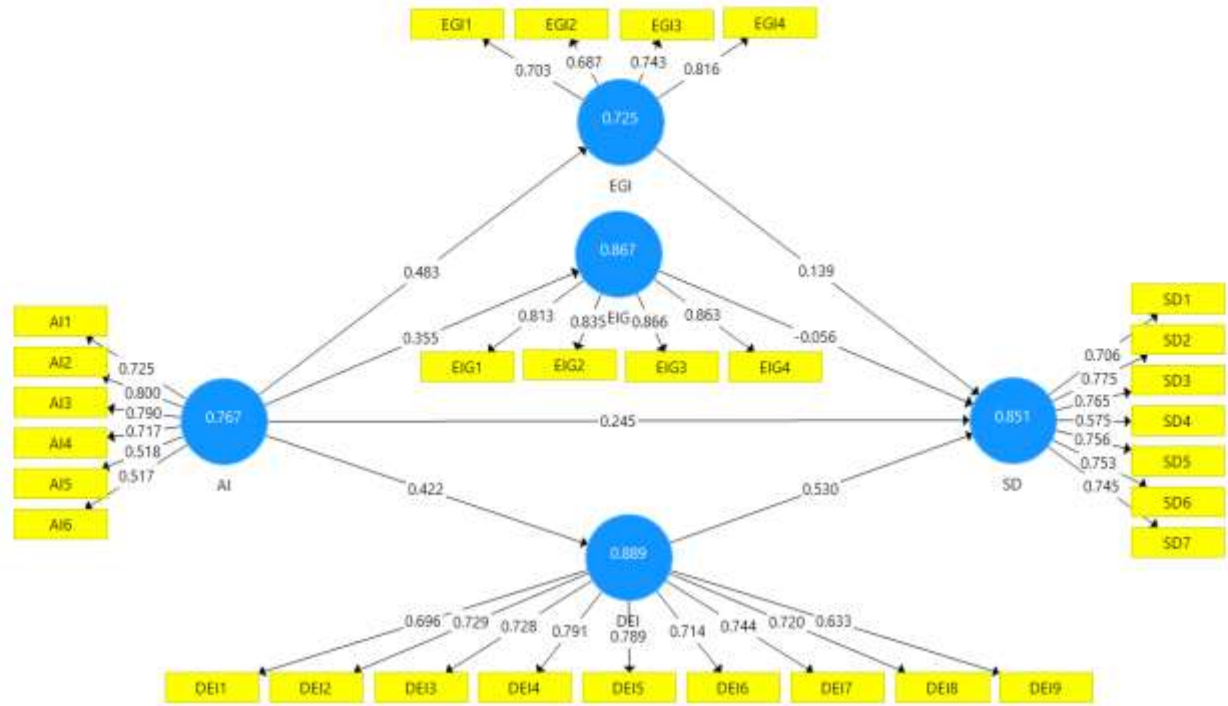

Figure. 3. PLS Algorithms Analysis

1.5. Structural Asessment Model

The structural model analysis (PLS-SEM) was conducted to test the proposed hypotheses and evaluate the robustness of the research framework. By examining path coefficients, t-values, and p-values, the study determines the statistical significance of each relationship, while variance inflation factor (VIF) scores are used to assess potential multicollinearity issues. The results provide empirical support for the theoretical framework and highlight the central role of AI Usage Intention in driving green innovation, enhancing DEI, and shaping sustainable development present in the table 8.

Table 8. PLS Structural Model Results

Relationships	Mean	SD	T-Value	P-Value	VIF
AI → DEI	0.429	0.049	8.700	0.000	1.671
AI → EGI	0.491	0.043	11.149	0.000	1.945
AI → EIG	0.365	0.048	7.402	0.000	1.527
AI → SD	0.246	0.044	5.543	0.000	1.364
DEI → SD	0.533	0.041	13.061	0.000	1.671
EGI → SD	0.140	0.057	2.451	0.015	1.945
EIG → SD	-0.061	0.045	1.251	**0.212**	1.527

The results from Table 8 indicate that most of the hypothesized relationships are statistically significant, confirming the reliability of the theoretical model. Most notably, the relationship DEI → SD ($\beta = 0.533$; $t = 13.061$; $p < 0.001$) demonstrates that Diversity, Equity, and Inclusion (DEI) are not peripheral values but rather the core social drivers of sustainable development. Firms that institutionalize DEI establish legitimacy, trust, and long-term competitiveness, thereby reinforcing the “Social pillar (S)” in ESG as a decisive institutional foundation rather than a supplementary element.

