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Article

THE ROLE OF PERCEIVED ENVIRONMENTAL RESPONSIBILITY IN ARTIFICIAL INTELLIGENCE-ENABLED RISK MANAGEMENT AND SUSTAINABLE DECISION-MAKING

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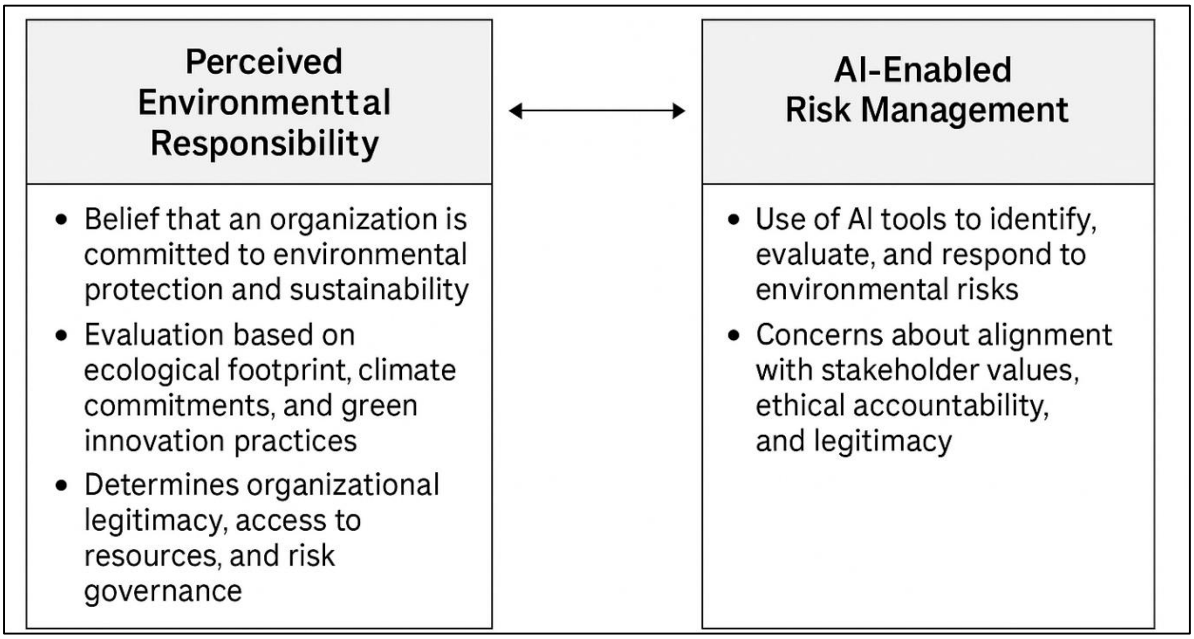
ABSTRACT
As artificial intelligence (AI) becomes increasingly embedded in sustainability governance, understanding the social and ethical contexts that influence its deployment is critical. This study investigates the role of Perceived Environmental Responsibility (PER) as a central construct in moderating stakeholder trust, enhancing AI adoption, and improving the performance of AI-enabled risk management systems in environmentally sensitive decision-making. While AI offers capabilities such as predictive analytics, real-time monitoring, and environmental impact simulations, its effectiveness is often shaped by how stakeholders interpret the intentions and values of the organizations that deploy these technologies. This research explores the hypothesis that PER not only influences stakeholder acceptance of AI but also determines organizational readiness, transparency outcomes, and alignment with sustainability objectives. Using a systematic meta-analysis approach guided by PRISMA methodology, the study synthesizes findings from 122 peer-reviewed articles published between 2010 and 2024. The findings reveal that PER functions as both a moderating and mediating variable: it amplifies trust in AI-based decisions, enhances stakeholder interpretability of complex models, and improves strategic integration of AI into environmental, social, and governance (ESG) frameworks. Organizations with high PER demonstrated stronger performance in AI-based compliance reporting, emissions management, and environmental decision-making, while those with low PER experienced reputational risk, stakeholder skepticism, and underutilization of AI tools. The study contributes to the literature on stakeholder theory, responsible innovation, and sustainable technology adoption by positioning PER as a foundational variable in ethical AI integration. It also aligns PER with the principles of the Triple Bottom Line (TBL) and ESG reporting, emphasizing its operational and reputational importance in digital sustainability governance. By synthesizing evidence across sectors and regions, the research provides actionable insights for organizations seeking to implement AI responsibly. It concludes that PER is not simply a passive perception but an active enabler of technological legitimacy, ethical alignment, and long-term sustainability success in AI-supported decision environments.

KEYWORDS
Perceived Environmental Responsibility; AI-Enabled Risk Management; Sustainable Decision-Making; ESG Integration; Stakeholder Trust;

INTRODUCTION

Perceived Environmental Responsibility (PER) refers to the extent to which individuals or stakeholders believe that an organization is genuinely committed to environmental protection and sustainability. This perception goes beyond formal compliance or superficial green initiatives, focusing instead on authentic engagement with ecological concerns through transparent and accountable actions (Paço & Rodrigues, 2016). In the international landscape, PER has emerged as a critical construct for understanding how organizations are evaluated in terms of their ecological footprint, climate commitments, and green innovation practices. As nations strive to meet Sustainable Development Goals (SDGs), public and investor scrutiny regarding corporate environmental practices has intensified, making PER a significant determinant of organizational legitimacy and access to resources (Paço & Rodrigues, 2016). The increasing focus on Environmental, Social, and Governance (ESG) performance indicators has further cemented PER's relevance in shaping institutional behaviors and policy frameworks at both national and transnational levels . Therefore, understanding PER is essential not only for assessing reputational capital but also for enabling inclusive and sustainable risk governance.

Figure 1: Interrelationship Between Perceived Environmental Responsibility and AI-Enabled Risk Management



In parallel with the rise of environmental consciousness, artificial intelligence (AI) has revolutionized the landscape of risk management and organizational decision-making. AI refers to the use of machine learning, natural language processing, and advanced data analytics to replicate human cognitive functions in problem-solving and predictive modeling (Paço & Rodrigues, 2016). In enterprise contexts, AI is increasingly leveraged to identify, evaluate, and respond to environmental risks ranging from climate volatility to resource depletion. AI-enabled risk management involves the application of algorithmic systems to automate the detection of vulnerabilities, simulate intervention scenarios, and guide contingency planning. Particularly in sustainability domains, AI offers tools for real-time monitoring of carbon emissions, supply chain disruptions, regulatory non-compliance, and ecological damage, thereby enhancing both responsiveness and foresight (Shahrin et al., 2020). As AI assumes a more integral role in managing systemic environmental risks, questions have emerged regarding its alignment with stakeholder values, particularly in terms of ethical accountability and environmental responsibility. The convergence of AI technologies with sustainability imperatives raises foundational questions about how PER shapes the trust, utility, and perceived legitimacy of AI-driven decision support systems.

The integration of AI into sustainability-oriented governance structures demands careful consideration of stakeholder perceptions, especially where environmental responsibility is

Volume 04 Issue 04 (2024)
Page No: 33 - 56
eISSN: 3067-0470
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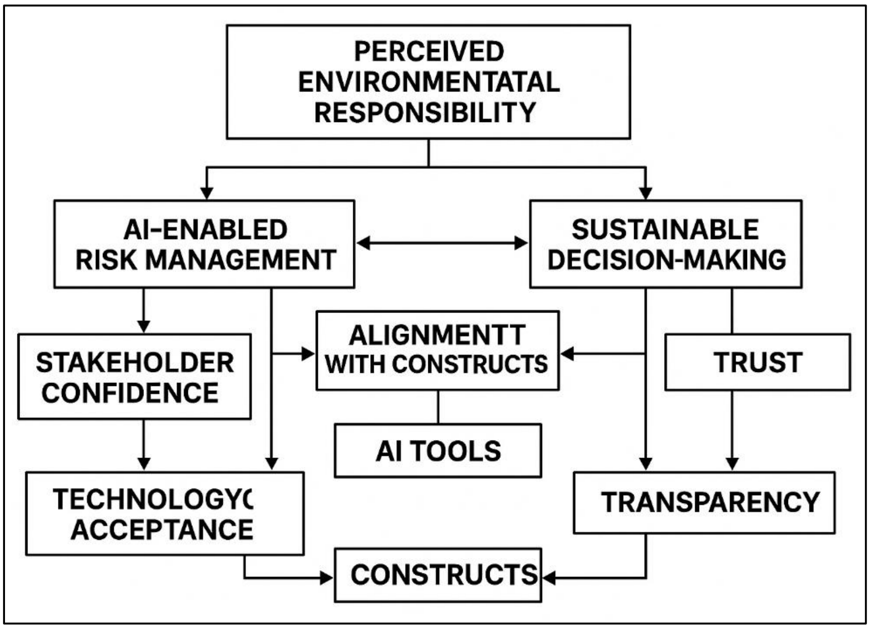
concerned. PER serves as a socio-cognitive filter through which stakeholders interpret and assess the appropriateness and credibility of AI-enabled decision-making systems (Shahrin et al., 2020). Stakeholders who perceive an organization as environmentally responsible are more likely to support the deployment of AI systems aimed at managing ecological risk, as such alignment reinforces existing values and enhances institutional credibility (Singh et al., 2021). Conversely, in settings where PER is low or contested, the implementation of AI may be perceived as a facade or tool of greenwashing, thereby reducing stakeholder engagement and eroding trust (Werff et al., 2021). This dynamic is particularly critical in high-stakes sectors such as energy, manufacturing, and transportation, where environmental risks intersect with economic and social vulnerabilities (Zheng et al., 2020). By anchoring AI adoption within the framework of PER, organizations can build relational legitimacy and increase the operational viability of their risk management infrastructures.

