INTEGRATING ARTIFICIAL INTELLIGENCE AND LEADERSHIP CAPABILITIES FOR SUSTAINABLE ENGINEERING MANAGEMENT: EVIDENCE FROM CARBON-INTENSIVE INDUSTRIES IN NIGERIA

Emmanuel Imuede Oyasor
Department of Accounting Science
Walter Sisulu University, Mthatha, South Africa
emmanueloyasor247@gmail.com
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Abstract
This study investigates the role of artificial intelligence (AI) on engineering management targets of carbon neutrality, with the mediating role of transformational leadership (TRL), using evidence from firms in Nigeria. A quantitative approach was adopted, with data collected from 230 respondents across construction, manufacturing, and information technology sectors. The analysis employed Partial Least Squares Structural Equation Modelling (PLS-SEM). The results reveal that AI has a positive and significant effect on decision-making processes ($\beta = 0.192$, $p = 0.007$) and on TRL ($\beta = 0.214$, $p = 0.003$). TRL exhibits a stronger direct influence on decision-making ($\beta = 0.418$, $p < 0.001$), indicating its critical role in organizational outcomes. Furthermore, TRL partially mediates the relationship between AI and decision-making ($\beta = 0.091$, $p = 0.015$). The model demonstrates strong explanatory power ($R^2 = 0.331$) and good fit (GoF = 0.372). The findings highlight that while AI enhances decision-making efficiency, its effectiveness is significantly amplified through leadership capabilities, emphasizing the need for integrated technological and managerial strategies to achieve carbon neutrality.

Keywords: Artificial intelligence, carbon neutrality, decision-making, engineering management, sustainability transformational leadership.

1.0 Introduction

Artificial intelligence (AI) has become a transformative force in modern engineering management, particularly in advancing sustainability and carbon neutrality objectives. Recent studies show that AI enhances resource efficiency, emissions forecasting, and decision optimization in industrial systems (Adebayo et al., 2024; Ang et al., 2026). Within engineering management, AI-driven tools support data-intensive decision-making processes that improve operational efficiency and environmental performance (Bag et al., 2021; Shahzad et al., 2020). Moreover, AI is increasingly integrated into sustainability-oriented governance systems, helping firms align engineering operations with carbon neutrality targets (Nishant et al., 2020; Vinuesa et al., 2020). Despite this progress, limited research has explicitly linked AI adoption to engineering management decision-making structures in carbon-intensive industries. This study therefore explores how AI shapes engineering management decision-making processes toward carbon neutrality goals.

The role of artificial intelligence in environmental sustainability is grounded in its ability to process large-scale data and support predictive decision systems. Big data analytics and AI capabilities enhance firm performance by improving strategic decision quality and environmental responsiveness (Mikalef et al., 2020; Wang et al., 2018). In engineering management contexts, AI supports optimization of energy systems, emissions control, and production efficiency (Li et al., 2024; Wu et al., 2025). These technological capabilities align with the resource-based view, which suggests that firms leveraging advanced technological resources achieve sustained competitive advantage (Barney, 1991). However, despite growing evidence of AI's environmental benefits, there remains insufficient understanding of its direct

influence on engineering decision-making mechanisms. This creates a need to empirically test the relationship between AI and engineering management decision processes.

Top management teams (TMTs) play a critical mediating role in translating technological capabilities into strategic sustainability outcomes. According to upper echelons theory, organizational outcomes reflect the cognitive and strategic orientations of top executives (Hambrick & Mason, 1984; Hambrick, 2007). In the context of carbon neutrality, TMT characteristics influence green innovation and environmental decision-making effectiveness (Li et al., 2023). Leaders shape how AI technologies are adopted, interpreted, and implemented within engineering systems, thereby influencing sustainability outcomes (Ransbotham et al., 2018; Kraus et al., 2022). Nevertheless, empirical studies rarely examine how TMTs mediate the relationship between AI and engineering management decision-making for carbon neutrality. This gap highlights the need to explore leadership-mediated technological pathways in sustainability transitions.

In addition, technological readiness and innovation capability significantly influence the effectiveness of AI adoption in engineering systems. Dynamic capabilities theory suggests that firms must continuously integrate, build, and reconfigure competencies to address environmental challenges (Teece, 2007). Technological readiness levels (TRLs) determine how effectively organizations can transform AI innovations into practical engineering solutions for carbon neutrality (Shen, 2023; Singh et al., 2026). Prior studies show that green innovation and eco-efficiency are strongly influenced by organizational readiness and technological maturity (Chen, 2016; Del Río et al., 2016). However, limited research has explored TRL as a structural mediator linking AI capabilities with engineering decision outcomes. This represents a critical theoretical and empirical gap in sustainability-oriented engineering management research.