*name of corresponding author

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In parallel, AI Usage Intention also plays a central role in the model. The relationship AI → DEI ($\beta = 0.429$; $t = 8.700$; $p < 0.001$) confirms that AI acts as a new governance tool ("the new face of Governance"), fostering transparency, fairness, and inclusion within organizations. Managers tend to adopt AI to minimize subjective bias in decision-making, recruitment, performance evaluation, and resource allocation helping shift governance processes from subjective to objective and transparent. This reinforces both Stakeholder Theory and Legitimacy Theory, wherein AI is not merely a supporting technology but also a governance component (G) that enables the realization of the social dimension (S) of ESG where fairness and transparency become substantive measures of sustainable development. Furthermore, the relationship AI → EGI ($\beta = 0.491$; $t = 11.149$; $p < 0.001$) stands out as one of the strongest effects, demonstrating that AI adoption in corporate governance helps exploit and optimize existing resources such as human capital, data, and production processes thereby enhancing operational performance and environmental efficiency. This finding aligns well with Dynamic Capabilities Theory, emphasizing that AI enables firms to restructure and recombine internal resources, transforming them into sustainable competitive advantages.

Conversely, the relationship AI → EIG ($\beta = 0.365$; $t = 7.402$; $p < 0.001$) suggests that AI also contributes to exploratory green innovation, albeit to a lesser extent than EGI. This difference reflects the exploration exploitation paradox (March, 1991): while exploitative innovation (EGI) yields immediate and feasible benefits, exploratory innovation (EIG) requires long-term vision, substantial investment, and high risk tolerance, causing its outcomes to emerge more slowly in the short term.

The direct effect of AI → SD ($\beta = 0.246$; $t = 5.543$; $p < 0.001$), though significant, is considerably weaker than the mediated effects. This demonstrates that AI does not directly generate sustainable development but rather serves as a governance bridge through mediating mechanisms such as DEI, EGI, and EIG. This finding reinforces the theoretical argument that "technology alone does not ensure sustainability; its value materializes only when coupled with organizational and social transformation." From an environmental perspective, the relationship EGI → SD ($\beta = 0.140$; $t = 2.451$; $p = 0.015$) is positive and significant, highlighting that process improvements and resource optimization yield short-term sustainable benefits. In contrast, EIG → SD ($\beta = -0.061$; $t = 1.251$; $p = 0.212$) is not statistically significant, reflecting the exploratory innovation paradox: although EIG holds the potential for breakthrough sustainable value creation, its costs, risks, and long payback periods hinder observable short-term effects.

In summary, these results reinforce three core insights: ***(1)*** DEI emerges as the strongest social driver of sustainable development. ***(2)*** AI Usage Intention functions as a governance enabler, bridging technology and social responsibility; ***(3)*** The contrast between EGI and EIG reflects a dual innovation logic where exploitative innovation delivers quick results, while exploratory innovation lays the foundation for long-term adaptive capability.

Table 9. Summary of Hypothesis Tests

Code	Hypothesis	Result
H1	AI Usage Intention positively influences Exploitative Green Innovation (EGI)	Supported
H2	AI Usage Intention positively influences Exploratory Green Innovation (EIG)	Supported
H3	Exploitative Green Innovation (EGI) positively influences Sustainable Development (SD)	Supported
H4	Exploratory Green Innovation (EIG) positively influences Sustainable Development (SD)	Not Supported
H5	AI Usage Intention positively influences Sustainable Development (SD) (direct effect)	Supported
H6	AI Usage Intention positively influences Diversity, Equity, and Inclusion (DEI)	Supported
H7	Diversity, Equity, and Inclusion (DEI) positively influences Sustainable Development (SD)	Supported