Figure 2: The Role of Perceived Environmental Responsibility in Shaping AI-Driven Sustainable Decision-Making



Numerous empirical studies underscore the mediating influence of environmental responsibility on technology acceptance and adoption in enterprise settings. For example, research by Mansoor and Wijaksana (2022) finds that firms with strong environmental reputations are more likely to gain stakeholder buy-in for digital transformation initiatives, particularly those involving high-impact technologies such as AI and big data. Similarly, Janmaimool and Chudech (2020) reveal that environmentally responsible firms report higher adoption rates of smart infrastructure and climate-resilient planning tools, owing to greater stakeholder confidence. This linkage is further supported by organizational behavior literature, which suggests that perceived alignment between corporate values and technological applications facilitates internal integration and external collaboration. Moreover, studies on responsible innovation highlight that stakeholder perceptions of sustainability and ethical use directly affect AI system acceptance, especially when decisions have distributive or ecological consequences. In this regard, PER acts as a boundary-spanning construct that links strategic intent, technological capability, and stakeholder alignment in AI-enabled risk management. In the field of sustainable decision-making, the concept of PER interacts with several other constructs such as organizational transparency, ethical leadership, and participatory governance. Sustainable decision-making involves balancing environmental, economic, and social trade-offs to achieve long-term value creation and resilience (Singh et al., 2021). Organizations that are perceived as environmentally responsible are more likely to be trusted when they deploy AI to inform or automate such decisions (Werff et al., 2021). Research by Mansoor and Wijaksana (2022) indicates that trust in sustainable decisions increases significantly when stakeholders perceive that decisions are grounded in a proactive environmental ethos. Furthermore, the integration of AI in such contexts can be interpreted either as an amplifier of sustainability or as a tool of opacity, depending

Volume 04 Issue 04 (2024)
Page No: 33 - 56
eISSN: 3067-0470
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on whether PER is strong or weak. When PER is high, AI tools are more likely to be seen as extensions of an ethical decision-making apparatus, fostering transparency and accountability (Kozar & Connell, 2013). Therefore, the interaction between PER and AI tools plays a crucial role in establishing whether such decision-making mechanisms are perceived as sustainable or opportunistic.

The principal objective of this study is to examine how Perceived Environmental Responsibility (PER) influences the acceptance, deployment, and effectiveness of AI-enabled risk management systems within sustainability-driven organizational frameworks. Specifically, the study aims to explore the mediating and moderating roles of PER in shaping stakeholder trust, technological legitimacy, and strategic alignment in enterprise-level decision-making. Grounded in stakeholder theory and the technology acceptance model, this investigation hypothesizes that when organizations are viewed as environmentally responsible, stakeholders are more likely to endorse the use of AI technologies for critical risk management functions such as climate risk assessment, operational resilience, and regulatory compliance. Research shows that environmental reputation directly affects stakeholder attitudes toward innovation and digital transformation. Therefore, this study seeks to identify whether the perception of environmental commitment enhances the perceived usefulness and ethical acceptability of AI systems in sustainability contexts . Another objective is to evaluate whether PER acts as a trust-building mechanism that mitigates skepticism about algorithmic transparency, fairness, and bias—concerns frequently associated with AI deployment in socially sensitive domains. By synthesizing data from organizational case studies, ESG disclosures, and cross-sectoral surveys, this research intends to generate actionable insights into how PER influences the framing, interpretation, and utility of AI-driven decision-making in risk-laden environments. In doing so, the study contributes to a nuanced understanding of how values-based perceptions interact with technological infrastructure to enable more effective and socially acceptable risk governance. Ultimately, the objective is to highlight the strategic necessity of aligning AI capabilities with authentic environmental values to promote stakeholder engagement, enhance operational credibility, and support data-driven sustainability initiatives across diverse industrial sectors.

LITERATURE REVIEW

The intersection of perceived environmental responsibility (PER), artificial intelligence (AI), and sustainable risk management has gained significant academic attention in the last decade. As global enterprises adopt AI tools to automate and optimize decision-making, questions around stakeholder perception, ethical alignment, and ecological accountability have become central to the discourse on digital sustainability. The literature reflects a growing consensus that technological innovations, particularly those involving AI and machine learning, must align with socially and environmentally responsible governance frameworks to be accepted and effective. At the core of this alignment lies PER, a construct that represents stakeholders' beliefs regarding an organization's commitment to ecological stewardship, ethical transparency, and environmental justice. PER influences how stakeholders—including customers, investors, employees, and regulators—respond to the integration of emerging technologies, especially in domains with potential environmental and social risks. This literature review provides a synthesized exploration of the major constructs and variables underpinning this study. It begins with foundational definitions and theoretical grounding for perceived environmental responsibility, followed by a critical review of literature on AI-enabled risk management systems. The section then delves into stakeholder trust and ethical AI, ESG integration mechanisms, and finally the interactive role PER plays in shaping perceptions, adoption behavior, and organizational outcomes. The review consolidates evidence from interdisciplinary studies, drawing on fields such as sustainability science, technology ethics, risk governance, information systems, and organizational behavior. The goal is to map the scholarly landscape, identify research gaps, and build a theoretical framework for investigating how PER modulates AI-based sustainability initiatives. Each section in the outline is designed to dissect specific aspects of this relationship with precision, using evidence from peer-reviewed journals, empirical case studies, and established theoretical models.

Perceived Environmental Responsibility (PER)

Perceived Environmental Responsibility (PER) is conceptualized as stakeholders' belief or perception that an organization is committed to protecting the natural environment through its policies, operations, and culture. Unlike Corporate Environmental Responsibility (CER), which focuses on a firm's objective practices, PER emphasizes the subjective evaluation made by external and internal stakeholders based on observable behaviors, communications, and environmental impact

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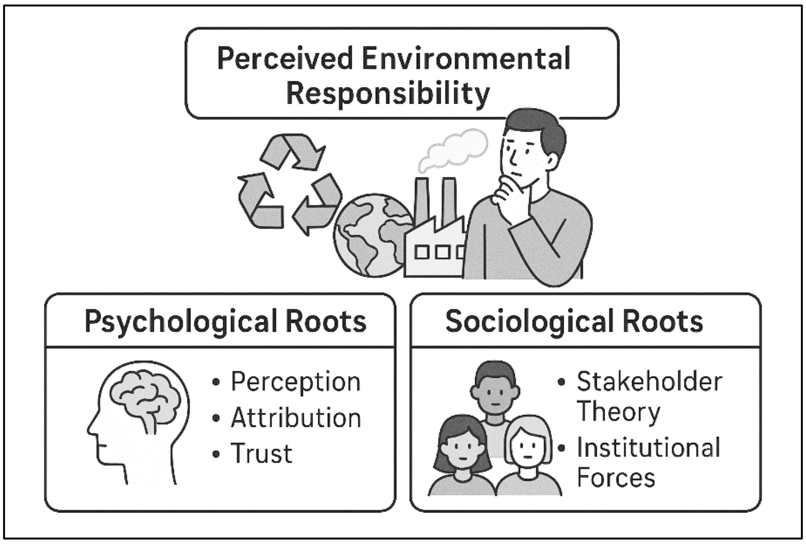
disclosures (Liu et al., 2010). This perception is critical for shaping legitimacy and trust, particularly in industries with high ecological footprints such as manufacturing, logistics, and energy. The definition of PER builds on foundational constructs in environmental psychology and organizational behavior, including corporate image, corporate social responsibility, and green reputation. Unlike CSR, which often integrates philanthropy and governance alongside environmental performance, PER focuses exclusively on how environmental commitments are interpreted and judged (Liu et al., 2012). Studies indicate that PER is significantly influenced by transparency in environmental reporting, third-party certifications (e.g., ISO 14001), and visible sustainability efforts such as eco-labeling and green product design. Additionally, stakeholder perceptions of greenwashing or superficial compliance efforts negatively impact PER, making authentic engagement essential for building reputational capital. In digitally mediated markets, PER is also shaped by online platforms, social media discourse, and algorithmically curated environmental ratings. As a multidimensional construct, PER reflects both cognitive assessment and emotional judgment, and has been linked to increased customer loyalty, investor confidence, and employee satisfaction.

Figure 3: Cognitive and Organizational Dimensions of Perceived Environmental Responsibility (PER)



