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Sensing, Seizing, and Transforming: How AI Adoption Enhances Green Dynamic Capabilities in High-Tech Enterprises

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ABSTRACT

The integration of artificial intelligence (AI) into corporate sustainability strategies has gained significant attention, yet the mechanisms through which AI adoption enhances green innovation remain underexplored. Drawing on dynamic capabilities theory, this conceptual paper examines how AI adoption enhances green dynamic capabilities, specifically sensing, seizing, and transforming capabilities, to drive green innovation in high-tech enterprises. Through a systematic review and synthesis of 24 empirical studies published between 2021 and 2026, an integrated conceptual framework is developed proposing that AI adoption does not directly lead to green innovation but rather operates through the mediating mechanism of green dynamic capabilities. Organizational readiness and environmental dynamism are further identified as key moderators that influence the effectiveness of this mediated relationship. The paper advances a set of nine testable propositions and presents a comprehensive model that distinguishes how each dimension of green dynamic capabilities (sensing, seizing, transforming) is differentially enhanced by specific AI applications. Theoretical contributions include extending dynamic capabilities theory to the AI green innovation context, clarifying the mediating role of green dynamic capabilities, and integrating contingency factors that shape AI-enabled green innovation. Practical implications for managers and policymakers in high-tech sectors are discussed. The paper acknowledges its conceptual nature and reliance on existing literature as key limitations, and a research agenda for future empirical validation across diverse organizational settings is proposed.

Keywords: Artificial intelligence adoption, green dynamic capabilities, green innovation, high-tech enterprises, dynamic capabilities theory

INTRODUCTION

The escalating urgency of environmental sustainability has positioned green innovation as a strategic imperative for high-tech enterprises worldwide (Borah et al., 2025; Guo, 2023). Concurrently, the rapid advancement of artificial intelligence (AI) technologies has opened new pathways for organizations to address environmental challenges while maintaining competitive advantage (Abdelfattah et al., 2025; Mijit et al., 2025). However, despite the growing recognition that AI can potentially transform organizational approaches to sustainability, a critical question remains inadequately addressed: how does AI adoption translate into green innovation outcomes?

Existing research has established important yet fragmented insights into the relationship between AI and green innovation. Some studies have demonstrated that AI adoption positively influences green innovation performance (Mijit et al., 2025; Liang et al., 2025), while others have highlighted the enabling role of digital capabilities in facilitating sustainable practices (Al-Husain et al., 2025; Li et al., 2024). Nevertheless, the underlying mechanisms through which AI adoption contributes to green innovation remain theoretically underdeveloped. This gap is particularly pronounced in the context of high-tech enterprises, where both AI sophistication and environmental pressures are acute (Rahman et al., 2026; Singh et al., 2022).

The dynamic capabilities framework, originally articulated by Teece and colleagues (Teece et al., 1997) and subsequently extended to sustainability contexts (Buzzao & Rizzi, 2021), offers a promising theoretical lens for addressing this gap. Dynamic capabilities, specifically the capacities to sense opportunities and threats, seize new possibilities, and transform organizational configurations, provide the micro foundations through which firms adapt to rapidly changing environments (Khan et al., 2021). In the context of AI adoption for green innovation, it is argued that green dynamic capabilities serve as the critical mediating mechanism: AI technologies enable firms to better sense environmental opportunities, seize green innovation possibilities, and transform existing processes, which in turn produce green innovation outcomes. This paper advances a conceptual framework that addresses three research questions:

1. How does AI adoption enhance the three dimensions of green dynamic capabilities (sensing, seizing, and transforming) in high-tech enterprises?
2. Through what mediating mechanism do green dynamic capabilities translate AI adoption into green innovation?
3. Under what contingent conditions (organizational readiness and environmental dynamism) is the AI adoption green dynamic capabilities green innovation relationship strengthened or weakened?

The paper makes three primary contributions. First, it extends dynamic capabilities theory to the AI green innovation context by specifying how AI adoption differentially enhances sensing, seizing, and transforming capabilities. Second, it clarifies the mediating role of green dynamic capabilities, resolving the ambiguity in prior research regarding whether AI directly or indirectly affects green innovation. Third, it integrates contingency factors that shape the effectiveness of AI-enabled green innovation, offering a more nuanced understanding of boundary conditions.

The remainder of this paper is structured as follows. The next section reviews relevant literature on AI adoption, green dynamic capabilities, and green innovation, identifying key gaps that motivate the conceptual framework. The integrated framework is then presented and nine testable propositions are developed. Subsequently, the theoretical and practical implications of the framework are discussed before concluding with limitations and future research directions.

LITERATURE REVIEW

Artificial intelligence adoption in high-tech enterprises

Artificial intelligence adoption has emerged as a strategic priority for high-tech enterprises seeking to leverage data-driven insights for competitive advantage (McElheran et al., 2024; Uren & Edwards, 2023). The Technology Organization Environment (TOE) framework and Diffusion of Innovation (DOI) theory have provided foundational lenses for understanding AI adoption determinants (Mpanza, 2025; Na et al., 2022). The TOE framework identifies technological, organizational, and environmental contexts as key adoption drivers, while DOI theory emphasizes innovation attributes such as relative advantage, compatibility, and complexity.