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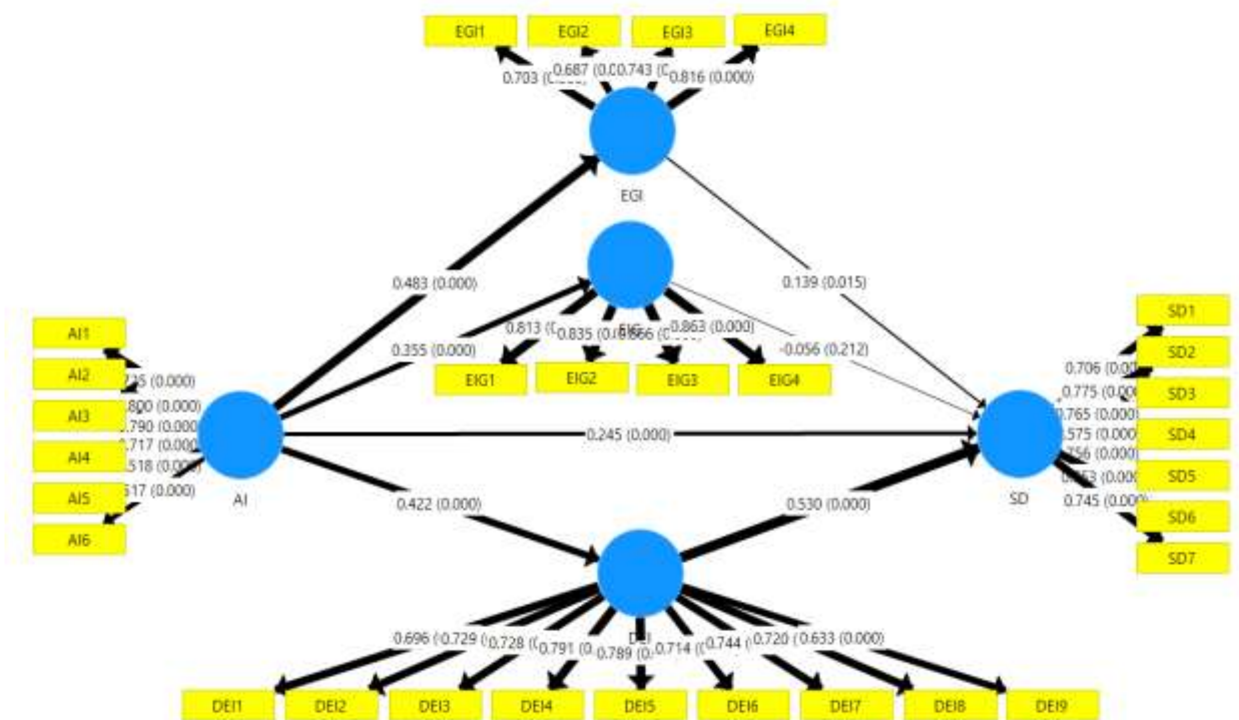
The hypothesis testing shows that six hypotheses (H1–H3, H5–H7) are supported, while H4 (EIG → SD) is not statistically significant. This indicates that AI Usage Intention plays a pivotal role, as it stimulates exploitative green innovation (EGI), strengthens DEI, and directly contributes to sustainable development (H5). Among all factors, DEI (H7) emerges as the strongest driver, emphasizing that the social dimension is fundamental for achieving long-term sustainability rather than being a secondary concern. In contrast, EIG (H4) fails to demonstrate a direct effect, reflecting the reality that exploratory innovation often requires more time and resources before translating into tangible sustainable outcomes. Overall, these results reinforce the dynamic ESG framework and highlight the novelty of this study in positioning AI and DEI as central pillars of Governance and Social in the pathway toward sustainable development.

Figure 4. PLS Structure analysis

1.6. Improtance performance Map (IPMA)



Structural equation modeling provides valuable insights into the significance of causal relationships, it often falls short of translating these effects into actionable managerial priorities. To address this gap, this study incorporates the Importance Performance Map Analysis (IPMA). Unlike predictive assessments, IPMA not only identifies which constructs exert the greatest influence on sustainable development but also evaluates their current performance levels as perceived by managers. This dual perspective is particularly relevant in the context of AI adoption, green innovation, and DEI, where understanding both the weight of each factor and its practical execution is crucial. By integrating IPMA, the research moves beyond theoretical validation to offer concrete managerial implications, thereby strengthening the bridge between academic insights and real-world business sustainability strategies.