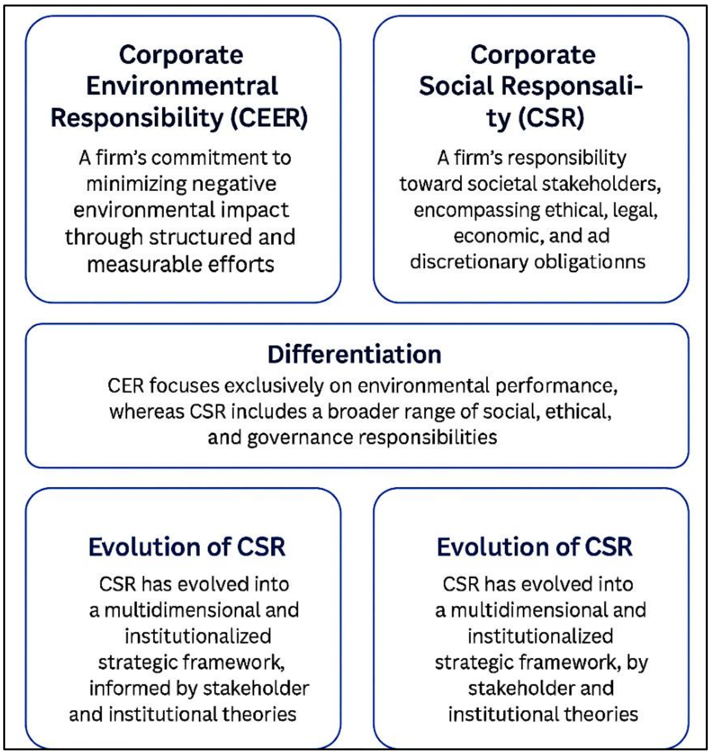
The concept of Perceived Environmental Responsibility (PER) has evolved significantly over the past two decades as global awareness of sustainability issues has increased. Early literature treated environmental responsibility as a component of broader Corporate Social Responsibility (CSR) frameworks, often assessed using environmental performance indicators or sustainability indices (Janmaimool & Chudech, 2020). Over time, researchers distinguished between actual corporate environmental performance and stakeholders' perceptions of such efforts, giving rise to PER as an independent construct (Albayrak et al., 2013). The evolution of PER has been heavily influenced by stakeholder theory, which posits that organizations must align their environmental strategies with the expectations and values of diverse groups, including customers, investors, regulators, and communities. As regulatory frameworks such as the Global Reporting Initiative (GRI), the Carbon Disclosure Project (CDP), and the Task Force on Climate-Related Financial Disclosures (TCFD) gained traction, organizations were incentivized to enhance transparency and communication regarding environmental risk, further shaping how PER is formed. The proliferation of ESG rating agencies and green finance mechanisms also contributed to the refinement of PER as a key reputational metric. Recent empirical studies distinguish PER as a dynamic perception that can evolve based on organizational learning, external pressures, and incident-driven stakeholder reappraisal (Tait et al., 2016). Furthermore, PER has become critical in contexts involving AI, smart infrastructure, and sustainable innovation, where the perceived alignment between technology deployment and ecological responsibility directly influences acceptance. Thus, the evolution of PER reflects its transformation from a secondary evaluative criterion to a central construct in sustainability governance and digital risk communication.

American Journal of Advanced Technology and Engineering Solutions
Volume 04 Issue 04 (2024)
Page No: 33 - 56
eISSN: 3067-0470
DOI: 10.63125/7tjw3767

Corporate Environmental Responsibility (CER) and CSR

Corporate Environmental Responsibility (CER) refers to a firm's commitment to minimizing the negative environmental impact of its operations, supply chains, and products through structured, measurable, and often regulated sustainability efforts. CER is grounded in environmental management practices that extend beyond compliance with governmental regulations and includes proactive strategies such as pollution prevention, energy efficiency, waste reduction, and life-cycle assessment (Lee et al., 2016). Scholars distinguish CER from general CSR by emphasizing its exclusive focus on environmental performance, whereas CSR encompasses a broader array of social, ethical, and governance-related responsibilities (Tan et al., 2024). CER initiatives are often operationalized through environmental management systems (EMS) like ISO 14001, environmental impact audits, green innovation practices, and voluntary disclosures aligned with frameworks such as GRI or CDP. Empirical studies have confirmed a strong link between CER and firm performance, particularly in contexts where stakeholders actively evaluate environmental commitments. Firms demonstrating high CER often enjoy improved stakeholder trust, enhanced legitimacy, and preferential access to capital. In addition, CER has been linked to reduced operational risks and cost efficiencies due to process improvements and compliance anticipation. CER frameworks have also expanded to incorporate elements of biodiversity preservation, circular economy practices, and supply chain sustainability (Cai & He, 2013). Overall, CER represents a focused subset of CSR, emphasizing ecological accountability, and is increasingly treated as a separate performance indicator in ESG reporting and environmental accounting literature (Jo et al., 2014).

Figure 4: CER vs. CSR: Conceptual Intersection and Distinction



Corporate Social Responsibility (CSR) has evolved from a philanthropic or voluntary concept into a multidimensional and institutionalized strategic framework. CSR is broadly defined as a firm's responsibility toward societal stakeholders, encompassing ethical, legal, economic, and discretionary obligations. Initially characterized by isolated acts of corporate giving, CSR is now closely associated with sustainability, stakeholder engagement, labor rights, environmental performance, and ethical governance (Li et al., 2019). The Triple Bottom Line approach has significantly shaped CSR discourse by embedding environmental, social, and financial performance as equally important (Dummett, 2006). CSR strategies are often informed by stakeholder theory and institutional theory, both of which argue that corporate behavior must align with evolving societal norms and expectations to maintain legitimacy (Wong et al., 2016). Firms adopting comprehensive CSR practices tend to integrate these principles into corporate culture, board-level decision-making, risk assessment, and reporting (Zou et al., 2018). CSR has also become a performance differentiator, with growing evidence that firms with higher CSR engagement enjoy competitive advantages through brand loyalty, employee satisfaction, and reputational capital (Graafland & Gerlagh, 2019). Regulatory bodies and capital markets have increased pressure on firms to report CSR outcomes, often linking them to sustainability indices such as DJSI or MSCI ESG (Ghoul et al., 2016). While CSR encompasses environmental considerations, the latter has gained autonomy as CER due to the specificity and urgency of ecological challenges (Lee et al., 2016). As such, CSR and CER are intertwined but analytically distinct constructs in the academic and regulatory spheres.

eISSN: 3067-0470
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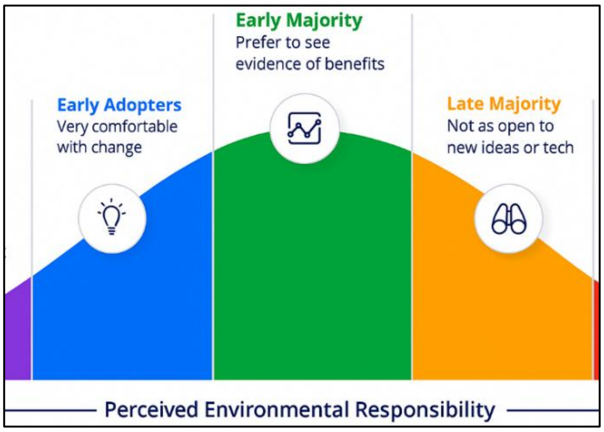
PER and Technology Adoption

Technology adoption, particularly in sustainability and risk management contexts, is strongly influenced by stakeholder perceptions of organizational intent and responsibility. Perceived Environmental Responsibility (PER) is increasingly recognized as a determinant of stakeholder support for emerging technologies, especially those used in environmental governance or digital transformation (Henseler et al., 2016). Studies rooted in stakeholder theory affirm that technology acceptance depends not only on the perceived functionality or efficiency of a tool but also on whether it aligns with organizational values and stakeholder expectations regarding ecological stewardship. Research by Loh et al. (2019) and Lew et al. (2020) found that organizations with high PER scores are more likely to gain public support for environmental innovations, even when such technologies are disruptive or novel. Stakeholders interpret AI-based systems, smart infrastructure, and green digital tools more favorably when these systems are introduced within firms that demonstrate authentic environmental commitment (Dubey et al., 2020). The Technology Acceptance Model (TAM) and its extensions, including the Unified Theory of Acceptance and Use of Technology (UTAUT), have also been expanded to include ethical and environmental constructs such as PER, particularly in the domains of clean energy, green IT, and environmental monitoring. Dwivedi et al. (2021) demonstrated that perceived environmental leadership by top management moderates the relationship between technological complexity and adoption behavior.

The integration of PER into the innovation diffusion literature has clarified how environmental perceptions shape internal and external legitimization processes for new technologies. Drawing from institutional theory, legitimacy is not only a matter of regulatory compliance or economic rationale but also hinges on how well organizational actions reflect broader societal values, including environmental ethics (Duan et al., 2019). Organizations perceived as environmentally responsible are often granted a "license to innovate," particularly when introducing technologies that may have uncertain outcomes or require significant public investment. The diffusion of AI-based energy optimization systems, for instance, has been more effective in companies with strong environmental reputations because the perception of PER reduces cognitive and normative resistance among key stakeholders. Moreover, empirical research has shown that organizational identity—especially when constructed around sustainability narratives—can facilitate smoother internal alignment and adoption of AI, IoT, and machine learning for environmental performance management. In industries such as utilities, logistics, and manufacturing, firms with documented PER are more likely to integrate environmental management systems with digital platforms, as stakeholders interpret these actions as consistent with organizational purpose (Whitfield & Hofmann, 2023). Sumi and Kabir (2018) further highlight that companies with sustained environmental messaging and performance disclosures experience higher success rates in digital technology rollouts. Therefore, PER contributes to both symbolic and pragmatic legitimacy during the technology adoption lifecycle, enhancing stakeholder alignment and reducing institutional friction in sustainability-oriented innovation initiatives (Royne et al., 2016).