In the high-tech sector, AI adoption is characterized by several distinctive features. First, high-tech enterprises typically possess greater technological readiness and digital infrastructure, facilitating AI integration. Second, these firms face intense competitive pressures that incentivize early AI adoption for innovation and efficiency gains (McElheran et al., 2024). Third, the knowledge-intensive nature of high-tech industries creates both opportunities and challenges for AI implementation, particularly regarding the integration of AI with existing technical and managerial routines (Uren & Edwards, 2023).

However, existing AI adoption research has predominantly focused on operational and financial outcomes, with limited attention to environmental sustainability implications (Rahman et al., 2026). This gap is significant given the potential for AI to enhance green innovation through improved resource efficiency, predictive analytics for environmental management, and optimization of sustainable supply chain operations (Giannakopoulos et al., 2025; Mijit et al., 2025).

Green dynamic capabilities

The concept of dynamic capabilities has evolved substantially since its introduction, with recent scholarship applying the framework to sustainability contexts (Buzzao & Rizzi, 2021). Teece and colleagues (1997, p. 516) originally defined dynamic capabilities as "the firm's ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments." In the sustainability domain, green dynamic capabilities refer to the organizational routines and processes through which firms sense environmental opportunities, seize green innovation possibilities, and transform existing configurations to achieve sustainability outcomes (Khan et al., 2021; Singh et al., 2022). Building on the Teece framework, green dynamic capabilities are conceptualized as comprising three distinct but interrelated dimensions, as shown in **Table 1**.

Table 1. Dimensions of Green Dynamic Capabilities

Dimension	Definition	Key Organizational Routines	Representative Literature
Sensing	Processes for identifying, interpreting, and prioritizing environmental opportunities and threats	Environmental scanning, stakeholder engagement, and technology monitoring	Khan et al. (2021); Qiu et al. (2020)
Seizing	Processes for mobilizing resources to address identified environmental opportunities	Resource allocation, investment decisions, and new product development	Borah et al. (2025); Marrucci et al. (2022)
Transforming	Processes for continuous renewal and reconfiguration of resources and routines	Organizational learning, process adaptation, structural change	Khan et al. (2021); Weber et al. (2025)

Sensing capabilities enable firms to detect emerging green technologies, anticipate environmental regulations, and identify customer preferences for sustainable products. Seizing capabilities involves investment decisions, resource allocation, and the development of new routines for green innovation implementation. Transforming capabilities include the capacity to learn from past experiences, adapt existing processes, and fundamentally restructure operations when necessary.

Empirical research has demonstrated that green dynamic capabilities positively influence various sustainability outcomes, including green product innovation (Borah et al., 2025; Qiu et al., 2020), green process innovation (Singh et al., 2022), and overall environmental performance (Marrucci et al., 2022). However, limited research has examined the antecedents of green dynamic capabilities, particularly the role of AI adoption in enhancing sensing, seizing, and transforming capacities.

Green innovation

Green innovation encompasses the development and implementation of products, processes, and organizational practices that reduce environmental impact. The literature distinguishes between green product innovation (for example, eco-friendly products and recyclable packaging) and green process innovation (for example, energy-efficient manufacturing and waste reduction systems). Both forms of green innovation contribute to environmental sustainability while potentially generating competitive advantages through cost reduction, differentiation, and regulatory compliance (Borah et al., 2025; Singh et al., 2022).

In high-tech enterprises, green innovation takes on particular characteristics. These firms often possess advanced technological capabilities that enable novel green solutions, yet they also face significant pressure to maintain rapid innovation cycles that may conflict with sustainability objectives (Guo, 2023; Yousaf, 2021). The integration of AI into green innovation processes represents an emerging frontier, with AI applications ranging from predictive analytics for energy optimization to machine learning for sustainable product design (Giannakopoulos et al., 2025; Liang et al., 2025).

Despite growing interest in AI-enabled green innovation, the mechanisms through which AI adoption influences green innovation outcomes remain underspecified. Prior research has suggested both direct effects (Mijit et al., 2025) and mediated pathways (Rahman et al., 2026), yet no consensus has emerged regarding the theoretical mechanisms. This ambiguity motivates the focus on green dynamic capabilities as the mediating mechanism linking AI adoption to green innovation.

Research gap and conceptual rationale

The intersection of AI adoption, green dynamic capabilities, and green innovation remains theoretically underexplored. **Table 2** summarizes key empirical studies in this domain, highlighting the fragmentation of existing research.