*name of corresponding author

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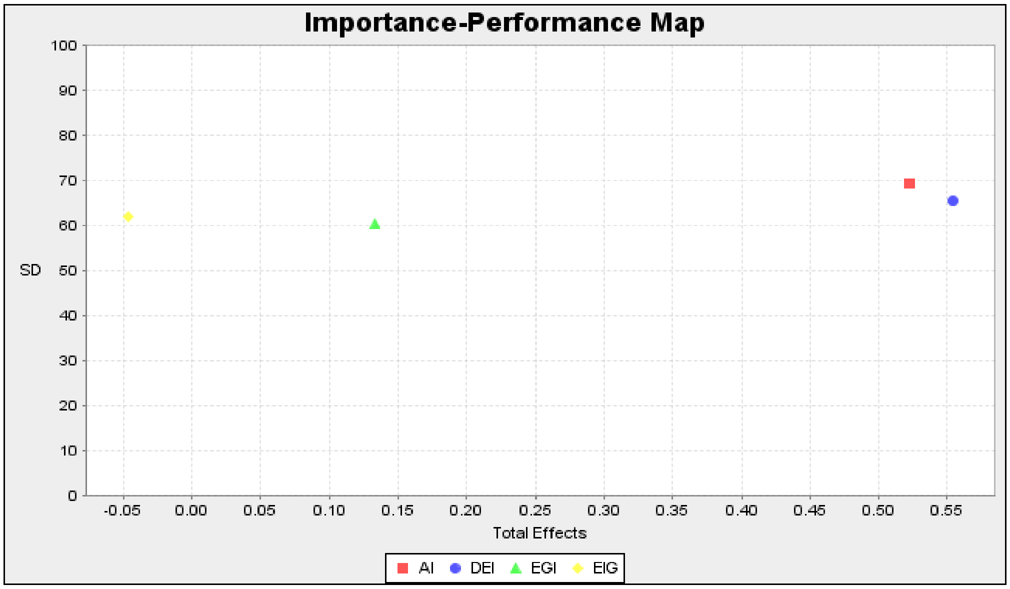

Figure 5. IPMA

The Importance Performance Map reveals that DEI and AI Usage Intention are the two most critical drivers of sustainable development, with total effects exceeding 0.50. Notably, DEI shows the highest importance (≈0.55) but only moderate performance (~65%), indicating that while firms recognize the centrality of DEI, substantial gaps remain in its practical implementation. AI Usage Intention also demonstrates a strong level of importance (≈0.52) with slightly higher performance (~70%), suggesting that AI is increasingly acknowledged as a governance pillar, yet it still needs to transition from intention to concrete action to maximize its impact.

In contrast, EGI has a modest effect (≈0.14) and lower performance (~60%), implying that exploitative improvements provide short-term value but have not been positioned as a strategic priority. More strikingly, EIG exhibits a negative and statistically insignificant effect, despite a relatively decent performance level (~63%). This paradox reflects the nature of exploratory innovation: while it receives attention and resources, its benefits for sustainability are delayed and uncertain, making its contribution less evident in the short term. The IPMA underscores that AI and DEI should be prioritized as strategic levers, with EGI playing a supporting role in the short run, while EIG requires strategic recalibration to realize long-term value. This reinforces the idea that sustainable development cannot be achieved solely through technology or incremental innovation but demands a balanced integration of smart governance (AI), social equity (DEI), and context-appropriate forms of green innovation across different stages of organizational transformation.

Artificial Neural Network (ANN)

The Artificial Neural Network (ANN) model is employed to complement the PLS-SEM analysis by simulating nonlinear decision-making processes and improving the predictive accuracy of sustainable development outcomes. While PLS-SEM effectively validates causal relationships among constructs, it assumes linearity and may overlook more complex interdependencies. To address this limitation, ANN is applied as a complementary approach, capable of capturing nonlinear associations between AI Usage Intention, Diversity–Equity–Inclusion (DEI), Exploitative Green Innovation (EGI), and Exploratory Green Innovation (EIG) in predicting Sustainable Development (SD).

The analysis was conducted using a Multilayer Perceptron (MLP) with a feed-forward back-propagation algorithm, which is particularly suitable for modeling complex relationships. To ensure robustness and avoid overfitting, the dataset was divided into 70% for training and 30% for testing, combined with a tenfold cross-validation procedure. The Scaled Conjugate Gradient (SCG) algorithm was employed to accelerate convergence and enhance computational efficiency. Model performance was assessed using the Root Mean Square Error (RMSE), where lower values indicate greater predictive accuracy and model fit. By integrating ANN with PLS-SEM, the study leverages the strengths of both methods: PLS-SEM provides theoretical validation, while ANN contributes predictive robustness and captures nonlinear effects. This hybrid design reinforces the reliability of the findings and offers deeper insights into how AI, DEI, and green innovation collectively drive sustainable development present in the table 10.