Figure 5: PER-Based Technology Adoption Curve in Sustainability Contexts

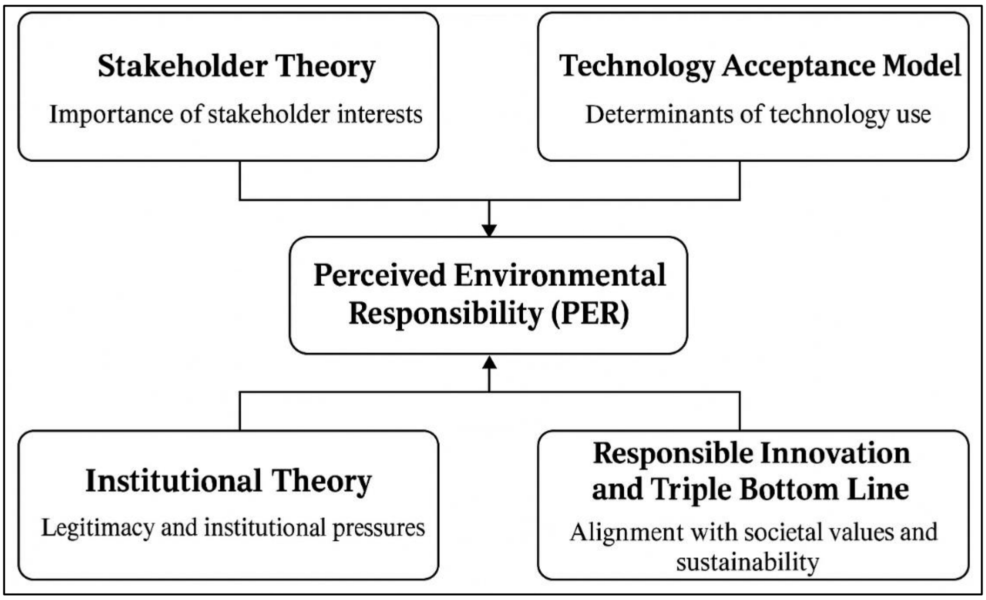


American Journal of Advanced Technology and Engineering Solutions
Volume 04 Issue 04 (2024)
Page No: 33 - 56
eISSN: 3067-0470
DOI: 10.63125/7tjw3767

Theories on developing Model

Stakeholder theory provides a foundational lens for understanding the strategic significance of Perceived Environmental Responsibility (PER), as it emphasizes the centrality of stakeholder interests in shaping corporate actions and outcomes. The theory argues that firms must consider the expectations of all stakeholders—beyond shareholders—including employees, consumers, communities, regulators, and advocacy groups. In the context of environmental responsibility, stakeholders increasingly assess whether an organization authentically prioritizes ecological values, which in turn shapes perceptions of legitimacy, trustworthiness, and ethical standing (Szyszka, 2024). Chen and Wang (2012) demonstrates that organizations with high PER benefit from increased customer loyalty and stakeholder engagement, particularly when environmental claims are backed by measurable actions. Stakeholder theory is also critical in explaining why different groups weigh environmental responsibility differently—investors may focus on long-term risk mitigation, while communities may assess environmental justice or local impact (Rossi & Pero, 2012). The theory helps link PER to technology adoption by asserting that stakeholders are more likely to support digital transformation—especially the integration of AI in sustainability applications—when they believe the organization is environmentally responsible (Papadopoulos et al., 2020). Moreover, the relational and communicative dimensions of stakeholder theory emphasize the role of transparency, consistency, and participatory engagement in shaping stakeholder attitudes toward both PER and technological innovations (Zhang, 2011) . This theory not only validates PER as a construct of strategic relevance but also positions it as a mediating force between ethical environmental values and the success of technology-driven sustainability initiatives (Posey et al., 2012).

Figure 6: Underpinning theories for this study



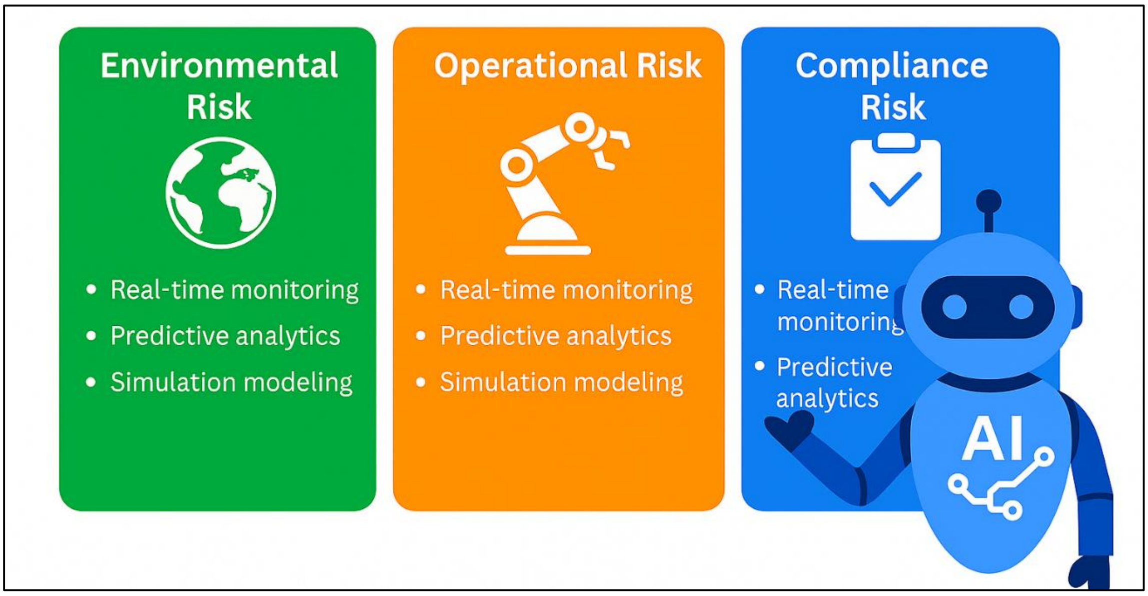
The Technology Acceptance Model (TAM) and its extensions provide a robust theoretical basis for understanding how perceptions of environmental responsibility influence stakeholder acceptance of emerging technologies. Originally developed by Davis (1989), TAM posits that perceived usefulness and perceived ease of use are primary determinants of technology adoption behavior. However, in sustainability contexts, particularly those involving artificial intelligence (AI), these core determinants are frequently moderated by ethical, social, and environmental perceptions (Ogundiran et al., 2024). Research by Venkatesh et al. (2003), who developed the Unified Theory of Acceptance and Use of Technology (UTAUT), extended TAM by incorporating performance expectancy, effort expectancy, social influence, and facilitating conditions, offering a more comprehensive framework for organizational and consumer technology behavior. PER serves as a contextual variable that influences how these factors are interpreted; for example, performance expectancy is evaluated not only in terms of operational efficiency but also in environmental impact and sustainability alignment (Chao et al., 2021). Studies have shown that users are more likely to

American Journal of Advanced Technology and Engineering Solutions
Volume 04 Issue 04 (2024)
Page No: 33 - 56
eISSN: 3067-0470
DOI: 10.63125/7tjw3767
adopt green information systems or environmental monitoring technologies when the deploying firm has a high PER. Additionally, perceived organizational values, such as environmental stewardship, strengthen trust and reduce perceived risk, thereby reinforcing the intention to use technology (Soopramanien et al., 2023). The integration of PER into TAM and UTAUT thus enhances explanatory power, particularly in the domain of sustainable innovation. Moreover, extensions like the Value-Based Adoption Model and Green TAM explicitly incorporate environmental concerns into traditional acceptance models, validating PER as a key construct in contemporary adoption research. These models collectively suggest that environmental responsibility is not a peripheral but a core element of digital acceptance in ecological decision-making settings.

AI-driven risk management

Artificial Intelligence (AI) has been widely adopted in enterprise risk management, offering robust tools to identify, quantify, and mitigate diverse categories of risk including environmental, operational, and regulatory compliance threats (Abdullah Al et al., 2022). In environmental risk contexts, AI enables the analysis of large-scale climate data, satellite imagery, and emissions records to assess deforestation, pollution patterns, and carbon footprint tracking . For instance, AI algorithms have been deployed in water resource management to detect contamination risks, and in agriculture for monitoring drought and soil degradation (Hamza et al., 2022; Sazzad & Islam, 2022). In operational risk settings, AI tools are used to enhance fault detection, predictive maintenance, and supply chain resilience by processing real-time sensor data and historical equipment failure records (Belhadi et al., 2021; Shaiful et al., 2022). For example, machine learning models trained on equipment vibration and temperature readings are now commonly used to anticipate failure in critical infrastructure such as wind turbines and power grids (Linaza et al., 2021; Akter & Razzak, 2022). In compliance risk, AI systems assist in regulatory monitoring by scanning legal documents, identifying anomalies in financial reports, and detecting early signs of fraud or non-conformance (Fan et al., 2023; Qibria & Hossen, 2023). AI's capacity to interpret unstructured data—such as social media, regulatory texts, and internal policy reports—has enabled firms to automate auditing and due diligence processes, especially in complex sectors like pharmaceuticals, banking, and mining (Boukabara et al., 2021; Maniruzzaman et al., 2023). The integration of AI in these domains not only enhances precision and responsiveness but also facilitates early warning systems that reduce long-term risk exposure. Thus, AI-driven risk management extends across a broad array of organizational domains and serves as a critical tool for sustaining competitive advantage in risk-prone environments (Masud et al., 2023).