Table 2. Summary of Key Empirical Studies on AI, Green Dynamic Capabilities, and Green Innovation

Study	**Focus**	**Key Findings**	**Gap Identified**
Abdelfattah et al. (2025)	GDC, AI, green innovation	AI moderates the GDC green innovation link	No direct test of mediation
Al-Husain et al. (2025)	Digital dynamic capabilities, green innovation	Digital capabilities enhance sustainability	AI not explicitly examined

Borah et al. (2025)	GDC, green product innovation	GDC positively affects green innovation	Antecedents of GDC have not been explored
Khan et al. (2021)	Sensing, seizing, reconfiguring for the circular economy	Dynamic capabilities facilitate the circular economy	AI role not considered
Mijit et al. (2025)	AI policy zones, green innovation	AI adoption increases green innovation	Mechanism not specified
Rahman et al. (2026)	Green innovation, AI, sustainable performance	AI moderates the GDC sustainability link	Theoretical mechanism unclear
Singh et al. (2022)	Stakeholder pressure, GDC, green innovation	GDC mediates stakeholder pressure	AI not examined

As shown in **Table 2**, prior research has examined various pairings of the three constructs. However, no study has fully integrated all three into a coherent framework that specifies how AI adoption enhances each dimension of green dynamic capabilities and how these capabilities subsequently drive green innovation. The present paper addresses this integrative gap.

CONCEPTUAL FRAMEWORK AND PROPOSITION DEVELOPMENT

Overview of the framework

Drawing on dynamic capabilities theory and the synthesis of prior empirical research, an integrated conceptual framework is proposed to explicate the mechanisms through which AI adoption influences green innovation in high-tech enterprises. The framework, illustrated in **Figure 1**, posits that green dynamic capabilities (sensing, seizing, and transforming) mediate the relationship between AI adoption and green innovation. Furthermore, organizational readiness and environmental dynamism are proposed to moderate the effectiveness of this mediated relationship.

The framework is grounded in three core theoretical premises. First, AI adoption does not directly produce green innovation outcomes. Rather, AI serves as an enabler that enhances organizational capabilities. Second, green dynamic capabilities are the proximal antecedents of green innovation. Firms must possess the capacity to sense environmental opportunities, seize innovation possibilities, and transform existing configurations to translate technological investments into sustainability outcomes. Third, the effectiveness of AI-enabled green dynamic capabilities depends on contextual factors, specifically the firm's readiness to absorb and utilize AI technologies and the dynamism of the external environment.

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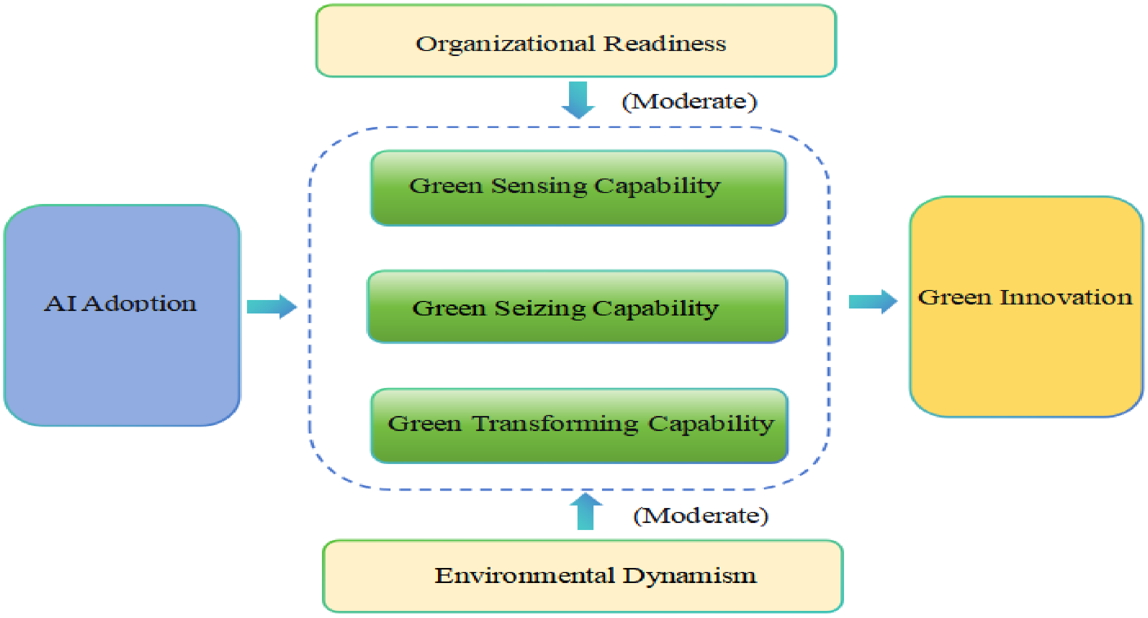

Figure 1. Conceptual Framework: AI Adoption, Green Dynamic Capabilities, and Green Innovation

AI adoption and green sensing capability

Green sensing capability refers to the organizational processes through which firms identify, interpret, and prioritize environmental opportunities and threats (Khan et al., 2021; Qiu et al., 2020). AI adoption enhances this capability through multiple mechanisms. First, AI-powered analytics enable firms to process vast amounts of environmental data from diverse sources, including regulatory announcements, scientific publications, social media sentiment, and competitor activities (Giannakopoulos et al., 2025). This data processing capacity allows firms to detect weak signals of emerging environmental trends that might otherwise remain unnoticed.