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Table 10. ANN Parameters and Configuration

Parameters	Function
ANN module sample	Multilayer perceptron with backpropagation
Sample	Training: 70 % dataset Testing: 30% dataset
Resampling	Tenfold cross-validation
Loss function	A sum of square errors (SSE)
Activation functions	Hidden layer: Sigmoid Output layer: Sigmoid
Optimizer	Scaled conjugate gradient (SCG) Lambda value: 0.0000005 Sigma value: 0.00005

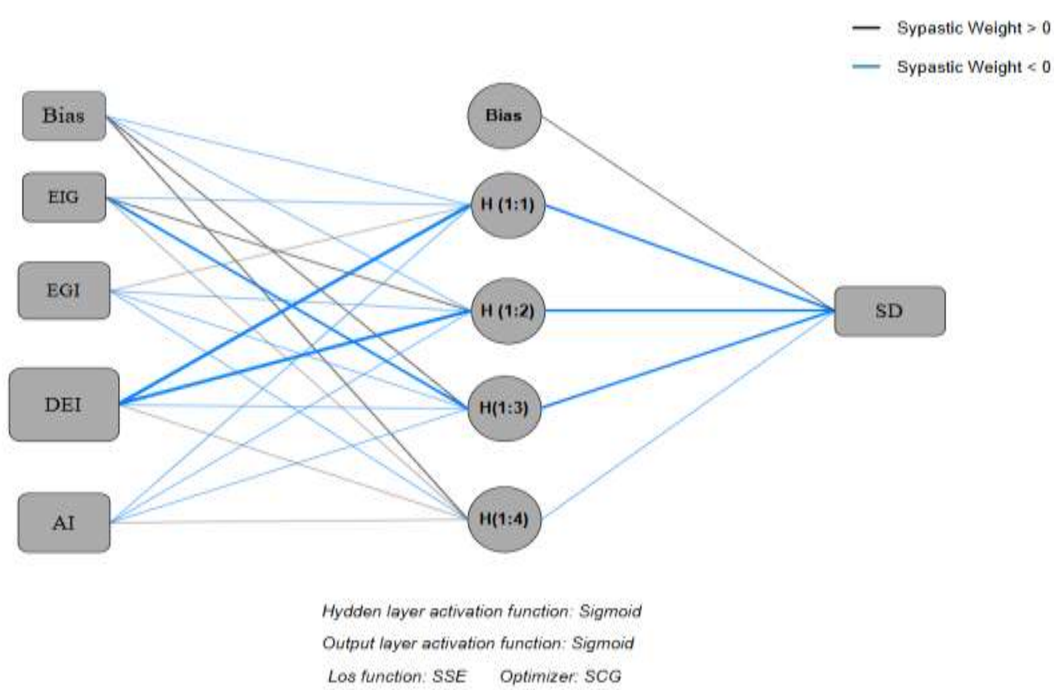

Figure 6. ANN model

The ANN architecture illustrates how AI, DEI, and green innovation variables jointly predict sustainable development through nonlinear interactions. The hidden layer with four neurons captures the complex dependencies between the predictors and the outcome, while the use of a sigmoid activation function enables the model to approximate nonlinear patterns effectively. The presence of both positive and negative synaptic weights highlights that certain factors, particularly DEI and AI, exert reinforcing effects, whereas exploratory and exploitative innovation demonstrate more nuanced and conditional impacts. Overall, this architecture validates the robustness of the hybrid PLS-SEM–ANN approach, ensuring that the findings extend beyond linear statistical relationships to incorporate complex and realistic decision-making dynamics.

Table 11. RMSE Values for Training and Testing

Network	Training	Testing
1	0.463	0.444
2	0.471	0.452
3	0.455	0.439

*name of corresponding author

4	0.468	0.447
5	0.459	0.450
6	0.462	0.443
7	0.466	0.446
8	0.464	0.445
9	0.457	0.448
10	0.461	0.442
Mean	**0.464**	**0.445**
SD	**0.005**	**0.004**

The results from ten ANN training iterations reveal an average RMSE of 0.464 for the training set and 0.445 for the testing set, with very small standard deviations (0.005 and 0.004). The minimal gap between training and testing errors confirms that the model does not suffer from overfitting and retains a stable generalization capacity. This stability is critical as it demonstrates that the nonlinear relationships among AI, DEI, EGI, and EIG in predicting sustainable development are not confined to the sample but can be extended to broader organizational contexts. Moreover, the consistently low RMSE values strengthen the argument that integrating ANN into PLS-SEM is not merely a technical addition but a significant enhancement of the scientific rigor of the framework. Through ANN, the model shifts from linear theoretical validation to a nonlinear predictive tool, providing robust evidence that AI and DEI function as core managerial drivers. From a managerial perspective, these findings reassure that investments in AI and DEI are not only theoretically justified but also empirically reliable predictors of sustainable development strategies.