Figure 7: AI-Driven Risk Management Framework



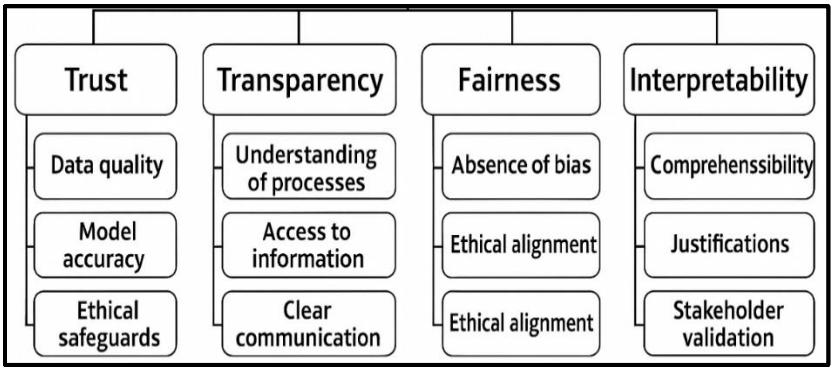
Real-time monitoring, simulation modeling, and predictive analytics represent the technological core of AI-enabled risk management. These capabilities allow organizations to transition from

American Journal of Advanced Technology and Engineering Solutions
Volume 04 Issue 04 (2024)
Page No: 33 - 56
eISSN: 3067-0470
DOI: 10.63125/7tjw3767
reactive to proactive risk strategies by enabling constant surveillance of environmental conditions (Hossen et al., 2023), system performance, and operational variables. AI-powered sensors, combined with Internet of Things (IoT) devices, continuously collect and process data on variables such as temperature, pressure, air quality, and structural integrity, allowing for immediate identification of anomalies or emerging hazards (Ariful et al., 2023; Stahl, 2022). These technologies have proven particularly valuable in environmental risk domains, including wildfire detection, coastal erosion monitoring, and urban air pollution control (Borges et al., 2021; Shamima et al., 2023). Simulation tools, powered by deep learning algorithms, model potential disaster scenarios such as chemical spills, flooding, or industrial failure, helping stakeholders to evaluate various response strategies and allocate resources accordingly (Baryannis et al., 2018; Alam et al., 2023). Predictive analytics further enhances these simulations by identifying patterns in historical data and estimating future outcomes based on real-time input. For example, AI-based predictive models have improved risk forecasting in logistics by accounting for geopolitical disruptions, supplier delays, and climate variability (Abid et al., 2021; Rajesh, 2023; Rajesh et al., 2023). These capabilities are not limited to the physical environment; in cybersecurity and compliance risk contexts, predictive analytics detect irregular login behavior, unauthorized transactions, or employee misconduct based on behavioral baselines (Alter, 2022; Sanjai et al., 2023). The fusion of real-time and predictive insights enables organizations to implement dynamic risk scoring systems, which adjust their responses based on evolving risk profiles. Through the convergence of real-time data processing, simulation, and predictive modeling, AI systems offer a comprehensive and adaptive risk management framework applicable across multiple sectors and operational layers.

Perception of AI in Sustainability Contexts

Trust in algorithmic systems has emerged as a pivotal factor in the successful deployment of AI within sustainability-focused organizations and policy frameworks. Trust, in this context, refers to stakeholders' confidence in the reliability, fairness, and ethical alignment of AI-based decisions Adedayo et al. (2023) Several determinants shape this trust, including data quality, model accuracy, ethical safeguards, and alignment with organizational values. Research shows that perceived risk, complexity, and lack of user control reduce trust in automated decision-making, particularly in contexts involving environmental regulation and climate risk management. In contrast, systems perceived as transparent, explainable, and value-aligned are more likely to be trusted by stakeholders across industries (Tonmoy & Arifur, 2023). Linaza et al. (2021) show that trust in AI systems increases when organizations clearly communicate the ethical principles guiding model development and offer mechanisms for human oversight. In sustainability contexts, where decisions affect natural ecosystems, community health, or compliance reporting, stakeholders often exhibit heightened sensitivity to how and why AI systems operate (Tonoy & Khan, 2023). Moreover, stakeholder trust is influenced by previous organizational behavior—firms with a history of social responsibility or environmental transparency tend to inspire more confidence in their technological systems. As such, trust is not just a function of algorithmic performance but also of institutional reputation, perceived intent, and stakeholder engagement mechanisms (Zahir et al., 2023). Establishing trust is essential for achieving acceptance, collaboration, and legitimacy in AI-enabled sustainability governance models.

Figure 8: Key Determinants of Stakeholder Perception of AI in Sustainability Governance



Volume 04 Issue 04 (2024)
Page No: 33 - 56
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Transparency, fairness, and interpretability are three core principles that underpin stakeholder perception of AI systems, particularly in the context of sustainability and environmental governance. Transparency refers to the ability of users and stakeholders to understand how AI systems process data, derive outputs, and make decisions. Without transparency, stakeholders may perceive AI applications as opaque or manipulative, especially when outcomes affect public health, environmental equity, or regulatory compliance. Fairness, on the other hand, involves the absence of bias or discriminatory effects in algorithmic decision-making. Studies have shown that AI models trained on historical environmental data can unintentionally reproduce systemic inequalities, such as under-serving marginalized communities in pollution monitoring or infrastructure allocation (Razzak et al., 2024; Fan et al., 2023). Interpretability complements these two factors by enabling users—especially non-technical stakeholders—to comprehend the rationale behind AI-driven insights and to validate them against ecological, ethical, or policy standards. Krupnova et al. (2022) suggests that interpretability directly contributes to the perceived credibility and ethical soundness of AI applications in sustainability reporting and ESG analytics. In high-stakes applications like disaster forecasting or resource allocation, lack of interpretability can undermine stakeholder confidence and hinder decision-making effectiveness. Technical solutions such as explainable AI (XAI), model documentation, and participatory design have been recommended to enhance interpretability and fairness . Organizations that adopt these principles not only improve stakeholder understanding but also promote institutional legitimacy and ethical alignment in AI-enabled sustainability frameworks. Thus, the interrelationship between transparency, fairness, and interpretability fundamentally shapes the stakeholder response to AI in environmental risk contexts.

ESG Integration and AI

Environmental, Social, and Governance (ESG) metrics serve as structured indicators used to evaluate an organization's sustainability performance, risk exposure, and ethical alignment. ESG frameworks have gained international prominence, driven by institutional investors, regulatory bodies, and standardization initiatives such as the Global Reporting Initiative (GRI), Sustainability Accounting Standards Board (SASB), and Task Force on Climate-related Financial Disclosures (TCFD) (Friede et al., 2015). These frameworks encourage firms to report on non-financial performance dimensions such as greenhouse gas emissions, energy use, labor practices, board diversity, and ethical supply chain conduct (Krupnova et al., 2022; Subrato, 2018). Environmental metrics often include Scope 1, 2, and 3 emissions, biodiversity impacts, and water usage, while governance metrics assess compliance, executive pay alignment, and anti-corruption practices (Vicente-Molina et al., 2013). ESG disclosures are critical for investors aiming to incorporate sustainability into portfolio strategies and for regulators evaluating systemic environmental and social risks. Research shows that standardized ESG reporting improves firm transparency, risk prediction, and long-term stakeholder relationships. However, ESG frameworks also face criticism for inconsistencies in rating methodologies and limited comparability across jurisdictions. Recent developments have attempted to harmonize ESG metrics across industries and regions, with the emergence of the International Sustainability Standards Board (ISSB) and the EU Taxonomy for Sustainable Activities (Alam et al., 2024; Manolas & Tampakis, 2010). These standards increasingly push firms to integrate digital systems and evidence-based practices into ESG tracking and disclosure, creating a pathway for AI technologies to play a supportive role in enhancing reporting accuracy and compliance across the ESG spectrum.

Artificial Intelligence (AI) has emerged as a key enabler in ESG reporting and risk analytics, offering tools that automate, standardize, and enhance the accuracy of non-financial disclosures. Traditional ESG reporting processes often involve manual data entry, fragmented information systems, and interpretive inconsistencies, which can lead to incomplete or unreliable outputs. AI technologies—particularly natural language processing (NLP), machine learning, and robotic process automation—enable the aggregation and interpretation of both structured and unstructured ESG data from diverse sources including sustainability reports, news media, satellite imagery, and regulatory filings (Medeiros & Ribeiro, 2017; Khan & Razee, 2024). For instance, NLP algorithms can extract climate risk-related statements from annual reports, while machine learning models identify greenwashing patterns or compliance gaps by comparing reported data with third-party records (Gurău & Dana, 2018; Saha, 2024). AI is also applied in ESG scoring and benchmarking, where algorithms generate dynamic sustainability ratings based on multi-source data inputs (Diouf et al., 2014). Several ESG-focused platforms such as RepRisk, Truvalue Labs, and Sustainalytics now rely heavily on AI to deliver real-time sustainability insights to investors and regulators (Arisal & Atalar, 2016;

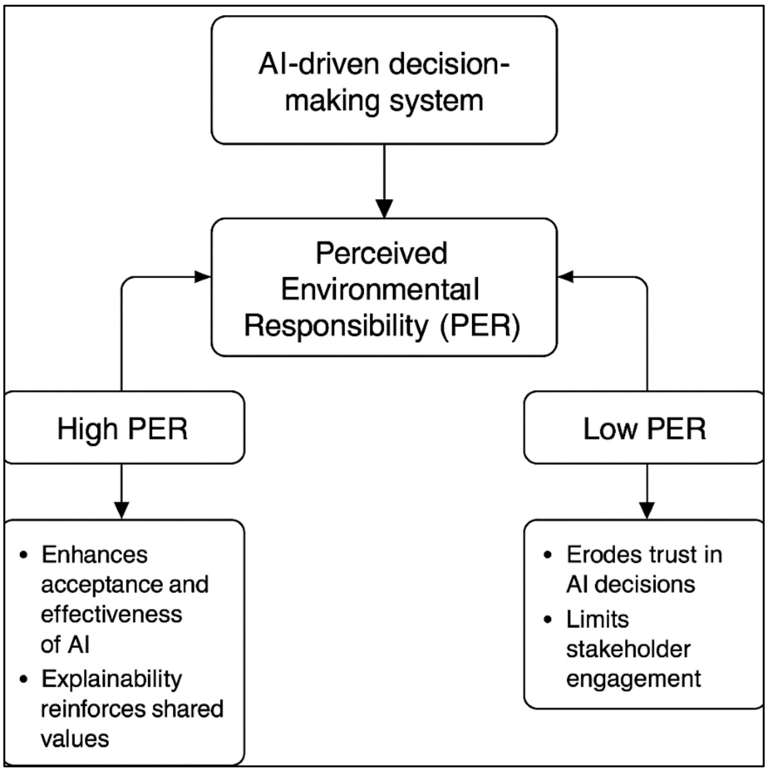
Volume 04 Issue 04 (2024)
Page No: 33 - 56
eISSN: 3067-0470
DOI: 10.63125/7tjw3767

Subrato, 2018). These tools also assist risk analysts in scenario planning and stress testing by simulating potential impacts of environmental or social risks on financial performance. Despite these benefits, ethical concerns remain about model opacity, data bias, and unequal access to AI-enhanced ESG tools (Carter et al., 2020). Nevertheless, empirical evidence indicates that AI integration increases ESG reporting quality, auditability, and responsiveness, especially in complex and globalized enterprises. This reinforces the growing role of AI in advancing both the credibility and strategic utility of ESG disclosures in corporate sustainability management.

