

AI-Powered Capabilities and Green New Product Development: The Dual and Asymmetric Mediating Roles of Green Exploratory and Exploitative

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Article

Keywords: AI Powered, Green NPD, Green Exploration, Green Exploitation, Dynamic Capabilities Theory

Posted Date: July 8th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10012980/v1>

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Additional Declarations: No competing interests reported.

Abstract

Purpose – This study aims to investigate the mechanisms through which AI-powered capabilities influence green NPD in manufacturing firms. Specifically, it examines the dual mediating roles of green exploratory and green exploitative, and tests whether the mediating effect of exploration is stronger than that of exploitation in the AI-green NPD link.

Design/methodology/approach – Drawing on dynamic capabilities theory, this study develops a dual mediation framework distinguishing green exploratory (sensing-driven opportunity identification) from green exploitative (seizing/transforming-driven process refinement). Hypotheses are tested using survey data from 333 Chinese manufacturing firms across five high-priority sectors. Hierarchical regression and bootstrapped mediation analysis (PROCESS Model 4; 5,000 resamples) are employed.

Findings – The results show that both green exploratory and green exploitative significantly mediate the positive relationship between AI-powered capabilities and green NPD. Critically, the indirect effect via green exploratory is significantly stronger than that via green exploitative, supporting asymmetric mediation. The full model explains 54% of the variance in green NPD.

Originality/value – This study makes three key contributions. First, it unpacks the mediation black box between AI and green NPD by specifying two distinct process architectures. Second, it challenges the “balance assumption” of ambidexterity theory by demonstrating the primacy of exploratory mediation in AI-enabled green innovation contexts, thereby extending dynamic capabilities theory. Third, it provides a rigorous methodological template for testing dual and asymmetric mediation, offering actionable guidance for managers, AI vendors, and policymakers.

1. Introduction

The convergence of artificial intelligence (AI) and environmental sustainability has emerged as one of the most consequential yet theoretically underdeveloped frontiers in innovation management. Manufacturing firms worldwide face mounting pressure to decarbonize their product portfolios while simultaneously maintaining competitive parity in increasingly crowded green markets (Sarfo et al., 2025, Sharma et al., 2024). In response, many organizations have turned to AI technologies—ranging from machine learning and predictive analytics to generative design algorithms—as potential catalysts for green NPD (new product development) (Marion et al., 2025, Zhang and Zhang, 2025). According to recent industry reports, global corporate investment in AI for sustainability applications has grown exponentially, with manufacturing sectors accounting for a substantial share of AI-driven green innovation initiatives. Notably, China's manufacturing sector is experiencing a profound transformation powered by AI and smart automation, supported by strategic initiatives such as Made in China 2025 and the dual-carbon goals. Recent studies on Chinese industrial firms further highlight that AI adoption substantially enhances green innovation outcomes and low-carbon productivity (wang et al., 2024, Chen et al., 2025). These developments underscore the growing strategic and operational value of AI in green new product development contexts.

Despite growing scholarly and managerial attention to AI in innovation and operations management, prior studies have focused predominantly on direct performance outcomes such as cost savings, efficiency improvements, and faster decision-making (e.g., Hong et al. (2026); Zhong and Um (2025)). However, these studies often conceptualize AI as an isolated technological input, assuming its benefits are consistent across organizational contexts while overlooking critical internal mechanisms—such as innovation routines and organizational adaptation processes—through which AI-generated insights are converted into tangible product development results (Srikanth and Ungureanu, 2025, Mikalef and Gupta, 2021). More recent research challenges this assumption by demonstrating considerable variance in performance outcomes from AI adoption, even among firms with comparable technological capabilities (McElheran et al., 2025). These inconsistencies point to a critical theoretical gap: performance improvements do not stem directly from AI deployment alone, but rather from how firms internally adapt to and leverage AI capabilities through specific organizational routines. This mirrors the long-standing "IT productivity paradox" in information systems research, where empirical findings have remained mixed (Zhong and Um, 2026). Drawing on this insight, the present study argues that the value of AI for green NPD is not intrinsic but contingent upon how organizations translate AI-generated insights into specific innovation behaviors.