Second, AI algorithms can identify patterns and correlations that human analysts might miss. For example, machine learning models can analyze the relationship between regulatory changes in one jurisdiction and subsequent innovation responses in another, enabling firms to anticipate rather than simply react to environmental pressures (Mijit et al., 2025). Third, AI-enabled predictive analytics can forecast future environmental scenarios, allowing firms to assess the potential impact of different technological pathways before committing substantial resources.

Empirical evidence supports this relationship. Abdelfattah and colleagues (2025) found that AI adoption significantly enhanced firms' capacity to identify green innovation opportunities. Similarly, Al-Husain et al. (2025) demonstrated that digital dynamic capabilities, which are closely related to AI-enabled sensing, positively influenced green knowledge management and technology innovation. The sensing-enhancing role of AI is also evident in the circular economy context, where Khan et al. (2021) showed that sensing capabilities are foundational for identifying circular opportunities. Based on the theoretical logic and empirical evidence presented above, the following proposition is advanced:

Proposition 1a: AI adoption has a positive effect on green sensing capability in high-tech enterprises.

AI adoption and green seizing capability

Green seizing capability encompasses the organizational processes for mobilizing resources to address identified environmental opportunities (Borah et al., 2025; Marrucci et al., 2022). AI adoption enhances seizing capability by improving resource allocation decisions, accelerating product development cycles, and enabling rapid experimentation.

AI contributes to seizing capability in several ways. First, AI-driven analytics provide decision support for resource allocation. Firms can use predictive models to evaluate the expected returns of different green innovation investments, reducing uncertainty and enabling more confident commitment of resources (Rahman et al., 2026). Second, AI tools such as generative design algorithms can accelerate the product development process by automatically generating and testing multiple design alternatives against environmental criteria (Liang et al., 2025). This capability allows firms to seize opportunities more quickly than competitors relying on traditional design methods.

Third, AI enables rapid experimentation through simulation and digital twins. Firms can test green innovation concepts in virtual environments before committing to physical prototypes, reducing both the time and cost of seizing new opportunities (Giannakopoulos et al., 2025). This experimentation capability is particularly valuable in high-tech sectors where first-mover advantages are substantial.

Empirical support for this relationship comes from multiple studies. Li and colleagues (2024) found that green technology adoption, which is facilitated by AI, positively influenced environmental performance. Mubeen et al. (2024) demonstrated that green dynamic capabilities, including seizing capabilities, mediated the relationship between organizational practices and green innovation. The resource mobilization function of AI is also evident in the findings of McElheran et al. (2024), who showed that AI-adopting firms displayed stronger growth-oriented business strategies. Based on the theoretical logic and empirical evidence presented above, the following proposition is advanced:

Proposition 1b: AI adoption has a positive effect on green seizing capability in high-tech enterprises.

AI adoption and green transforming capability

Green transforming capability refers to the organizational capacity for continuous renewal and reconfiguration of resources and routines to maintain alignment with changing environmental conditions (Khan et al., 2021; Weber et al., 2025). AI adoption enhances transforming capability by enabling organizational learning, facilitating process adaptation, and supporting structural change.

The contribution of AI to transforming capability operates through three mechanisms. First, AI systems capture and codify organizational knowledge about what works and what does not in green innovation efforts. Machine learning algorithms can analyze historical project data to identify success factors and failure modes, creating an organizational memory that supports continuous improvement (Uren & Edwards, 2023). Second, AI enables real-time process adaptation. For example, AI-powered manufacturing systems can automatically adjust production parameters to optimize energy efficiency or reduce waste, representing a form of ongoing transformation (Khan et al., 2021).

Third, AI adoption itself often triggers structural changes in organizations. Firms that successfully integrate AI into their operations typically need to reconfigure teams, modify reporting relationships, and develop new coordination mechanisms (Na et al., 2022). These structural changes, while initially focused on AI implementation, create organizational conditions that also support the ongoing transformation of green innovation processes.

Evidence for the transformation-enhancing role of AI is emerging. Mijit and colleagues (2025) found that AI policy zones significantly enhanced firms' operational efficiency, which subsequently fostered advanced green innovation. This finding suggests that AI-induced operational improvements represent a form of transforming capability. Similarly, Singh et al. (2022) demonstrated that green dynamic capabilities, including transforming capabilities, mediated the relationship between external pressures and green innovation outcomes. Based on the theoretical logic and empirical evidence presented above, the following proposition is advanced:

Proposition 1c: AI adoption has a positive effect on green transforming capability in high-tech enterprises.

The mediating role of green dynamic capabilities

The central theoretical argument of this paper is that green dynamic capabilities mediate the relationship between AI adoption and green innovation. This mediating role is grounded in the logic that AI is an enabling technology rather than a direct driver of innovation outcomes. Firms cannot simply purchase AI systems and expect automatic improvements in green innovation. Rather, they must develop the organizational capabilities to sense, seize, and transform based on AI-generated insights. **Table 3** summarizes the hypothesized mediation pathways, specifying how each dimension of green dynamic capabilities translates AI adoption into specific green innovation outcomes.