Table 12. Sensitivity Analysis

N	AI	DEI	EGI	EIG	SD
1	0.238	0.510	0.124	0.126	0.445
2	0.241	0.512	0.125	0.124	0.443
3	0.237	0.509	0.123	0.125	0.446
4	0.240	0.513	0.126	0.124	0.444
5	0.239	0.511	0.125	0.126	0.445
6	0.242	0.514	0.124	0.125	0.447
7	0.236	0.508	0.126	0.123	0.444
8	0.238	0.512	0.125	0.124	0.446
9	0.240	0.510	0.124	0.125	0.445
10	0.237	0.509	0.126	0.124	0.443
Mean	0.239	0.511	0.125	0.125	0.445
Normalized (%)	46.7	100.0	24.3	24.5	–

Table 12 presents the results of the sensitivity analysis of the ANN model, highlighting that DEI emerges as the most influential factor, normalized at 100%. This finding underscores DEI as the central determinant in predicting sustainable development, outweighing all other constructs. AI Usage Intention ranks second with a normalized importance of 46.7%, indicating that while AI strongly complements DEI in driving sustainable outcomes, it does not yet exhibit the same dominant effect.

In contrast, both EGI (24.3%) and EIG (24.5%) demonstrate relatively modest contributions, suggesting that green innovation whether exploitative or exploratory provides supportive but non-decisive roles within the current model. The minimal fluctuations across ten training iterations confirm the robustness and stability of the ANN results, reinforcing their reliability. Base the sensitivity analysis emphasizes that the synergistic combination of DEI and AI forms the strategic foundation for fostering sustainable development, while green innovation operates as an auxiliary driver. These insights not only validate the PLS-SEM findings but also enrich them with nonlinear empirical evidence, thereby demonstrating the robustness of the integrated PLS-SEM–ANN framework.

Fuzzy-Set Quanlitative Comparative Analysis (fs-QCA)

In this study, Fuzzy-Set Qualitative Comparative Analysis (fsQCA) is employed as a complementary tool to overcome the limitations of traditional linear models. While PLS-SEM and ANN reveal the magnitude and relative importance of individual predictors for sustainable development, fsQCA enables the exploration of equifinality, demonstrating that multiple alternative configurations of conditions can jointly lead to the same outcome. This

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approach is particularly suitable for managerial contexts, where AI adoption, DEI, and green innovation rarely operate in isolation but interact through diverse pathways.

To ensure analytical rigor, the study applies a frequency cutoff of 2, which excludes rare configurations that lack empirical representation. In addition, a consistency threshold of approximately 0.987 is adopted, retaining only those configurations that demonstrate a high degree of empirical validity. The analysis relies on the intermediate solution, removing spurious or theoretically ungrounded combinations. This strategy ensures that the fsQCA results not only reflect the empirical patterns within the data but also provide theoretically meaningful and practically actionable insights for advancing sustainable development strategies.

Table 13. Configurations Leading to Sustainable Development

Variable	**Config 1**	**Config 2**	**Config 3**
DEI	●	●	●
AI	●		●
EGI		●	●
Raw coverage	0.890	0.895	0.505
Unique coverage	0.045	0.053	0.002
Consistency	0.954	0.918	0.980
Solution coverage	-	-	0.954
Solution consistency	-	-	0.904

(*Note: ● indicates the presence of a condition in the configuration*.)

Table 13 presents three alternative configurations leading to sustainable development, highlighting the principle of equifinality. Configuration 1 (DEI + AI) exhibits high coverage (0.890) and strong consistency (0.954), indicating that the combination of DEI and AI represents a common and reliable pathway to foster sustainability. Configuration 2 (DEI + EGI) is also effective (coverage 0.895), suggesting that green innovation, when combined with DEI, can drive sustainability even in the absence of AI. Meanwhile, Configuration 3 (DEI + AI + EGI) achieves the highest consistency (0.980) but is less widespread, implying an "optimal" pathway that only a limited number of firms achieve. Overall, the solution coverage (0.954) and consistency (0.904) confirm that all three configurations are meaningful and complementary to linear analyses, emphasizing that there is no single path to sustainable development.