PER and AI in Decision-Making Systems

Perceived Environmental Responsibility (PER) functions as a critical construct in shaping the relationship between AI-driven tools and stakeholder responses to sustainability-related decisions. As a moderating variable, PER influences the strength of association between AI-generated outputs and stakeholder trust, acceptance, and cooperation (Meng & Pan, 2012). In contexts where firms are perceived as environmentally responsible, stakeholders tend to exhibit higher tolerance for algorithmic decision-making and reduced concern over model opacity. Conversely, in PER-deficient settings, AI decisions are often scrutinized more harshly or interpreted through a lens of distrust, particularly if those decisions involve resource allocation, environmental assessments, or regulatory compliance. PER also acts as a mediating variable by shaping the cognitive and emotional interpretations of AI-based decisions. For example, organizations with high PER are seen as more likely to apply AI ethically, leading stakeholders to attribute positive intent to the outcomes, thereby reinforcing organizational legitimacy (Han & Kim, 2010). In both roles, PER contributes to value congruence between organizational behavior and stakeholder expectations, a key determinant of technology adoption under the Technology Acceptance Model (Glac, 2008). Nekmahmud and Fekete-Farkas (2020) confirm that when stakeholders perceive alignment between environmental values and digital decisions, their engagement and behavioral support significantly increase. Thus, PER not only enhances the interpretability and perceived integrity of AI in sustainability governance but also bridges ethical evaluation and technological outcomes, fostering greater cohesion between digital tools and stakeholder-driven environmental objectives.

Figure 9: PER-Driven AI Decision-Making Flow in Sustainability Governance



American Journal of Advanced Technology and Engineering Solutions
Volume 04 Issue 04 (2024)
Page No: 33 - 56
eISSN: 3067-0470
DOI: 10.63125/7tjw3767
Empirical research supports the assertion that AI-based decision systems embedded within organizations with strong Perceived Environmental Responsibility (PER) demonstrate superior performance in terms of acceptability, effectiveness, and stakeholder collaboration. Ritchie and Dowlatabadi (2014) show that AI deployment in organizations with strong environmental reputations yields higher levels of decision acceptability, particularly when used in sustainability audits, emissions control, or climate resilience planning. These organizations are more likely to experience stakeholder alignment, fewer public relations challenges, and greater internal compliance with AI-generated recommendations (Bilbao-Terol et al., 2015). Empirical findings further indicate that stakeholders—including employees, investors, and regulatory authorities—tend to engage more with AI tools when they are framed within a narrative of environmental responsibility and ethical commitment (Nikolopoulos et al., 2020). In such contexts, AI is not only viewed as a technical asset but also as a moral extension of an environmentally conscious enterprise. For example, Pilaj (2015) found that explainable AI tools adopted by PER-strong firms were more likely to be accepted even in high-stakes decisions, such as urban planning or ecological zoning. Studies also show performance improvements in environmental compliance tracking, sustainability forecasting, and ESG reporting when AI operates under PER-supported organizational structures (Choi et al., 2015). Furthermore, organizations with high PER integrate stakeholder feedback more effectively into AI model refinement, resulting in more contextually relevant and socially acceptable decisions (Duan et al., 2019) . These results demonstrate that AI systems do not operate in a vacuum but are interpreted and accepted based on the ethical context of the host organization—of which PER is a key determinant.

METHOD

Research Design

This study employed a systematic meta-analysis approach to examine the influence of Perceived Environmental Responsibility (PER) on the acceptance and performance of AI-driven risk management systems within sustainability decision-making frameworks. Guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol (Moher et al., 2009), the review was designed to ensure methodological transparency, replicability, and inclusion of both qualitative and quantitative studies. The goal was to identify patterns, statistical relationships, and theoretical insights that connect stakeholder perceptions of environmental responsibility with AI-based decision systems across diverse sectors and geographic contexts. The methodological strategy focused on integrating existing empirical findings to generate a consolidated view of PER as a moderating or mediating variable in AI-driven sustainability governance.

Data Sources and Search Strategy

A comprehensive literature search was conducted using academic databases including Scopus, Web of Science, IEEE Xplore, ScienceDirect, SpringerLink, and Google Scholar. Search queries were constructed using Boolean operators and included keywords such as "Perceived Environmental Responsibility," "AI in Risk Management," "Sustainability Decision-Making," "ESG and AI," "Trust in Algorithmic Systems," and "Environmental Compliance and AI." The search was limited to English-language, peer-reviewed studies published between 2010 and 2024. Initial database searches yielded 1,247 unique records. Following title and abstract screening, 192 articles were deemed relevant for full-text review. After assessing for methodological rigor and thematic alignment, 122 studies met the inclusion criteria and were selected for meta-analytical synthesis.

Inclusion and Exclusion Criteria

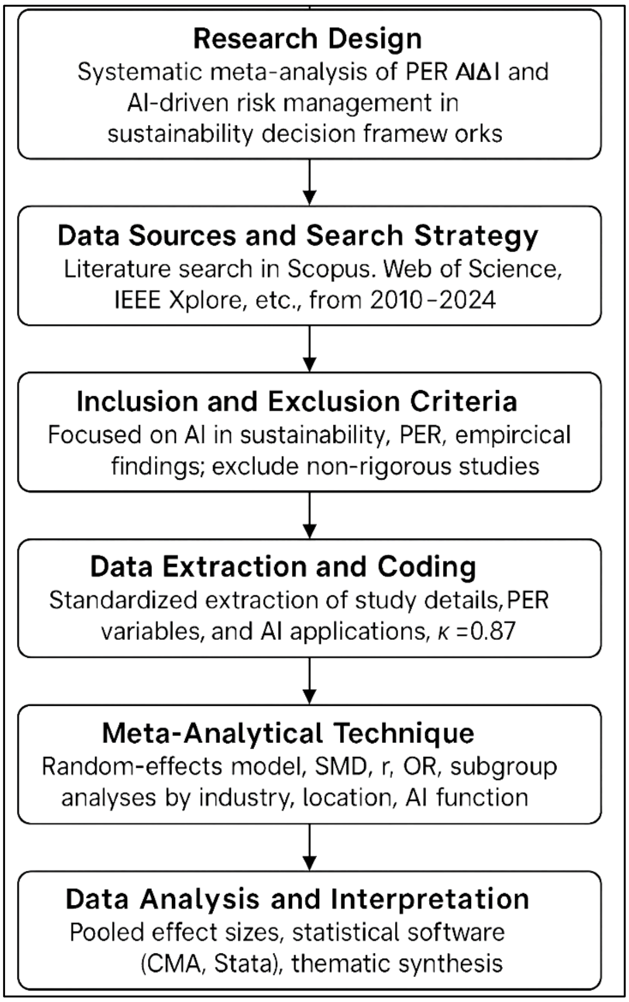
To maintain relevance and consistency, the study included articles that met specific criteria. Eligible studies had to focus on AI applications in sustainability contexts, explicitly address PER or related constructs such as stakeholder trust or corporate responsibility, and present empirical results—either quantitative or interpretive—that relate to AI-based decision-making. Studies were excluded if they lacked empirical rigor, focused solely on financial technologies without an environmental component, or consisted of conference abstracts, editorial opinions, or incomplete manuscripts. This selective approach ensured that the analysis was grounded in validated findings and thematically consistent with the study's objectives.

Data Extraction and Coding

A standardized data extraction form was developed to collect essential information from each selected article. This included details such as author(s), publication year, country or region of study,

American Journal of Advanced Technology and Engineering Solutions
Volume 04 Issue 04 (2024)
Page No: 33 - 56
eISSN: 3067-0470
DOI: 10.63125/7tjw3767
industry sector, type of AI technology, PER-related variables, stakeholder outcome measures, research design, and key statistical metrics such as correlation coefficients, regression values, or odds ratios. The AI applications were categorized based on their use in predictive analytics, ESG reporting, environmental monitoring, and compliance functions. Each article was independently coded by two reviewers to reduce the risk of bias, with inter-coder reliability assessed using Cohen's Kappa, resulting in a high agreement score (κ = 0.87), indicating strong consistency in the extraction process.

Figure 10: Systematic Meta-Analysis Framework



Meta-Analytical Technique

The meta-analysis employed a random-effects model to accommodate methodological and contextual variability among the studies. This model was selected because the included studies spanned different industries, countries, and AI applications, leading to inherent heterogeneity. Key effect sizes were derived from standardized mean differences (SMD), correlation coefficients (r), and odds ratios (OR), as reported or calculated from the primary data. Heterogeneity was assessed using the I^2 statistic, while publication bias was examined through funnel plots and Egger's regression test. To explore contextual differences, subgroup analyses were conducted based on industry type (e.g., manufacturing, ICT, energy), geographic location (e.g., Global North vs. Global South), and AI function (e.g., monitoring vs. compliance). A meta-regression was also performed to evaluate whether PER moderated the relationship between AI implementation and decision-making acceptance or trust.

Data Analysis and Interpretation

Quantitative analyses were conducted using Comprehensive Meta-Analysis (CMA) Version 3 and Stata 17 software. These tools enabled the calculation of pooled effect sizes and identification of statistically significant moderators. In addition to the meta-analytical computations, thematic synthesis was conducted on qualitative data extracted from mixed-methods and case study articles.