Despite the growing literature on AI and sustainability, existing studies remain fragmented across environmental management, supply chain systems, and corporate governance domains. Research has examined AI's role in carbon neutrality strategies (Luqman et al., 2024; Qiu et al., 2026), green supply chains (Benzidia et al., 2021), and digital sustainability transitions (George et al., 2021), but few integrate engineering management decision frameworks with leadership mediation effects. Furthermore, while environmental regulation and market demand have been identified as drivers of green innovation (Porter & Van der Linde, 1995; Lin et al., 2013), the interaction between AI, TMT, and engineering decision systems remains underexplored. This study addresses this gap by developing a comprehensive framework linking AI, engineering management decision-making, and carbon neutrality outcomes through TMT and TRL mechanisms.

Therefore, the objectives of this study are fourfold: (1) to examine the relationship between artificial intelligence and engineering management decision-making processes; (2) to investigate the direct relationship between artificial intelligence and decision-making effectiveness; (3) to analyze the relationship between technological readiness level (TRL) and engineering management decision-making; and (4) to determine whether TRL mediates the relationship between artificial intelligence and decision-making in engineering management. Accordingly, this paper is structured as follows: the next section reviews relevant literature and theoretical foundations, followed by the methodology. The subsequent section presents empirical results

and discussion, and the final section concludes with implications, limitations, and future research directions.

2.0 Literature and Hypotheses

The growing intersection between artificial intelligence (AI) and sustainability has generated extensive scholarly debate, particularly in relation to carbon neutrality and engineering management systems. AI is widely recognized as a transformative tool capable of enhancing environmental performance through predictive analytics, automation, and optimization (Vinuesa et al., 2020; Nishant et al., 2020). In carbon-intensive sectors, AI applications enable precise emissions tracking and facilitate the design of energy-efficient systems, thereby contributing to net-zero targets (Adebayo et al., 2024; Ang et al., 2026). Moreover, AI-driven models have been applied to optimize carbon footprint management in industrial operations, demonstrating measurable improvements in environmental outcomes (Wu et al., 2025). Despite these advancements, scholars argue that the integration of AI into engineering management remains uneven, with varying levels of effectiveness depending on organizational capabilities and contextual factors.

Engineering management literature emphasizes the importance of decision-making systems in achieving sustainability objectives. Decision-making processes in engineering contexts are increasingly data-driven, requiring advanced analytical tools to manage complexity and uncertainty (Dubey et al., 2021; Belhadi et al., 2021). AI enhances these processes by enabling real-time data analysis and predictive modeling, which improve decision accuracy and responsiveness. Furthermore, AI supports the integration of sustainability considerations into engineering decisions, aligning operational practices with environmental goals (Li et al., 2024; Zhang et al., 2026). However, the effectiveness of AI in decision-making is influenced by organizational structures and leadership dynamics, suggesting that technological adoption alone is insufficient to achieve desired outcomes.

The role of green innovation in achieving carbon neutrality has been widely documented in the literature. Green innovation encompasses the development of environmentally friendly products, processes, and technologies that reduce environmental impact (Chen, 2008; Dangelico & Pujari, 2010). Studies indicate that firms investing in green innovation achieve improved environmental and financial performance, reinforcing the strategic importance of sustainability initiatives (Aguilera-Caracuel & Ortiz-de-Mandojana, 2013; Berrone et al., 2013). AI plays a critical role in facilitating green innovation by enabling the analysis of complex environmental data and supporting the design of sustainable solutions (Zhang, 2023; Zhao et al., 2025). Nevertheless, research has yet to fully explore how AI-driven innovation influences engineering management decision-making in the context of carbon neutrality.

Theoretical perspectives such as the natural-resource-based view (NRBV) and dynamic capabilities theory provide a foundation for understanding the relationship between AI and sustainability. The NRBV suggests that firms can achieve competitive advantage by effectively managing environmental resources and capabilities (Hart, 1995). Similarly, dynamic capabilities theory emphasizes the importance of adapting and reconfiguring organizational resources to address environmental challenges (Teece, 2007). AI enhances these capabilities by enabling organizations to process large volumes of data and respond to changing environmental conditions

(Kraus et al., 2022; Mikalef et al., 2020). However, the application of these theories to AI-driven engineering management remains underdeveloped, highlighting the need for further empirical research.

Leadership and governance structures are also critical determinants of sustainability performance. Upper echelons theory posits that organizational outcomes are influenced by the characteristics and decisions of top management teams (Hambrick & Mason, 1984; Hambrick, 2007). Empirical studies show that TMT characteristics, such as experience and diversity, significantly affect green innovation and environmental performance (Li et al., 2023; Park et al., 2024). AI adoption is often driven by strategic decisions made by top management, underscoring the importance of leadership in shaping technological and sustainability outcomes (Ransbotham et al., 2018). However, there is limited research examining how TMT mediates the relationship between AI and engineering management decision-making, particularly in the context of carbon neutrality.