Table 3. Hypothesized Mediation Pathways from AI Adoption to Green Innovation

Pathway	Mechanism	Green Innovation Outcome	Representative Evidence
AI adoption → Sensing capability → Green innovation	Enhanced environmental scanning and opportunity identification	Green product innovation (novel eco-friendly products)	Abdelfattah et al. (2025); Guo (2023)
AI adoption → Seizing capability → Green innovation	Improved resource allocation and accelerated development	Green process innovation (efficient manufacturing)	Borah et al. (2025); Rahman et al. (2026)
AI adoption → Transforming capability → Green innovation	Continuous renewal and adaptive reconfiguration	Both product and process innovation	Khan et al. (2021); Mijit et al. (2025)

The mediation logic for sensing capabilities is that AI enables firms to identify more and better green innovation opportunities, but opportunity identification alone does not produce innovation. Firms must still act on these opportunities through product and process development. However, without the sensing capability enabled by AI, firms would lack the opportunity pipeline necessary for sustained green innovation.

The mediation logic for seizing capabilities is that AI improves the efficiency and effectiveness of resource mobilization for green innovation. Firms can use AI to evaluate investment alternatives, accelerate development cycles, and reduce experimentation costs. These seizing capabilities directly translate into green innovation outputs because they address the implementation gap between opportunity identification and actual innovation.

The mediation logic for transforming capabilities is that AI enables ongoing adaptation and learning. Green innovation is not a one-time event but a continuous process. Firms must constantly refine their products,

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processes, and practices in response to evolving environmental standards, technological changes, and stakeholder expectations. AI-enabled transforming capabilities support this continuous improvement cycle.

Empirical support for the mediating role of green dynamic capabilities comes from several studies. Borah and colleagues (2025) found that green dynamic capabilities mediated the relationship between organizational capabilities and green product innovation. Singh et al. (2022) demonstrated that green dynamic capabilities mediated the effect of stakeholder pressure on green innovation. Rahman et al. (2026) showed that green dynamic capabilities mediated the relationship between green innovation and sustainable performance, with AI moderating these relationships. Based on the theoretical logic and empirical evidence presented above, the following propositions are advanced:

Proposition 2a: Green sensing capability mediates the positive relationship between AI adoption and green innovation in high-tech enterprises.

Proposition 2b: Green seizing capability mediates the positive relationship between AI adoption and green innovation in high-tech enterprises.

Proposition 2c: Green transforming capability mediates the positive relationship between AI adoption and green innovation in high-tech enterprises.

The moderating role of organizational readiness

Organizational readiness refers to the extent to which a firm possesses the necessary resources, skills, and supportive culture to effectively implement and utilize AI technologies (Uren & Edwards, 2023; Na et al., 2022). Organizational readiness is proposed to moderate the relationship between AI adoption and green dynamic capabilities. Firms with higher organizational readiness will derive greater enhancements in sensing, seizing, and transforming capabilities from their AI investments.

The moderation logic is straightforward. AI adoption alone does not guarantee capability development. Firms must have complementary assets in place to translate AI investments into enhanced capabilities. These complementary assets include technical skills (for example, data scientists and AI engineers), managerial skills (for example, leaders who understand both AI and sustainability), supportive organizational culture (for example, willingness to experiment and tolerate failure), and adequate technological infrastructure (for example, data storage and computing capacity).

Empirical evidence supports this moderation effect. McElheran and colleagues (2024) found that AI adoption was highest among firms with more educated, more experienced, and younger owners, suggesting that human capital readiness matters for AI capability development. Uren and Edwards (2023) proposed a model suggesting that people, process, and data readiness are required in addition to technology readiness for long-term operational success with AI. This finding directly supports the notion that organizational readiness moderates the effectiveness of AI adoption. Based on the theoretical logic and empirical evidence presented above, the following propositions are advanced:

Proposition 3a: Organizational readiness positively moderates the relationship between AI adoption and green sensing capability, such that the positive effect of AI adoption on sensing capability is stronger when organizational readiness is high.

Proposition 3b: Organizational readiness positively moderates the relationship between AI adoption and green seizing capability, such that the positive effect of AI adoption on seizing capability is stronger when organizational readiness is high.

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Proposition 3c: Organizational readiness positively moderates the relationship between AI adoption and green transforming capability, such that the positive effect of AI adoption on transforming capability is stronger when organizational readiness is high.

The moderating role of environmental dynamism

Environmental dynamism refers to the rate and unpredictability of change in a firm's external environment, including technological change, regulatory shifts, and market volatility (Singh et al., 2022). It is proposed that environmental dynamism moderates the relationship between green dynamic capabilities and green innovation. Under conditions of high environmental dynamism, the positive effect of green dynamic capabilities on green innovation will be stronger.