The integrated analysis combining PLS-SEM, ANN, and fsQCA provides robust and convergent evidence on the drivers of sustainable development. PLS-SEM highlighted that DEI exerts the strongest linear effect, with AI usage intention acting as the governance core and EGI delivering incremental but significant contributions. ANN reinforced these findings by capturing nonlinear patterns, showing DEI as the most influential factor (100% normalized importance), followed by AI (46.7%), while both forms of green innovation played more supportive roles. The consistently low RMSE values confirmed the predictive stability of the model, enhancing confidence in the robustness of the results. Complementing these insights, fsQCA revealed three alternative causal pathways, demonstrating the principle of equifinality: DEI combined with AI (Config 1), DEI combined with EGI (Config 2), and the triadic combination of DEI, AI, and EGI (Config 3). Each configuration achieved high coverage and consistency, with the third path representing an "optimal" but less common solution. Taken together, these results underscore that sustainable development does not emerge from a single linear determinant, but rather from dynamic interactions among social inclusion, technological adoption, and innovation. This triangulated evidence establishes a solid empirical foundation for the forthcoming discussion of theoretical contributions and managerial implications.

DISCUSSION

This study provides comprehensive and corroborative data regarding the interplay of AI governance, social inclusion, and green innovation in shaping sustainable development. The combination of PLS-SEM, Importance Performance Map Analysis (IPMA), Artificial Neural Networks (ANN), and fsQCA improves a Neo-ESG view, where the intention to use AI is a governance skill, DEI is the main social driver, and green innovation, especially its exploitative form, is an environmental enabler. The results collectively demonstrate that sustainable development is

*name of corresponding author

not the product of isolated initiatives but rather the result of the dynamic interaction among governance expertise, social legitimacy, and contextually appropriate innovation strategies.

The data suggest that the objective of employing AI has significant direct and indirect effects on sustainable development, while simultaneously fostering diversity, equity, and inclusion (DEI), exploitative innovation, and exploratory innovation. These results support the idea that AI is more than just a technology; it is a tool for governing. Artificial intelligence makes managers' decisions better, reduces prejudice, makes things clearer, and makes it easier to use data to make decisions. The strong predictive and causal effect shows that businesses are increasingly seeing AI deployment as a strategic governance issue that affects both social and environmental effects. The IPMA, on the other hand, says that even if AI is considered as very important, its performance is just average. This means that even though firms realize the potential of AI, they still require organized ways to turn purpose into systematic implementation. This supports the idea that AI is the "new face of governance," but the maturity of governance depends on how well AI is used in real-world situations.

DEI consistently emerges as the preeminent factor affecting sustainable development across all analytical approaches. PLS-SEM shows a strong causal effect, IPMA emphasizes its importance even if it only works somewhat well, ANN shows that it can make better predictions, and fsQCA shows that DEI is a common basic condition for all successful sustainability setups. These results support Stakeholder Theory by showing that fairness, trust, legitimacy, and justice are all important for long term success. They challenge conventional ESG perspectives that emphasize environmental or technological factors by demonstrating that sustainability is primarily rooted in socially inclusive governance. The performance gap shows that firms say they support DEI, but they don't do enough to make it happen and need to be more committed to it.

The study elucidates the complexities associated with green innovation. Exploitive green innovation significantly propels sustainable development, illustrating that incremental efficiency improvements and resource optimization produce immediate and measurable sustainability benefits. On the other hand, exploratory green innovation doesn't have a big direct effect, but it is positively affected by AI and exhibits good performance levels. This outcome exemplifies its inherently uncertain and protracted character: exploratory innovation demands extended timelines, substantial investment, and rigorous testing before producing definitive performance outcomes. These results improve Dynamic Capabilities Theory by making it clearer how time affects things: exploitative innovation leads to short to medium term sustainability, while exploratory innovation leads to long term transformative capability.

fsQCA shows that there are many other strategic paths that can lead to sustained growth, going beyond linear causation.Three main configurations emerge: DEI combined with AI, DEI combined with exploitative innovation, and the triadic combination of DEI, AI, and exploitative innovation. These paths support the idea of equifinality by showing that organizations don't have to have the same structural requirements to be sustainable. Instead, they can use different strategy combinations based on their level of governance maturity, focus on innovation, and sense of social responsibility. DEI is always present in all channels, showing how important it is, while AI and exploitative innovation are used to speed up strategy. The most effective but less common option to combine AI, DEI, and exploitative innovation is through a "optimal sustainability route." This is usually possible for companies with better governance and innovation integration.