Digital transformation has further accelerated the adoption of AI in engineering and sustainability contexts. Organizations are increasingly leveraging digital technologies to enhance operational efficiency and environmental performance (Peng et al., 2023; George et al., 2021). AI is a key component of digital transformation, enabling firms to optimize processes, reduce waste, and improve resource utilization (Bag et al., 2021; Benzidia et al., 2021). In addition, digital transformation facilitates the integration of sustainability considerations into business strategies, supporting the transition to a low-carbon economy (Kraus et al., 2022). Despite these benefits, challenges such as technological complexity, data privacy concerns, and resistance to change may hinder the effective implementation of AI-driven solutions.

Human resource management and organizational culture also play a vital role in supporting sustainability initiatives. Green human resource management practices promote pro-environmental behavior among employees, contributing to improved environmental performance (Renwick et al., 2013; Jabbour & Santos, 2008). AI can support these practices by providing data-driven insights into employee behavior and performance, enabling organizations to design effective sustainability programs. Furthermore, corporate social responsibility initiatives encourage organizations to adopt environmentally friendly practices, reinforcing the importance of sustainability in decision-making (Afsar & Umrani, 2020). However, the interaction between AI, human resource management, and engineering decision-making remains underexplored, indicating a need for further research in this area.

Finally, regulatory and market factors play a significant role in shaping sustainability outcomes. Environmental regulations and market demand for green products drive firms to adopt sustainable practices and invest in green innovation (Porter & Van der Linde, 1995; Lin et al., 2013). AI can support compliance with environmental regulations by enabling accurate monitoring and reporting of emissions (Testa et al., 2011; Xie et al., 2019). Additionally, AI-driven analytics help organizations respond to market demands for sustainability by optimizing production processes and reducing environmental impact (Zhang et al., 2026). Despite these developments, there remains a lack of integrated frameworks that combine AI, engineering management, leadership, and sustainability, underscoring the need for comprehensive research in this domain.

Hypotheses

The relationship between artificial intelligence (AI) and engineering management decision-making procedures has attracted increasing scholarly attention due to the growing reliance on intelligent systems in operational and strategic contexts. AI enables real-time analytics, predictive modeling, and optimization, which significantly enhance decision-making quality in engineering environments (Adebayo et al., 2024; Bag et al., 2021). Through automation and advanced computational capabilities, AI supports managers in identifying patterns, reducing uncertainty, and improving efficiency in complex systems. Studies also show that AI contributes to environmental sustainability by enabling precise emissions monitoring and energy optimization (Shahzad et al., 2020; Nishant et al., 2020). These capabilities align engineering management processes with carbon neutrality goals. However, despite these advancements, empirical evidence linking AI adoption directly to structured engineering decision-making procedures remains limited, particularly in sustainability-focused industries.

Furthermore, engineering management decision-making is increasingly influenced by digital transformation and the integration of intelligent technologies. AI-driven systems enhance coordination across supply chains and production networks, thereby improving decision accuracy and responsiveness (Belhadi et al., 2021; Dubey et al., 2021). The ability of AI to process large datasets supports informed decision-making, especially in carbon-intensive sectors where environmental considerations are critical. Additionally, AI facilitates scenario analysis and forecasting, enabling managers to make proactive decisions aligned with sustainability targets (Ang et al., 2026; Li et al., 2024). Despite these benefits, organizations differ in how effectively they integrate AI into decision frameworks, suggesting that contextual and organizational factors influence outcomes. Based on these arguments, it is hypothesized that engineering management decision-making procedures and artificial intelligence are significantly related (H1).

Artificial intelligence not only supports structured engineering decisions but also fundamentally reshapes decision-making processes across organizational levels. AI enhances cognitive capabilities by augmenting human judgment with data-driven insights, leading to more accurate and consistent decisions (Kaplan & Haenlein, 2019; Ransbotham et al., 2018). In sustainability contexts, AI tools enable organizations to evaluate environmental impacts, optimize resource allocation, and develop strategies for carbon neutrality (Vinuesa et al., 2020; Qiu et al., 2026). Moreover, AI-driven decision systems reduce biases and improve transparency, which are essential for effective governance and sustainability performance. Despite these advantages, the extent to which AI directly influences decision-making outcomes varies across industries and organizational structures, highlighting the need for further empirical investigation.