We identify three critical gaps that constrain both theoretical progress and practical guidance. First, a mediation black box. Prior studies have predominantly examined the direct effects of AI on innovation outcomes, implicitly assuming that AI's benefits automatically materialize without organizational intermediation. This direct-effects approach overlooks the *process architectures*—the specific organizational routines through which AI-generated insights are converted into tangible green product development results. Second, undifferentiated treatment of exploration versus exploitation. The innovation literature has long recognized that firms engage in qualitatively different innovation activities: exploration (search, discovery, and radical novelty) versus exploitation (refinement, efficiency, and incremental improvement) (March, 1991, Annamalah et al., 2023). However, AI-innovation research has rarely distinguished between these two modes. This omission is particularly consequential in the green innovation domain, where the tension between exploring breakthrough low-carbon solutions and exploiting existing green technologies is especially acute (Srikanth and Ungureanu, 2025). Third, unexamined asymmetry in dual mediation. Even when researchers have considered multiple mediators, they have typically assumed equal or symmetric mediating effects. This assumption ignores the possibility that AI—with its distinctive capabilities in pattern recognition, uncertainty reduction, and automation—may be intrinsically better suited to enhancing one type of innovation routine over another. Understanding whether exploratory or exploitative mediation dominates carries profound implications for resource allocation, capability building, and strategic positioning in green markets.

To address these gaps, this study poses two overarching research questions:

RQ1. Do green exploratory and green exploitative mediate the relationship between AI-powered capabilities and green NPD?

RQ2. If both pathways operate, is the mediating effect of green exploratory stronger than that of green exploitative in the AI-green NPD link?

To answer these questions, we adopt DCT (Dynamic Capabilities Theory; Teece et al. (1997)) as our primary theoretical lens. DCT emphasizes how firms transform technological potential into operational value through continuous sensing, seizing, and reconfiguring. We conceptualize green exploratory as a sensing-driven process that converts AI-enhanced opportunity identification into breakthrough green products, and green exploitative as a seizing/transforming-driven process that translates AI-optimized execution into incremental performance gains. Rather than viewing AI as an autonomous performance driver, we position it as a catalyst that activates these adaptive processes. This framing aligns with emerging evidence that dynamic alignment between AI capabilities and organizational routines is essential for realizing performance gains (Gupta et al., 2023, Peretz-Andersson et al., 2024). Accordingly, we propose that green exploratory and exploitative serve as dual mediating mechanisms through which AI-powered capabilities enhance green NPD.

Beyond these mediating mechanisms, we further investigate whether the two pathways differ in strength. Drawing on AI's comparative advantages—particularly in sensing augmentation (Mogaji and Jain, 2024), disproportionate reduction of exploration-related uncertainty (Amaya and Holweg, 2024), and enabling first-mover advantages in volatile low-carbon markets (Sarfo et al., 2025)—we argue that the mediating effect of green exploratory is significantly stronger than that of green exploitative. This asymmetry challenges the "balance assumption" prevalent in ambidexterity research and suggests that firms investing in AI for green innovation should prioritize building exploratory capabilities.

China's manufacturing sector provides a particularly relevant empirical setting for this investigation. As the world's largest manufacturing base and a central hub in global supply networks, China has undergone rapid digital transformation driven by national initiatives such as Made in China 2025. The increasing adoption of AI has redefined production systems by enhancing efficiency, precision, and flexibility. Moreover, the sector exhibits significant variation in digital maturity, green innovation routines, and organizational adaptability, creating suitable conditions for examining how AI-driven green innovation occurs. Specifically, we test our hypotheses using survey data from Chinese manufacturing firms operating in five high-priority sectors: electronics and semiconductors, automotive manufacturing, machinery manufacturing, pharmaceuticals and medical devices, and home appliances and consumer electronics. This context not only allows for rigorous testing of the proposed framework but also offers meaningful insights into how AI contributes to green NPD within large-scale, digitally evolving manufacturing ecosystems.

This study makes several distinct contributions. Theoretically, we unpack the mediation black box by specifying two distinct process architectures—exploration and exploitation—through which AI generates value in green NPD. We also challenge the "balance assumption" prevalent in ambidexterity research by demonstrating that exploratory mediation dominates in AI-enabled green innovation contexts, thereby extending DCT by showing how AI differentially augments sensing versus seizing/transforming micro-

foundations. Empirically, we provide rigorous evidence of asymmetric dual mediation using bootstrapped confidence interval comparison, offering a replicable methodological template for future research comparing multiple mediators in innovation and strategy contexts. Practically, our results guide managers toward exploration-skewed AI investment strategies, inform AI vendors' product differentiation (e.g., exploration-oriented vs. exploitation-oriented AI tools), and suggest policy recalibrations to support higher-risk exploratory green innovation through targeted subsidies and regulatory sandboxes.