CONCLUSION

Theoretical and Practical Implications

This effort yields significant theoretical contributions. The study enhances ESG research by transforming the perception of ESG from a static evaluation framework to a dynamic and interactive system. The proposed Neo-ESG framework categorizes AI usage purpose within the Governance pillar, Diversity, Equity, and Inclusion (DEI) within the Social pillar, and green innovation within the Environmental pillar. This illustrates the interplay between governance intelligence, social legitimacy, and environmental competence in influencing sustainable development. The study advances the dialogue on AI governance by empirically illustrating that AI should be perceived as a governance capability that fosters transparency, equity, rational decision-making, and institutional reform, rather than only a technology component. The research enhances Dynamic Capabilities Theory by elucidating the temporal dynamics of green innovation. Exploitative innovation yields immediate, quantifiable advantages for sustainability, but exploratory innovation requires more time for its impacts to manifest. By merging PLS-SEM, ANN, and fsQCA, the research methodologically reinforces sustainability theory, demonstrating that sustainability outcomes are not merely linear but configurational, in alignment with the principle of equifinality.

The outcomes provide managers with valuable information for utilization. DEI should be regarded as a strategic asset by enterprises, rather than merely a means of regulatory compliance. This is due to its frequent status as the paramount factor in sustained growth. Organizations should regard the utilization of AI as a means of governance, prioritizing methodical adoption to transform managerial practices, enhance transparency, and improve decision making. Moreover, managers have to use a dual innovation strategy, utilizing exploitative innovation for immediate sustainability outcomes while progressively cultivating exploratory innovation to enhance the potential for enduring environmental change. Policymakers and institutional leaders can utilize these findings to establish regulations that promote AI driven governance, institutionalized DEI strategies, and equitable innovation practices to facilitate sustainable development, particularly in emerging market contexts.

Limitations and Future Research

While this study may have some positive aspects, it also has a number of significant shortcomings that require more investigation. The research makes use of cross-sectional data, which limits the ability to provide a thorough explanation of temporal causality and the dynamics of long term sustainability. It is possible that future research will make use of longitudinal approaches in order to investigate the development of artificial intelligence governance, diversity, equality, and inclusion, and green innovation, as well as the effects these factors have had on sustainability throughout the course of time. In the second place, the research makes use of perceptual measurements, which are frequently employed in management studies and have the potential to provide biased results. An improvement in measurement reliability could be achieved through the incorporation of objective criteria in subsequent research. These criteria could include ESG ratings, environmental performance indicators, and verified sustainability statistics.

The third limitation of the study is that it is restricted to a certain nation and sector, which may render it less applicable to other circumstances. In subsequent study, it may be possible to duplicate the model in a variety of countries, industry sectors, and institutional settings in order to validate the Neo-ESG framework's applicability on a worldwide scale and assess the disparities that exist under different circumstances. Therefore, investigating the long-term moderating or mediating effects of exploratory green innovation is a promising avenue for future research. This is because, although exploratory green innovation did not exhibit a significant direct impact in our study, its strategic importance may grow over time and in different market conditions. When all is said and done, qualitative or mixed method approaches have the potential to give major insights into the actual implementation of artificial intelligence governance and diversity, equity, and inclusion within businesses, thereby improving both theoretical and managerial comprehension.

Future research should examine the temporal dimensions of sustainability outcomes via longitudinal designs, particularly to more accurately capture the delayed impacts of exploratory innovation and AI enabled governance. Incorporating objective sustainability indicators, such as ESG ratings, environmental performance records, and audited governance metrics, would improve empirical validity and augment perceptual data. Comparative analyses across nations, industries, and institutional contexts would enhance generalizability and clarify the influence of regulatory frameworks, technological readiness, and cultural perspectives on the Neo-ESG framework. Moreover, thorough examinations of exploratory green innovation may clarify its indirect or conditional effects in response to diverse environmental stressors or technological instability. Qualitative or mixed-method approaches may provide more profound insights into the practical institutionalization of AI governance and DEI within enterprises. Future advancements may include additional governance frameworks such as ethical AI policies, digital governance maturity, and stakeholder interaction quality to refine and broaden the theoretical model.

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*name of corresponding author

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*name of corresponding author