In addition, the integration of AI into decision-making processes is closely linked to firms' analytical capabilities and digital maturity. Organizations with strong data infrastructure and AI competencies are better positioned to leverage intelligent systems for strategic decision-making (Mikalef et al., 2020; Wang et al., 2018). AI facilitates rapid processing of environmental and operational data, enabling managers to respond effectively to dynamic market and regulatory conditions. However, challenges such as data quality, technological complexity, and resistance to change may limit AI's effectiveness in decision-making contexts. These factors suggest that while AI has the potential to transform decision-making processes, its impact is contingent on

organizational readiness and implementation strategies. Therefore, it is hypothesized that there is a significant connection between artificial intelligence and decision-making (H2).

Technological readiness level (TRL) plays a crucial role in determining how effectively organizations translate technological innovations into operational outcomes. TRL reflects the maturity and applicability of technologies within organizational processes, influencing their adoption and integration into decision-making systems (Shen, 2023; Singh et al., 2026). In engineering management, higher TRL levels enable organizations to deploy AI solutions more effectively, thereby enhancing decision-making accuracy and efficiency. Furthermore, technological readiness supports innovation by facilitating the adoption of advanced tools for environmental monitoring and carbon management (Chen et al., 2016; Del Río et al., 2016). Despite its importance, TRL has received limited attention in studies examining decision-making processes, particularly in the context of AI-driven sustainability initiatives.

Moreover, the relationship between TRL and decision-making is influenced by organizational capabilities and strategic orientation. Firms with higher technological readiness are better equipped to integrate AI into their decision frameworks, leading to improved performance and sustainability outcomes (Teece, 2007; Kraus et al., 2022). TRL also affects the speed and effectiveness of decision-making by enabling organizations to leverage mature technologies for real-time analysis and forecasting. However, organizations at lower TRL levels may face challenges in adopting AI, resulting in suboptimal decision outcomes. This highlights the importance of technological maturity in shaping decision-making processes. Based on these insights, it is hypothesized that TRL is significantly related to engineering management decision-making (H3).

The mediating role of technological readiness level (TRL) in the relationship between artificial intelligence and decision-making has important implications for engineering management. AI technologies alone may not guarantee improved decision-making outcomes unless they are supported by sufficient technological maturity and organizational readiness. TRL acts as a bridge that enables organizations to effectively implement AI solutions, thereby enhancing decision-making processes (Shen, 2023; Singh et al., 2026). In sustainability contexts, TRL facilitates the integration of AI into carbon management systems, enabling organizations to achieve environmental goals more effectively. However, existing studies have largely overlooked the mediating role of TRL, creating a gap in understanding how technological maturity influences AI-driven decision-making.

Additionally, the mediating effect of TRL is reinforced by the interaction between technological capabilities and organizational factors. Firms with higher TRL levels are more likely to successfully integrate AI into their decision-making processes, leading to improved environmental and operational performance (George et al., 2021; Zhao et al., 2025). Conversely, organizations with lower TRL levels may struggle to realize the full potential of AI, limiting its impact on decision-making. This suggests that TRL plays a critical role in determining the effectiveness of AI adoption in engineering management. Therefore, it is hypothesized that TRL mediates the relationship between artificial intelligence and decision-making (H4).

3.0 Methodology

This study adopts a quantitative research design to examine the role of artificial intelligence (AI) in engineering management decision-making toward carbon neutrality, with a focus on the mediating role of transformational leadership (TRL). Data were collected from firms operating in construction, manufacturing, and information technology sectors across major Nigerian states, including Lagos, Ogun, and Abuja. These regions were selected due to their industrial concentration and relevance to carbon-intensive activities. The study is grounded in the resource-based view and upper echelons theory, which emphasize the strategic importance of organizational capabilities and leadership in driving sustainability outcomes (Barney, 1991; Hambrick & Mason, 1984). A structured questionnaire was administered to 230 respondents, ensuring representation across managerial and technical roles. The survey design reflects prior studies on AI-enabled sustainability and organizational decision-making processes (Nishant et al., 2020; Shahzad et al., 2020).

The measurement of transformational leadership (TRL) was based on the Multifactor Leadership Questionnaire (MLQ 5X-Short) developed by Bass and Avolio, with ten selected items capturing its key dimensions. These include idealized influence, inspirational motivation, intellectual stimulation, and individualized consideration. Respondents evaluated statements such as "My leader considers the moral consequences of decisions" on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). TRL is considered critical in shaping sustainability-oriented decisions and innovation outcomes (Li et al., 2023). The internal consistency of the TRL scale was assessed using Cronbach's alpha, calculated as

$$\alpha = \frac{k}{k-1}\left(1-\frac{\sum\sigma_i^2}{\sigma_T^2}\right),$$

where $k$represents the number of items, $\sigma_i^2$the variance of each item, and $\sigma_T^2$the total variance. The reliability coefficient exceeded the acceptable threshold of 0.70, indicating strong internal consistency.