The logic for this moderation effect draws on contingency theory. Dynamic capabilities are most valuable in dynamic environments (Teece et al., 1997). When the external environment is stable and predictable, firms may achieve satisfactory performance through existing routines without needing to exercise dynamic capabilities. However, when the environment is turbulent, the ability to sense new opportunities, seize emerging possibilities, and transform existing configurations becomes critical for survival and success.

In the context of green innovation, environmental dynamism takes specific forms. Regulatory dynamism refers to rapid changes in environmental policies and standards. Technological dynamism refers to the emergence of new green technologies that may disrupt existing practices. Market dynamism refers to shifting customer preferences for sustainable products. Under conditions of high dynamism in any of these domains, green dynamic capabilities become more valuable because they enable firms to adapt quickly and maintain alignment with environmental requirements.

Empirical evidence for the moderating role of environmental dynamism can be found in recent studies. Singh and colleagues (2022) demonstrated that stakeholder pressure effects on green innovation were mediated by green dynamic capabilities, suggesting that environmental pressures activate the capability innovation linkage. Additionally, Rahman et al. (2026) found that AI moderates the relationship between green dynamic capabilities and sustainable performance, providing indirect support for the role of environmental dynamism as a boundary condition. Although direct tests of environmental dynamism as a moderator of the capability green innovation relationship are limited, the theoretical logic is well established in the dynamic capabilities literature. Based on the theoretical logic and empirical evidence presented above, the following propositions are advanced:

Proposition 4a: Environmental dynamism positively moderates the relationship between green sensing capability and green innovation, such that the positive effect of sensing capability on green innovation is stronger

when environmental dynamism is high.

Proposition 4b: Environmental dynamism positively moderates the relationship between green seizing capability and green innovation, such that the positive effect of seizing capability on green innovation is stronger when environmental dynamism is high.

Proposition 4c: Environmental dynamism positively moderates the relationship between green transforming capability and green innovation, such that the positive effect of transforming capability on green innovation is stronger when environmental dynamism is high.

Summary of propositions

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Table 4 provides a consolidated summary of all nine propositions organized by research question.

Table 4. Summary of Theoretical Propositions

Research Question	Proposition	Description
RQ1: AI adoption → GDC	P1a	AI adoption → Green sensing capability (+)
	P1b	AI adoption → Green seizing capability (+)
	P1c	AI adoption → Green transforming capability (+)
RQ2: Mediation mechanism	P2a	Green sensing capability mediates AI adoption → Green innovation
	P2b	Green seizing capability mediates AI adoption → Green innovation
	P2c	Green transforming capability mediates AI adoption → Green innovation
RQ3: Moderation effects	P3a	Organizational readiness moderates AI adoption → Sensing capability
	P3b	Organizational readiness moderates AI adoption → Seizing capability
	P3c	Organizational readiness moderates AI adoption → Transforming capability
	P4a	Environmental dynamism moderates Sensing capability → Green innovation
	P4b	Environmental dynamism moderates Seizing capability → Green innovation
	P4c	Environmental dynamism moderates Transforming capability → Green innovation

DISCUSSION

Theoretical contributions

This paper makes three primary theoretical contributions to the intersection of AI adoption, green dynamic capabilities, and green innovation in high-tech enterprises.

First, the paper extends dynamic capabilities theory to the AI and green innovation context. Prior applications of dynamic capabilities theory have focused primarily on general innovation and competitive advantage as reviewed in recent sustainability-focused scholarship (Buzzao & Rizzi, 2021; Khan et al., 2021). More recent scholarship has extended the framework to sustainability (Buzzao & Rizzi, 2021; Khan et al., 2021), yet the role of AI as an enabler of green dynamic capabilities has remained undertheorized. The present paper addresses this gap by specifying how AI adoption differentially enhances the three dimensions of green dynamic capabilities.

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As summarized in **Table 5**, each dimension of green dynamic capabilities is enabled by distinct AI applications and mechanisms.

Table 5. AI Applications and Mechanisms Enabling Each Dimension of Green Dynamic Capabilities

Green Dynamic Capability Dimension	Primary AI Applications	Enabling Mechanisms	Representative Evidence
Sensing capability	Predictive analytics, environmental scanning algorithms, and pattern recognition	Detection of weak signals, trend identification, scenario forecasting	Abdelfattah et al. (2025); Giannakopoulos et al. (2025)
Seizing capability	Generative design algorithms, simulation models, digital twins	Accelerated prototyping, resource allocation optimization, and rapid experimentation	Liang et al. (2025); Mubeen et al. (2024)
Transforming capability	Machine learning systems, organizational memory algorithms, real time process control	Knowledge codification, adaptive reconfiguration, continuous improvement	Khan et al. (2021); Mijit et al. (2025)

The differentiation among sensing, seizing, and transforming capabilities is critical because it reveals that AI is not a monolithic enabler. Different AI applications contribute to different capability dimensions, and firms seeking to leverage AI for green innovation must invest in the specific AI tools that align with their most pressing capability gaps. For example, a firm struggling to identify green opportunities would benefit most from AI applications that enhance sensing capability, such as environmental scanning algorithms. In contrast, a firm with abundant opportunities but slow implementation would benefit from AI applications that enhance seizing capability, such as generative design tools.