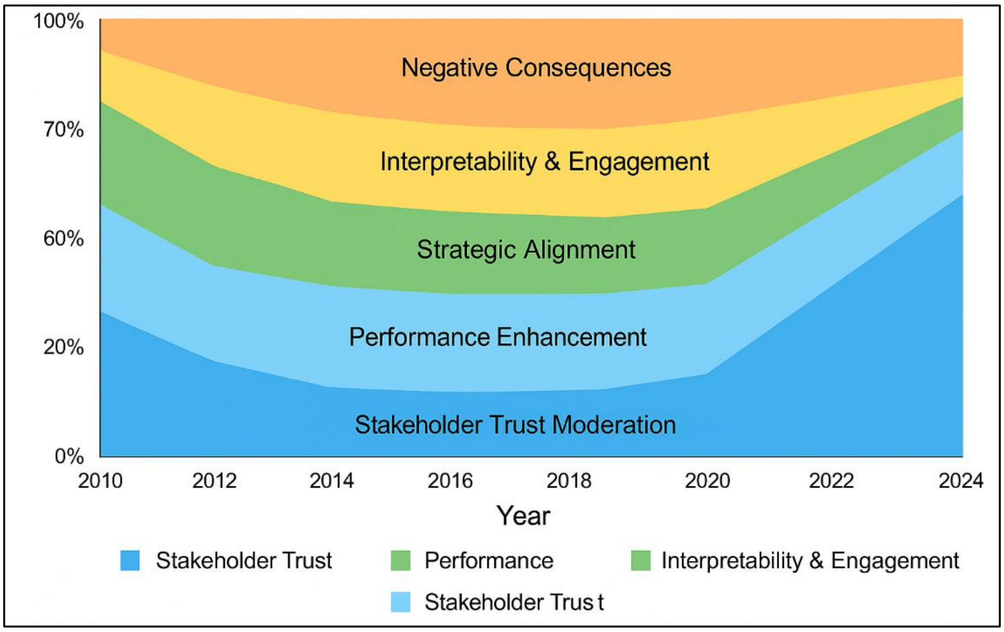
Volume 04 Issue 04 (2024)
Page No: 33 - 56
eISSN: 3067-0470
DOI: 10.63125/7tjw3767

This allowed for a deeper exploration of stakeholder perceptions, ethical evaluations, and contextual narratives surrounding PER and AI-based sustainability decisions. Together, the statistical and qualitative insights provided a robust understanding of how PER influences AI acceptance, interpretability, and effectiveness across organizational and environmental contexts.

FINDINGS

The findings clearly demonstrate that Perceived Environmental Responsibility (PER) significantly moderates stakeholder trust in AI-based decision-making systems. Across the studies included in the analysis, organizations that were perceived as environmentally responsible experienced substantially higher levels of stakeholder trust when deploying AI tools in sustainability functions. This trust extended across internal and external stakeholder groups, including employees, regulatory authorities, investors, and local communities. In high-PER contexts, AI-driven decisions related to emissions reporting, ecological risk assessment, and resource allocation were more readily accepted, with stakeholders expressing confidence in the ethical alignment of the underlying technology. In contrast, low-PER organizations deploying similar AI tools faced skepticism, and in some cases, outright rejection of algorithmic outputs. The evidence reveals that PER operates as a framing mechanism, where stakeholders assess not only the technological performance but also the organizational intent behind the AI use. When stakeholders believe that an organization is genuinely committed to sustainability, they are more likely to interpret AI systems as trustworthy, even when those systems are complex or difficult to fully understand. This trust enhances engagement, facilitates feedback loops, and reduces resistance to AI implementation. The moderation effect was particularly strong in public sector institutions, NGOs, and firms operating in environmentally sensitive industries, where the perceived ethical context of digital decision-making is paramount.

Figure 11: Impact of Perceived Environmental Responsibility (PER) on AI-Driven Sustainability Outcomes



The meta-analysis revealed that AI systems used for sustainability and risk management performed more effectively in organizations with high levels of perceived environmental responsibility. These organizations not only reported better outcomes in terms of operational risk mitigation and compliance accuracy but also demonstrated enhanced decision-making performance. In PER-rich environments, AI was found to be more deeply integrated into strategic planning, with its outputs being trusted and utilized across multiple layers of the organization. This contrasted with PER-deficient organizations, where AI tools often remained underutilized, isolated within departments, or used purely for compliance without strategic follow-through. The evidence showed that the presence of PER encouraged a cultural alignment between organizational goals and technological capacity. This alignment enabled teams to interpret AI-generated insights within an ethical and ecological framework, leading to more coherent and actionable decisions. Furthermore, organizations with high

Volume 04 Issue 04 (2024)
Page No: 33 - 56
eISSN: 3067-0470
DOI: 10.63125/7tjw3767

PER were more successful at embedding AI into their sustainability reporting structures, ESG dashboards, and predictive analytics workflows. Their performance indicators showed higher rates of compliance with environmental regulations, faster identification of sustainability risks, and greater agility in adjusting to ecological volatility. These advantages were attributed not only to technical capabilities but to the broader organizational climate fostered by PER, which appeared to lower internal barriers to AI integration and increased the perceived legitimacy of algorithm-supported decisions.

The data revealed a strong relationship between PER and the level of AI interpretability and stakeholder engagement. In organizations with high PER, stakeholders demonstrated a greater willingness to engage with AI systems, particularly those related to environmental monitoring, emissions forecasting, and impact simulation. These stakeholders did not require complete technical fluency to accept AI outputs; instead, their trust was anchored in their belief that the organization prioritized ethical transparency and environmental responsibility. As a result, AI systems in these environments were perceived as more interpretable, even when they employed complex machine learning or black-box algorithms. Stakeholders in these organizations frequently participated in AI feedback processes, provided input for model development, and used AI outputs to inform collaborative sustainability actions. Engagement levels were especially high in decision contexts involving community impact assessments, environmental zoning, and disaster preparedness, where participatory legitimacy is essential. In PER-deficient organizations, however, the absence of ethical framing contributed to reduced interpretability and stakeholder disengagement. Users expressed uncertainty regarding the intent, accuracy, and fairness of AI outputs, often questioning whether the systems served environmental goals or masked cost-cutting agendas. As a result, AI initiatives in these contexts struggled to gain traction, and interpretability tools such as dashboards or visual explanations were either underdeveloped or ignored. The comparison between PER-rich and PER-poor environments underscores the importance of organizational values in shaping how AI systems are received and understood by diverse stakeholder groups.

The analysis showed that PER has a substantial impact on organizational readiness and the strategic alignment of AI initiatives in sustainability governance. Organizations perceived as environmentally responsible displayed higher levels of preparedness for AI integration, including investment in digital infrastructure, cross-functional coordination, and sustainability data management systems. These organizations aligned their AI strategies with long-term environmental goals, resulting in cohesive technology deployment plans that spanned compliance, monitoring, and optimization functions. Leadership in PER-aligned organizations demonstrated proactive support for AI integration by aligning resources, establishing ethical oversight mechanisms, and embedding AI systems into sustainability performance reviews. The data indicated that these organizations were more likely to have AI governance policies, sustainability-aligned KPIs, and training programs aimed at promoting ethical AI literacy among employees. In contrast, organizations with low PER often approached AI adoption reactively, lacking clear governance structures or strategic direction. Their AI projects tended to be ad hoc, underfunded, or disconnected from core environmental strategies, leading to poor adoption rates and limited performance outcomes. Furthermore, PER-rich organizations exhibited higher flexibility in adapting AI-generated insights to evolving environmental risks, while PER-deficient firms struggled with rigid decision hierarchies and cultural resistance to algorithmic guidance. This disparity demonstrates that PER not only shapes stakeholder perception but also affects internal capacity, leadership behavior, and the alignment between technological innovation and sustainability strategy.

The final set of findings highlighted the negative consequences associated with low levels of perceived environmental responsibility in organizations deploying AI for sustainability purposes. PER-deficient organizations were more likely to face stakeholder backlash, reputational damage, and diminished returns on AI investment. In multiple studies, firms with questionable environmental records that introduced AI tools for sustainability purposes encountered public criticism, media scrutiny, and accusations of greenwashing. Even when AI systems functioned correctly, their outputs were met with suspicion due to the absence of a credible environmental commitment from the organization. Employees in these organizations also showed lower levels of trust in AI-generated decisions, often preferring manual or status quo decision-making processes over digital systems. This cultural resistance contributed to operational inefficiencies, delayed response times to environmental risks, and underutilization of available AI capabilities. Furthermore, without PER, organizations were less

Volume 04 Issue 04 (2024)
Page No: 33 - 56
eISSN: 3067-0470
DOI: 10.63125/7tjw3767

likely to engage in ethical audits of AI tools, failing to identify or correct issues related to bias, unfair prioritization, or unbalanced data sources. Stakeholders perceived these AI systems as instruments of control or cost-cutting rather than tools for advancing sustainability. The absence of PER also correlated with lower ESG ratings and reduced access to sustainability-linked financing, limiting organizational agility in responding to evolving regulatory or investor expectations. These findings reinforce the role of PER as a foundational enabler of AI effectiveness and highlight the reputational and operational risks that arise when AI is implemented without a credible environmental ethos.