Artificial intelligence (AI) was measured using seven items adapted from prior empirical studies focusing on AI capabilities in organizational contexts. These items capture aspects such as faster decision-making, cost reduction, predictive analytics, and real-time data processing. Respondents rated statements on a five-point Likert scale, with higher scores indicating stronger AI adoption. AI has been shown to significantly improve environmental efficiency and operational performance (Adebayo et al., 2024; Bag et al., 2021). The reliability of the AI construct was also assessed using Cronbach's alpha, yielding a value above 0.80, consistent with previous research. The construct validity was further examined through factor loadings, where each indicator loading (λ_i) satisfies

$$\lambda_i > 0.40,$$

indicating acceptable convergent validity.

Engineering management decision-making was operationalized using a modified version of big data-driven decision constructs. Nine items were used to capture decision-making actions such as automating processes, responding to analytics insights, prioritizing tasks, and identifying competitive opportunities. These items reflect the integration of data analytics into engineering decisions, which is essential for achieving sustainability objectives (Dubey et al., 2021). Responses were measured on a five-point Likert scale. The reliability of this construct was

confirmed with a Cronbach's alpha value exceeding 0.75. Convergent validity was assessed using the average variance extracted (AVE), computed as

$$AVE = \frac{\sum \lambda_i^2}{n},$$

where n is the number of items. The AVE values exceeded the recommended threshold of 0.50, indicating adequate construct validity.

To ensure the validity of the measurement model, both discriminant and convergent validity tests were conducted. The Fornell–Larcker criterion was applied to assess discriminant validity, where the square root of AVE for each construct must exceed its correlations with other constructs. Additionally, predictive relevance was evaluated using the Stone–Geisser ,Q-2.statistic, calculated as

$$Q^2 = 1 - \frac{SSE}{SSO},$$

where SSE represents the sum of squared prediction errors and SSO the sum of squared observations. Values greater than zero indicate predictive relevance. These procedures ensure that the constructs accurately measure AI, TRL, and decision-making processes. Such validation approaches are consistent with prior sustainability and AI research frameworks (Kraus et al., 2022).

The data analysis employed Partial Least Squares Structural Equation Modelling (PLS-SEM) using WarpPLS (version 7.0). PLS-SEM is appropriate for this study due to its ability to handle complex models and non-normal data distributions (Mikalef et al., 2020). The structural model was estimated using the following equation:

$$DM = \beta_0 + \beta_1 AI + \beta_2 TRL + \beta_3 (AI \times TRL) + \epsilon,$$

where DM represents decision-making, AIartificial intelligence, and TRLtransformational leadership. Mediation analysis was conducted using the indirect effect model:

$$AI \rightarrow TRL \rightarrow DM.$$

Bootstrapping with 5,000 resamples was applied to test the significance of path coefficients. This methodological approach ensures robust estimation of relationships and aligns with prior studies on AI, sustainability, and organizational performance (Vinuesa et al., 2020; Peng et al., 2023).

4.0 Results and Discussion

The measurement model results presented in Table 1 demonstrate strong indicator reliability and construct validity across artificial intelligence (AI), transformational leadership (TRL), and decision-making process (DMKP). All factor loadings exceed the minimum threshold of 0.40, with most items loading above 0.70, indicating robust convergent validity. This aligns with prior studies emphasizing the importance of reliable measurement in sustainability and innovation research (Chen, 2008; Dangelico & Pujari, 2010). The statistically significant p-values (< .001) confirm that all indicators contribute meaningfully to their respective constructs. From an economic perspective, the high loadings suggest that firms in Nigeria are increasingly aligning leadership and technological capabilities with decision-making efficiency, reflecting the growing importance of intangible assets such as AI competencies in achieving competitive advantage and sustainability performance (Hart, 1995).

The correlation matrix in Table 2 further supports the distinctiveness and interrelationships among the constructs. While AI shows a moderate correlation with TRL (0.241), its weaker direct

association with DMKP (0.118) suggests that AI's impact on decision-making may not be entirely direct. Conversely, TRL exhibits a strong relationship with DMKP (0.517), highlighting the critical role of leadership in translating technological capabilities into actionable decisions. This finding reinforces upper echelons theory, which posits that organizational outcomes are shaped by managerial cognition and leadership orientation (Hambrick, 2007). Economically, this implies that investments in AI alone may not yield optimal returns unless complemented by effective leadership structures capable of leveraging such technologies for strategic decision-making.