Second, the paper clarifies the mediating role of green dynamic capabilities in the AI adoption green innovation relationship. Prior research has presented conflicting findings regarding whether AI directly affects green innovation (Mijit et al., 2025) or operates through mediating mechanisms (Rahman et al., 2026). The present paper resolves this ambiguity by theoretically specifying that green dynamic capabilities serve as the proximal mechanism through which AI adoption translates into green innovation outcomes. This mediation logic has important implications for both theory and practice. Theoretically, it suggests that scholars should not expect to observe direct AI green innovation effects without accounting for organizational capabilities. Practically, it implies that firms cannot simply purchase AI technologies and expect automatic green innovation improvements; they must deliberately develop the sensing, seizing, and transforming capabilities that mediate the relationship.

Third, the paper integrates contingency factors that shape the effectiveness of AI-enabled green innovation. By introducing organizational readiness and environmental dynamism as moderators, the framework acknowledges that the AI adoption capability green innovation relationship is not universal but depends on contextual conditions. This contingency perspective is consistent with the dynamic capabilities literature, which has long recognized that capabilities are most valuable in dynamic environments (Teece et al., 1997). The inclusion of organizational readiness as a moderator also addresses a practical concern: many firms invest in AI technologies without developing the complementary organizational resources and skills necessary to realize value from those investments (Uren & Edwards, 2023). The framework suggests that organizational readiness determines whether AI adoption actually translates into enhanced green dynamic capabilities.

Practical implications

The framework offers several actionable implications for managers and policymakers in high-tech sectors.

For managers, the primary implication is that AI adoption should be viewed as a capability-building exercise rather than a technology procurement project. Firms should assess their existing green dynamic capabilities, identify gaps in sensing, seizing, or transforming capacities, and prioritize AI investments that address those specific gaps. **Table 5** provides guidance on which AI applications map to which capability dimensions, enabling managers to make informed technology investment decisions.

Second, managers should invest in organizational readiness complementarily to AI adoption. Hiring data scientists, training existing employees in AI literacy, developing supportive data infrastructure, and fostering a culture that tolerates experimentation are all necessary conditions for realizing value from AI investments. Without these complementary investments, AI adoption may fail to enhance green dynamic capabilities.

Third, managers should recognize that environmental dynamism is not merely a constraint but potentially an opportunity. Under conditions of high regulatory, technological, or market dynamism, green dynamic capabilities become more valuable. Firms that have developed strong sensing, seizing, and transforming capabilities through AI adoption may be better positioned to navigate turbulent environments than competitors who have not made such investments.

For policymakers, the framework suggests several intervention points. First, policies that support AI adoption in high-tech sectors should be coupled with capability-building programs. Subsidies for AI technology purchases alone may be insufficient; training programs, technical assistance, and knowledge sharing platforms may also be necessary. Second, policymakers should consider the role of industry-level factors that shape organizational readiness. For example, developing shared data infrastructure or industry-specific AI tools for green innovation could lower the readiness barriers faced by individual firms. Third, regulatory policies that increase environmental dynamism (for example, ambitious but predictable emissions reduction targets) may activate the value of green dynamic capabilities, creating incentives for firms to invest in AI-enabled capability development.

Methodological guidance for future empirical research

The propositions advanced in this paper require empirical validation. Future research should test the hypothesized relationships using appropriate research designs. The following methodological guidance is provided to facilitate such empirical work.

Construct measurement. Valid and reliable measures of the key constructs are essential. Green sensing, seizing, and transforming capabilities can be measured using scales adapted from prior research. Khan and colleagues (2021) developed and validated measurement scales for sensing, seizing, and reconfiguring capabilities in the circular economy context, achieving satisfactory reliability (Cronbach's alpha ranging from 0.82 to 0.89). These scales can be adapted for green innovation contexts with minor modifications. AI adoption can be measured using either objective indicators (for example, whether the firm has implemented specific AI technologies) or perceptual measures (for example, manager assessments of AI adoption extent). McElheran et al. (2024) provide examples of objective AI adoption measurement using survey data from 850,000 firms. Green innovation can be measured using patent-based indicators (for example, number of green patents granted) or survey-based measures of green product and process innovation. Organizational readiness can be assessed using scales that

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capture technological, human, and cultural readiness dimensions. Environmental dynamism can be measured using perceptual scales that assess managers' perceptions of the rate and unpredictability of change in regulatory, technological, and market conditions. Alternative approaches include objective indicators such as the frequency of environmental policy changes or the volatility of green technology patent filings within an industry.

Sampling and data collection. The propositions should be tested using samples of high-tech enterprises. The high-tech sector can be defined using industry classification codes (for example, NAICS codes for computer and electronic product manufacturing, software publishing, and scientific research and development services). Survey-based data collection from managers is a feasible approach, though common method bias concerns must be addressed through procedural remedies (for example, temporal separation of predictor and criterion variable measurement) and statistical remedies (for example, Harman's single factor test). Alternatively, secondary data sources can be used. AI adoption data from firm surveys, green patent data from patent office records, and financial performance data from commercial databases can be combined to create multi-source datasets that reduce common method bias concerns.