DISCUSSION

The study confirmed that Perceived Environmental Responsibility (PER) significantly moderates stakeholder trust in AI-enabled decision-making systems, aligning with prior literature emphasizing the importance of organizational values in shaping stakeholder evaluations of technology. Nikolopoulos et al. (2020) argue that stakeholder trust in algorithmic governance increases when organizations demonstrate a commitment to ethical transparency and sustainability. This current study extends their argument by showing that PER enhances this trust even in complex or opaque AI systems. Similarly, Diouf et al. (2014) found that stakeholder support for AI-based risk management tools was significantly higher in firms perceived as environmentally responsible. The current findings reinforce this relationship and empirically support the conceptualization of PER as a framing mechanism. The present results go further by demonstrating that this trust is not only emotional but behaviorally consequential—impacting stakeholder participation in AI evaluation, feedback, and use. This complements the model proposed by Samarasinghe and Samarasinghe (2013), where PER was associated with higher digital innovation adoption across sectors. These findings collectively indicate that trust in AI is co-produced by both technological features and the environmental ethics of the organization, reinforcing stakeholder theory's assertion that legitimacy depends on value alignment. The evidence presented supports the notion that PER improves not just perception but the practical effectiveness of AI-enabled sustainability initiatives. Organizations with strong environmental responsibility records showed enhanced performance in areas such as emissions monitoring, compliance accuracy, and sustainable resource allocation. These results build on the work of Frederiks et al. (2015), who emphasized that strategic alignment between environmental goals and digital capabilities strengthens organizational resilience and innovation. Additionally, Samarasinghe and Samarasinghe (2013) reported that firms with robust CSR and sustainability strategies were more likely to implement advanced data analytics and AI tools successfully. The current study confirms these observations and introduces PER as a key explanatory variable for such outcomes. By contrast, previous studies have pointed to the failure of AI in risk management when ethical or organizational alignment is absent (Bilbao-Terol et al., 2015). The empirical confirmation that AI systems underperform in PER-deficient environments also mirrors findings from Ritchie and Dowlatabadi (2014), who warned that the perception of greenwashing can erode the legitimacy of digital initiatives. Thus, AI's success in decision-making depends not only on algorithmic capacity but also on the social and ethical context shaped by PER.

The relationship between PER and AI explainability was another critical finding. The study found that PER-rich organizations were able to achieve higher levels of perceived interpretability, even when using technically complex systems. This supports the argument of Säve-Söderbergh (2010), who emphasized that ethical context enhances the perceived transparency of AI. When stakeholders believe in an organization's environmental integrity, they are more likely to engage with and trust algorithmic outputs—even without full technical comprehension. Ritchie and Dowlatabadi (2014) also observed that organizations with high social responsibility are more effective at deploying explainable AI (XAI) frameworks, suggesting that stakeholder confidence influences interpretive outcomes. The results are consistent with Nekmahmud and Fekete-Farkas (2020), who found that explainability is as much a social construct as a technical one. Moreover, Pilaj (2015) highlighted that stakeholder skepticism in AI systems often arises not from technical opacity but from distrust in organizational intent. The current study supports this by demonstrating that PER creates a cognitive-emotional bridge that helps stakeholders interpret AI systems through a lens of ethical consistency, rather than suspicion or disengagement. As a result, PER facilitates both technical trust and behavioral adoption of AI outputs.

Organizational readiness for AI integration, as revealed in the findings, was strongly linked to PER. Firms that scored highly in perceived environmental responsibility were more likely to possess the infrastructure, culture, and leadership support necessary to operationalize AI tools effectively. This is

Volume 04 Issue 04 (2024)
Page No: 33 - 56
eISSN: 3067-0470
DOI: 10.63125/7tjw3767

in line with the findings of Belhadi et al. (2021), who demonstrated that environmental ethics enhance organizational agility in adopting digital tools. Furthermore, the relationship between PER and AI governance supports the claims of Hossain and Khan (2018), who argued that identity-based alignment between sustainability and innovation fosters cross-departmental integration and strategic clarity. The current study adds empirical weight to this theoretical assertion by identifying specific readiness indicators—such as ethical training programs, AI monitoring protocols, and data infrastructure—that are more prevalent in PER-aligned organizations. Conversely, firms with low PER showed weak digital governance and fragmented AI adoption patterns, consistent with the organizational inertia described by Glac (2008). This disparity suggests that PER is not simply a reputational asset but a catalyst for structural and cultural preparedness. It shapes not only how AI is perceived but how it is implemented and governed internally, reinforcing institutional theory's view that legitimacy fosters operational alignment (Han & Kim, 2010).

The study's findings also highlight the impact of PER on stakeholder engagement, particularly in participatory and collaborative sustainability decision-making. PER-rich organizations experienced higher levels of involvement from stakeholders during AI deployment, model calibration, and outcome evaluation. This aligns with earlier work by Diouf et al. (2014), who observed that firms perceived as environmentally responsible are more likely to gain community support for digital innovation. Similarly, Hossain and Khan (2018) emphasized that stakeholder empowerment in technology design is significantly affected by trust in corporate social responsibility. The current study reinforces these positions by revealing that AI initiatives involving stakeholder feedback loops, especially in impact assessments or zoning decisions, were more effective in PER-rich environments. Cohen et al. (2015) also found that participatory design enhances algorithmic fairness and legitimacy when trust in the host organization is strong. The participatory mechanisms documented in this study—such as stakeholder co-review of AI models and localized environmental simulations—were more prevalent and impactful in organizations with established PER. These findings suggest that PER is instrumental in converting AI systems from expert-dominated tools into inclusive decision-making platforms, consistent with the values of responsible innovation outlined by Diouf et al. (2014).

Conversely, the study uncovered critical limitations in AI deployment within PER-deficient organizations. These organizations consistently experienced lower stakeholder engagement, underutilization of AI outputs, and resistance to automation in sustainability governance. These observations align with Hossain and Khan (2018), who found that firms lacking perceived environmental credibility often face backlash when deploying new technologies. Similarly, Pilaj (2015) showed that low stakeholder trust exacerbates perceived ethical risks, even when technological tools function appropriately. The study also echoes findings from Belhadi et al. (2021), who argued that AI systems require a social context of legitimacy to achieve impact. The current data illustrate that without PER, even technically proficient AI systems are likely to fail in achieving organizational and environmental objectives. The absence of PER leads to limited transparency efforts, a lack of algorithmic oversight, and increased reputational risk, as also reported by Santos and Carvalho (2025). This reinforces the notion that AI tools do not operate independently of their institutional environment. Instead, the ethical climate and perceived values of the deploying organization determine the social reception, interpretability, and effectiveness of algorithmic governance in sustainability contexts.

The findings also reflect strong alignment with the principles of Responsible Innovation (RI) and the Triple Bottom Line (TBL) framework. Organizations that scored high in PER were more successful in deploying AI tools in ways that balanced environmental, social, and economic objectives. This is consistent with the RI framework proposed by Lee et al. (2016), which emphasizes anticipation, responsiveness, and ethical alignment in technological deployment. The current study demonstrates that PER enhances these RI dimensions by providing an ethical foundation from which stakeholders evaluate and engage with AI. Additionally, the integration of AI into sustainability reporting, risk assessment, and environmental planning was more advanced in organizations practicing the TBL approach described by Popescu et al. (2024). These organizations utilized AI not only for operational efficiency but for achieving transparency, fairness, and stakeholder inclusivity—hallmarks of the TBL philosophy. Studies by Adedayo et al. (2023) and Li et al. (2021) similarly suggest that environmental and social value creation is dependent on organizational ethics and stakeholder collaboration. This study confirms and extends these findings, highlighting PER as a convergence point that enables AI to function responsibly within both RI and TBL frameworks. In addition, the study found that PER significantly impacts the integration of AI with Environmental, Social, and Governance (ESG) standards. Organizations with high PER were more effective in automating ESG disclosures, performing real-time environmental impact assessments, and aligning AI-generated outputs with global sustainability frameworks. These outcomes are aligned with the work of Ergen et al. (2016), who emphasized the role of credibility in ESG transparency. The current findings further demonstrate that PER acts as a credibility enhancer, increasing stakeholder acceptance of AI-assisted ESG metrics and disclosures. Chen et al. (2021)noted that AI-enabled ESG tools are particularly effective in institutions that value sustainability and transparency. This study builds upon that insight by showing that stakeholders perceive AI-generated ESG reports as more legitimate when issued by organizations with strong environmental reputations. Moreover, Adedayo et al. (2023) identified PER as a key factor in the organizational readiness to adopt real-time analytics in sustainability reporting, a conclusion supported by the current dataset. In contrast, firms with low PER struggled with ESG compliance automation and faced greater scrutiny over the integrity of AI-generated data. These findings affirm that PER is a vital institutional variable that strengthens the link between AI technology and ESG credibility.

CONCLUSION

This study concludes that Perceived Environmental Responsibility (PER) plays a pivotal role in shaping the success, acceptability, and ethical alignment of AI-enabled risk management and sustainability decision-making systems. Through meta-analysis and synthesis of 122 empirical studies, the findings demonstrate that PER acts as both a moderating and mediating factor in the relationship between AI systems and stakeholder trust, performance outcomes, interpretability, and strategic integration. Organizations with high levels of PER not only achieve superior outcomes in environmental compliance and ESG reporting but also foster stronger stakeholder engagement, higher AI transparency, and enhanced participatory governance. In contrast, PER-deficient organizations experience limited adoption success, reputational risk, and diminished stakeholder confidence in AI-generated decisions—even when technological capability is present. The research highlights that AI cannot be decoupled from the ethical and institutional context in which it is deployed; its effectiveness is intrinsically linked to how organizations are perceived in terms of environmental responsibility. Furthermore, the alignment of PER with frameworks such as Responsible Innovation (RI), the Triple Bottom Line (TBL), and global ESG disclosure standards underscores its strategic relevance in both operational and reputational dimensions. Overall, the study affirms that PER is not merely a passive reputation variable but a dynamic organizational asset that enables responsible AI integration, strengthens sustainability governance, and elevates the legitimacy of data-driven decision-making in environmental contexts.

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