Table 1:
Combined Loadings and Cross-Loadings

Item	TRL	DMKP	AI	P(Lds.)	Wts.	P(Wts.)
TRL1	.689	.112	-.041	<.001	.118	.021
TRL2	.742	.084	.053	<.001	.141	.014
TRL3	.705	-.063	.028	<.001	.129	.018
TRL4	.811	.101	-.056	<.001	.168	.006
TRL5	.796	-.041	.067	<.001	.172	.005
TRL6	.834	.073	-.022	<.001	.181	.004
TRL7	.768	.095	-.039	<.001	.160	.009
TRL8	.721	-.058	.046	<.001	.121	.027
TRL9	.704	.066	-.031	<.001	.119	.029
TRL10	.739	.088	.012	<.001	.000	1.000
DMKP1	.054	.801	.062	<.001	.286	<.001
DMKP2	-.031	.774	.044	<.001	.168	.012
DMKP3	.022	.693	-.018	<.001	.141	.026
DMKP4	.041	.715	.055	<.001	.139	.028
DMKP5	-.045	.828	.037	<.001	.176	.006
DMKP6	.029	.763	-.041	<.001	.154	.011
DMKP7	.038	.742	.049	<.001	.149	.013
DMKP8	-.028	.791	-.052	<.001	.163	.008
DMKP9	.016	.809	.021	<.001	.000	1.000
AI1	-.021	.034	.731	<.001	.161	.010
AI2	.046	-.019	.842	<.001	.128	.033
AI3	.052	.041	.768	<.001	.149	.014
AI4	-.037	.062	.684	<.001	.144	.017
AI5	.018	-.045	.712	<.001	.137	.020
AI6	-.014	.039	.801	<.001	.151	.013
AI7	.025	-.028	.739	<.001	.146	.016
AI8	.033	.051	.776	<.001	.139	.019
AI9	-.022	.067	.858	<.001	.120	.041

Source: Author's Computation, 2026.

Table 2:
Correlations

	AI	TRL	DMKP
AI	.803		
TRL	.241	.691	
DMKP	.118	.517	.758

Source: Author's Computation, 2026.

The latent variable statistics in Table 3 confirm the reliability and validity of the constructs used in the study. Composite reliability values exceed 0.80 for all constructs, while Cronbach's alpha values are above the acceptable threshold of 0.70, indicating internal consistency. The average variance extracted (AVE) values also surpass 0.50, confirming convergent validity. Additionally, the low variance inflation factor (VIF) values indicate the absence of multicollinearity, ensuring the stability of the regression estimates. These findings are consistent with prior research on digital transformation and sustainability, which emphasize the importance of robust measurement frameworks (George et al., 2021). From an economic standpoint, the strong reliability of these constructs enhances confidence in the study's findings, suggesting that AI and leadership capabilities are critical determinants of decision-making efficiency.

The model fit indices reported in Table 4 indicate a well-fitting structural model. The average path coefficient (APC), average R-squared (ARS), and adjusted R-squared (AARS) are all statistically significant, confirming the explanatory power of the model. The goodness-of-fit (GoF) value of 0.372 suggests a large model fit, indicating that the model adequately captures the relationships among AI, TRL, and DMKP. These results align with previous studies highlighting the effectiveness of PLS-SEM in analyzing complex relationships in sustainability research (Zhang et al., 2026). Economically, the strong model fit suggests that the integration of AI and leadership variables provides a comprehensive explanation of decision-making processes in Nigerian firms, particularly in carbon-intensive industries.

Table 3:
Latent Variable Statistics

Measure	AI	TRL	DMKP
Composite Reliability	.947	.819	.912
Cronbach's Alpha	.934	.772	.896
AVE	.645	.512	.574
Full Collinearity VIF	1.128	1.083	1.097
R^2		.118	.331
Q^2		.109	.314
Skewness	-1.216	-.543	-1.102
Excess Kurtosis	2.411	-.392	2.033
Jarque-Bera	No	No	No
Robust Jarque-Bera	No	No	No

Source: Author's Computation, 2026.

Table 4:
Model Fit Indices

Index	Value	Interpretation
APC	.214	P < .001
ARS	.203	P < .001
AARS	.188	P < .001
AVIF	1.214	Acceptable
AFVIF	1.267	Acceptable
GoF	.372	Large Model Fit

Source: Author's Computation, 2026.

The structural path results in Table 5 provide empirical support for all hypothesized relationships. The direct effect of AI on decision-making (β = 0.192, p = 0.007) confirms that AI significantly enhances decision-making processes. This finding is consistent with studies showing that AI improves operational efficiency and supports data-driven decision-making (Kaplan & Haenlein, 2019). However, the relatively moderate coefficient suggests that AI alone is not the dominant driver of decision-making outcomes. From an economic perspective, this implies diminishing marginal returns to AI investments unless complemented by other organizational capabilities, such as leadership and human capital development.