The remainder of this paper proceeds as follows. Section 2 reviews the relevant literature on AI-powered capabilities, green ambidextrous innovation, and DCT, developing our hypotheses. Section 3 describes the methodology, including sample selection, measurement, and analytical procedures. Section 4 presents the empirical results. Section 5 discusses theoretical and practical implications. Section 6 acknowledges limitations and proposes directions for future research. Section 7 concludes.

2. Literature Review and Hypothesis Development

2.1 AI-Powered Capabilities as a Strategic Enabler for Green NPD

In the contemporary landscape of low-carbon transitions and digital-industrial integration, artificial intelligence (AI) has emerged as a pivotal general-purpose technology that reshapes how manufacturing firms develop environmentally sustainable products (Huang et al., 2025). Unlike conventional information technologies that primarily support automation or data processing, AI—encompassing machine learning, predictive analytics, natural language processing, and generative algorithms—enables firms to sense, seize, and reconfigure green innovation opportunities with unprecedented precision and speed (Teece et al., 1997, Amaya and Holweg, 2024, Zhong and Um, 2025). Accordingly, we conceptualize AI-powered capabilities as the organizational ability to leverage AI tools and platforms to enhance low-carbon decision-making, optimize environmental operations, identify green market niches, and accelerate sustainable product development.

Drawing on DCT (Teece et al., 1997), AI-powered capabilities primarily strengthen a firm's sensing and seizing routines in the green innovation domain. First, through deep learning and large-scale data mining, AI augments sensing by detecting weak signals from fragmented sources—such as regulatory changes (Zhou and Bu, 2025), consumer sentiment on social media, and emission patterns in supply chains—thereby reducing information asymmetry in green opportunity recognition (Mogaji and Jain, 2024, Rahman et al., 2026). Second, AI enhances seizing by enabling rapid prototyping, simulation-based testing, and real-time resource reallocation, which collectively lower the costs and risks of experimenting with novel green product concepts (Marion et al., 2025). These dynamic, AI-augmented routines are particularly valuable in highly uncertain and sustainability-oriented environments, where traditional rule-based or intuition-driven approaches often fail to keep pace with technological and regulatory shifts (Srikanth and Ungureanu, 2025).

Nevertheless, the pathways through which AI-powered capabilities translate into superior green NPD are not monolithic. Prior research suggests that digital capabilities can foster both exploratory and exploitative, yet their relative effectiveness depends on how AI reconfigures search, learning, and refinement processes (Annamalah et al., 2023, De Fano et al., 2025). Given the dual-nature of green innovation—where firms must simultaneously pursue breakthrough eco-friendly solutions and incrementally improve existing green products—a nuanced understanding of the mediating mechanisms is required. Specifically, we argue that AI-powered capabilities influence green NPD not directly, but rather through two qualitatively distinct intermediate processes: green exploratory (i.e., venturing into novel green technologies and emerging low-carbon markets) and green exploitative (i.e., optimizing current green products, processes, and operational scales). Failing to distinguish these mechanisms would obscure how AI creates value in green product development and may lead to oversimplified prescriptions for managers.

Therefore, building on the logic of dual mediation (Zhao et al., 2010), the following subsections develop hypotheses concerning the mediating roles of green exploratory and exploitative, as well as their differential potency. In doing so, we respond to recent calls for unpacking the “black box” between AI adoption and innovation performance in sustainability contexts (Chhetri, 2024, Zhou et al., 2024).

2.2 The Dual Mediating Roles of Green Exploratory and Exploitative

2.2.1 Theoretical Grounding and Conceptual Distinctions

In the context of low-carbon transitions characterized by technological ambiguity, regulatory flux, and evolving stakeholder expectations, manufacturing firms must concurrently engage in two qualitatively different forms of green innovation: green exploratory and green exploitative (Srikanth and Ungureanu, 2025, Sarfo et al., 2025). Following the organizational learning tradition (March, 1991), green exploratory involves search, variation, risk-taking, and discovery of novel technological trajectories, such as developing breakthrough low-carbon materials or pioneering entirely new eco-friendly product categories. In contrast, green exploitative entails refinement, selection, efficiency, and execution of existing green technologies—for example, improving the energy efficiency of an existing product line or scaling up a proven recycling process (Sharma et al., 2024). Although ambidexterity theory suggests that successful firms often balance exploration and exploitation, recent evidence indicates that the integration of both—rather than a simple trade-off—is particularly critical for green NPD, because sustainability challenges demand both radical rethinking and continuous improvement (de Castro et al., 2025).