Analytical approach. Structural equation modeling (SEM) is appropriate for testing the full mediation model proposed in this paper. Partial least squares SEM (PLS-SEM) is particularly suitable for studies with complex models and relatively smaller sample sizes (Hair et al., 2019). The mediation hypotheses can be tested using bootstrapping procedures with confidence intervals for indirect effects. Moderation hypotheses can be tested using product term analysis or multi-group analysis. For the moderated mediation relationships implied by the full framework (that is, organizational readiness moderating the AI adoption capability relationship and environmental dynamism moderating the capability green innovation relationship), conditional process modeling (for example, PROCESS macro in SPSS or the moderation function in SmartPLS) is recommended.

Longitudinal and quasi-experimental designs. Cross-sectional survey designs can establish associations but cannot conclusively demonstrate causality. Future research should employ longitudinal designs that measure AI adoption at Time 1, green dynamic capabilities at Time 2, and green innovation at Time 3, with appropriate time lags. Quasi-experimental designs that leverage natural experiments, such as the AI Innovation and Development Pilot Zone policy studied by Mijit et al. (2025), can provide stronger causal evidence. Difference in differences approaches that compare firms in pilot zones to similar firms outside pilot zones before and after policy implementation can estimate the causal effect of AI adoption.

Qualitative and mixed methods approaches. The propositions could also be examined using qualitative methods. Comparative case studies of high-tech firms with varying levels of AI adoption could reveal how sensing, seizing, and transforming capabilities develop over time. Process tracing methods could identify whether the hypothesized mediation mechanisms actually operate in practice. Mixed methods designs that combine qualitative exploration of mechanisms with quantitative testing of relationships would be particularly valuable for validating and refining the framework.

Limitations and future research directions

Several limitations of the present paper should be acknowledged. First, as a conceptual paper, the framework has not been empirically tested. The propositions advanced here require validation through the empirical methods described above. Second, the framework focuses on high-tech enterprises, which may limit generalizability to other sectors. Future research should examine whether the same relationships hold in low-tech manufacturing, service industries, or small and medium enterprises. Third, the framework treats AI adoption as a general construct, but different AI technologies (for example, machine learning versus natural language processing versus computer vision) may have different effects on green dynamic capabilities. Future research should disaggregate AI adoption into specific technology types and examine their differential effects.

Additional future research directions emerge from the framework. First, the interaction among the three green dynamic capability dimensions deserves investigation. Do sensing, seizing, and transforming capabilities operate independently, or do they interact synergistically? For example, do firms with both high sensing and high seizing capabilities achieve greater green innovation than would be predicted by the sum of their individual effects? Second, the temporal dynamics of AI-enabled capability development require attention. How long does it take for AI adoption to translate into enhanced sensing capability? Do the three capability dimensions develop simultaneously or sequentially? Longitudinal research could address these questions. Third, the role of human AI interaction in green dynamic capabilities warrants investigation. The framework focuses on AI as a technological enabler, but human judgment remains essential for sensing, seizing, and transforming. Future research should examine how managers and AI systems interact in the capability development process.

CONCLUSION

This paper has advanced a conceptual framework explaining how AI adoption enhances green innovation in high-tech enterprises through the mediating mechanism of green dynamic capabilities. Drawing on dynamic capabilities theory and synthesizing 24 empirical studies, the paper specified how AI adoption differentially enhances sensing, seizing, and transforming capabilities. Nine propositions were advanced, and organizational readiness and environmental dynamism were identified as key moderators that shape the effectiveness of AI-enabled green dynamic capabilities.

The paper makes three primary contributions. First, it extends dynamic capabilities theory to the AI and green innovation context by specifying the distinct AI applications and mechanisms that enable each dimension of green dynamic capabilities. Second, it clarifies the mediating role of green dynamic capabilities, resolving ambiguity in prior research regarding whether AI directly or indirectly affects green innovation. Third, it integrates contingency factors that acknowledge contextual dependence, offering a more nuanced understanding of boundary conditions.

For managers, the framework implies that AI adoption should be approached as a capability-building exercise requiring complementary investments in organizational readiness. For policymakers, the framework suggests that AI adoption subsidies should be coupled with capability-building programs and that regulatory policies increasing environmental dynamism may activate the value of green dynamic capabilities. For researchers, the framework provides a theoretically grounded foundation for empirical investigation, and detailed methodological guidance is provided to facilitate such work.

The integration of AI and green innovation represents a critical frontier for both scholarly inquiry and managerial practice. As environmental challenges intensify and AI technologies continue to advance, understanding how organizations can effectively leverage AI for sustainability becomes increasingly urgent. The framework advanced in this paper provides a foundation for this important work, but empirical validation remains essential. Future research is encouraged to test, refine, and extend the propositions advanced here.

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