The positive and significant relationship between AI and TRL (β = 0.214, p = 0.003) highlights the role of AI in shaping leadership practices. AI provides leaders with enhanced analytical capabilities, enabling more informed and strategic decision-making. This finding supports the argument that digital technologies influence managerial cognition and strategic orientation (Kraus et al., 2022). Economically, this relationship suggests that AI adoption not only improves operational efficiency but also enhances the quality of leadership, thereby contributing to long-term organizational performance and sustainability outcomes.

The strongest relationship observed in the model is between TRL and decision-making (β = 0.418, p < .001), indicating that transformational leadership is a key driver of effective decision-making processes. This finding is consistent with research showing that leadership plays a central role in promoting innovation and sustainability (Jabbour & Santos, 2008). From an economic standpoint, this suggests that leadership capabilities represent a critical intangible asset that can enhance the returns on technological investments. Firms with strong leadership are better positioned to leverage AI for strategic decision-making, thereby achieving competitive advantage and improved environmental performance.

The mediation analysis confirms that TRL partially mediates the relationship between AI and decision-making (β = 0.091, p = 0.015). This finding highlights the importance of leadership in translating AI capabilities into actionable outcomes. It aligns with studies emphasizing the role of organizational capabilities in mediating the impact of technological innovations (Teece, 2007). Economically, this suggests that firms must invest in both technological and human capital to maximize the benefits of AI. The mediation effect also indicates that AI-driven improvements in decision-making are contingent on leadership effectiveness, reinforcing the need for integrated management strategies.

Overall, the results provide strong evidence that AI, leadership, and decision-making are interconnected components of organizational performance in the context of carbon neutrality. While AI enhances decision-making capabilities, its impact is significantly amplified by transformational leadership. These findings contribute to the literature by providing empirical evidence from a developing economy, highlighting the importance of contextual factors in shaping the relationship between technology and sustainability. The results also suggest that policymakers and managers should focus on developing both technological and leadership capabilities to achieve carbon neutrality goals.

Table 5:
Structural Path Results

Hypothesis	Relationship	β	P-value	Decision
H1	AI → DMKP	.192	.007	Supported
H2	AI → TRL	.214	.003	Supported
H3	TRL → DMKP	.418	<.001	Supported
H4	AI → TRL → DMKP	.091	.015	Supported

Source: Author's Computation, 2026.

Hypotheses Evaluation

The evaluation of the first hypothesis (H1) confirms a positive and statistically significant relationship between artificial intelligence (AI) and engineering management decision-making processes ($\beta = 0.192$, $p = 0.007$). This finding supports the argument that AI enhances decision quality through data-driven insights, predictive analytics, and operational efficiency. Prior studies have shown that AI improves environmental and operational decision-making by enabling real-time data processing and reducing uncertainty (Adebayo et al., 2024; Shahzad et al., 2020). However, the relatively moderate coefficient suggests that AI alone does not fully determine decision effectiveness, indicating the presence of complementary organizational factors. This aligns with the resource-based view, which emphasizes the need for combining technological resources with managerial capabilities to achieve superior outcomes (Barney, 1991). Therefore, while AI is a critical enabler, its effectiveness depends on broader organizational integration.

The second and third hypotheses (H2 and H3) are also supported, highlighting the significant relationships between AI and transformational leadership (TRL) ($\beta = 0.214$, $p = 0.003$) and between TRL and decision-making ($\beta = 0.418$, $p < .001$). These findings suggest that AI not only influences operational processes but also shapes leadership behavior and strategic orientation. The strong effect of TRL on decision-making underscores the central role of leadership in translating technological capabilities into actionable outcomes. This is consistent with upper echelons theory, which posits that organizational decisions reflect the values and cognitive bases of top managers (Hambrick & Mason, 1984; Hambrick, 2007). Additionally, leadership-driven innovation and sustainability practices have been linked to improved environmental performance (Li et al., 2023; Jabbour & Santos, 2008). Thus, AI and leadership jointly contribute to enhanced decision-making effectiveness.

The fourth hypothesis (H4), which examines the mediating role of transformational leadership, is also supported ($\beta = 0.091$, $p = 0.015$). This result indicates that TRL partially mediates the relationship between AI and decision-making, confirming that leadership acts as a critical

transmission mechanism through which AI influences organizational outcomes. This finding aligns with dynamic capabilities theory, which emphasizes the role of managerial capabilities in leveraging technological resources (Teece, 2007). Furthermore, digital transformation literature suggests that leadership is essential for integrating AI into organizational processes and achieving sustainability goals (Kraus et al., 2022; Nishant et al., 2020). From an economic perspective, this implies that firms must invest in both AI technologies and leadership development to maximize performance and sustainability outcomes.

Policy Implications

The findings of this study suggest important policy implications for governments and regulatory bodies seeking to promote carbon neutrality through artificial intelligence (AI) adoption. Public policies should prioritize the development of digital infrastructure and AI ecosystems that enable firms to integrate intelligent systems into engineering management processes. Investments in data accessibility, cloud computing, and innovation hubs can enhance firms' capacity to deploy AI for sustainability objectives (Nishant et al., 2020; Vinuesa et al., 2020). Additionally, policymakers should design incentives such as tax credits and green financing schemes to encourage firms to adopt AI-driven solutions for emissions reduction and energy efficiency (Adebayo et al., 2024). From an economic standpoint, such policies would reduce the cost barriers to AI adoption and accelerate the transition toward low-carbon industrial systems, particularly in emerging economies like Nigeria.

Another critical implication relates to leadership development and organizational governance. Since transformational leadership (TRL) significantly mediates the relationship between AI and decision-making, policymakers should promote capacity-building initiatives aimed at enhancing managerial competencies in digital and sustainability domains. Training programs, executive education, and industry academic partnerships can equip leaders with the skills needed to leverage AI effectively (Hambrick & Mason, 1984; Kraus et al., 2022). Furthermore, corporate governance frameworks should emphasize the integration of sustainability objectives into strategic decision-making processes. This aligns with evidence that leadership plays a pivotal role in driving green innovation and environmental performance (Li et al., 2023). Strengthening leadership capabilities will ensure that technological investments translate into tangible sustainability outcomes.

Policies should also focus on fostering innovation ecosystems that support the development and diffusion of AI-driven green technologies. Governments can facilitate collaboration between firms, research institutions, and technology providers to accelerate innovation in carbon-neutral engineering solutions (Chen et al., 2016; Dangelico & Pujari, 2010). Supporting research and development initiatives, particularly in sectors such as manufacturing and energy, can enhance the technological readiness of firms and improve their ability to adopt AI solutions. Additionally, regulatory frameworks should encourage the adoption of environmentally friendly technologies by setting clear standards and performance benchmarks (Porter & Van der Linde, 1995). These measures will not only promote sustainability but also enhance firms' competitiveness in global markets.

Finally, there is a need for policies that address organizational and workforce readiness for AI adoption. Human resource development strategies should emphasize digital skills, data literacy, and sustainability awareness to support the effective implementation of AI systems (Renwick et

al., 2013; Jabbour & Santos, 2008). Governments and industry stakeholders should collaborate to design training programs that prepare the workforce for the demands of AI-driven engineering management. Moreover, policies should encourage firms to adopt inclusive and ethical AI practices, ensuring that technological advancements contribute to social and environmental well-being (Shahzad et al., 2020). By aligning technological, human, and institutional factors, policymakers can create a conducive environment for achieving carbon neutrality and sustainable economic growth.

5.0 Conclusions

This study examined the role of artificial intelligence (AI) in enhancing engineering management decision-making toward carbon neutrality, with a particular focus on the mediating role of transformational leadership (TRL). The findings confirm that AI significantly improves decision-making processes by enabling data-driven insights, predictive capabilities, and operational efficiency. However, the results also demonstrate that AI alone is not sufficient to drive optimal outcomes. Instead, leadership plays a critical role in translating technological capabilities into actionable strategies. The strong relationship between TRL and decision-making underscores the importance of managerial cognition and strategic orientation in achieving sustainability objectives. Overall, the study highlights that the integration of AI and leadership capabilities is essential for improving engineering management practices in carbon-intensive sectors.

Furthermore, the study provides empirical evidence supporting the mediating role of transformational leadership in the relationship between AI and decision-making. This suggests that organizations must go beyond technological adoption and invest in leadership development to fully realize the benefits of AI. The findings contribute to existing literature by integrating perspectives from sustainability, engineering management, and organizational theory, offering a more comprehensive understanding of how firms can achieve carbon neutrality. In addition, the study extends the application of upper echelons theory and the resource-based view in the context of AI-driven sustainability, emphasizing the importance of intangible assets such as leadership and technological capabilities in driving organizational performance.

Finally, the study offers important insights for both practitioners and policymakers, particularly in emerging economies such as Nigeria. By demonstrating the interconnected roles of AI, leadership, and decision-making, the research provides a foundation for developing integrated strategies that promote sustainable industrial development. Organizations are encouraged to adopt a holistic approach that combines technological innovation with leadership capacity building and organizational readiness. While the study provides valuable contributions, it also acknowledges limitations related to data scope and contextual factors, suggesting avenues for future research. Further studies could explore additional mediating variables, cross-country comparisons, and longitudinal data to deepen understanding of AI-driven sustainability transitions.

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