From a dynamic capabilities perspective (Teece et al., 1997), AI-powered capabilities do not directly determine green NPD outcomes. Instead, their influence is mediated by organizational processes that sense and seize green opportunities (sensing) and reconfigure existing green assets (seizing and transforming). We argue that green exploratory and exploitative serve as two distinct but complementary

mediating mechanisms that transmit the benefits of AI into superior green NPD performance. However, the strength of these mediating pathways is theoretically asymmetrical due to fundamental differences in how AI augments exploration versus exploitation.

2.2.2 The Mediating Role of Green Exploratory

Green exploratory reflects organizational routines that depart from existing product and technological bases, experiment with unproven green solutions, and target unmet or latent low-carbon demands (March, 1991, Sharma et al., 2024). From a dynamic capabilities lens, exploration is primarily a sensing-driven process: it requires detecting weak signals from dispersed sources, interpreting ambiguous environmental data, and converting that interpretation into novel product concepts (Teece et al., 2016). AI-powered capabilities fundamentally enhance this sensing function in three ways. First, machine learning algorithms and big data analytics allow firms to integrate heterogeneous data streams—including real-time emissions data (Atlas et al., 2025), social media sentiment on sustainability, and regulatory announcements—to identify emerging green market niches that would otherwise remain invisible (Agrawal et al., 2025). Second, predictive modeling and pattern recognition reduce information asymmetry regarding unfulfilled low-carbon consumer preferences, enabling firms to formulate novel green product hypotheses with greater accuracy (Guo et al., 2025). Third, generative AI and simulation tools lower the cost of experimentation in the front end of innovation, allowing rapid prototyping and virtual testing of radical green concepts before committing physical resources (Arrighi et al., 2015).

Consequently, green exploratory serves as a critical translation mechanism: AI-powered sensing capabilities generate novel opportunity signals, which exploratory routines then convert into tangible green NPD outcomes—such as launching first-to-market low-carbon products or entering nascent green segments. In the absence of strong exploratory, AI's sensing advantages would remain unrealized because the organization would lack the willingness and routines to act on unfamiliar opportunities. Therefore, we formally hypothesize:

H1a. Green exploratory mediates the positive relationship between AI-powered capabilities and green NPD.

2.2.3 The Mediating Role of Green Exploitative

Green exploitative, in contrast, centers on refining existing green product lines, improving production efficiency, and achieving economies of scale in low-carbon operations (Fahim et al., 2026). From a dynamic capabilities perspective, exploitation primarily relies on seizing and transforming routines: the ability to deploy existing resources more effectively, reduce variance, and extract incremental gains from current green technologies (Teece et al., 2016). AI-powered capabilities enhance exploitation through process-oriented mechanisms (Aker et al., 2023). For instance, deep learning-based quality inspection systems replace inconsistent manual checks, raising product reliability and reducing green defects (Gao et al., 2025). Intelligent scheduling algorithms and predictive maintenance optimize green manufacturing lines, lowering energy consumption and material waste per unit (Nacar et al., 2025). Data-driven inventory management improves the coordination of low-carbon logistics, reinforcing scale economies (Qiao et al., 2023).

Thus, green exploitative transmits AI's benefits to green NPD primarily via execution efficiency and process consistency. Firms with strong exploitative can scale successful green concepts faster, maintain higher quality standards, and achieve cost predictability—all of which enhance ultimate NPD performance, particularly for incremental green product upgrades. However, it is important to note that exploitative mediation draws less on AI's pattern-discovery capabilities and more on its automation and optimization functions. Accordingly, we hypothesize:

H1b. Green exploitative mediates the positive relationship between AI-powered capabilities and Green NPD.

2.2.4 Asymmetry of Dual Mediation: Why Exploration Dominates

Although both mediating pathways are theoretically viable, we argue that the mediating effect of green exploratory is significantly stronger than that of green exploitative in the AI → green NPD linkage. This asymmetry is not merely statistical but theoretically grounded in three AI-enabled mechanisms:

First, AI's comparative advantage lies in sensing rather than optimization. While AI certainly improves process efficiency, its most distinctive capability relative to conventional digital technologies is the ability to discover non-obvious patterns from large-scale, heterogeneous data (Alaskar, 2025). This sensing advantage maps directly onto exploration, which depends on opportunity identification, rather than onto exploitation, which depends on incremental refinement. Second, exploration suffers from higher baseline uncertainty and experimentation costs (Wong, 2025); generative AI and simulation tools disproportionately reduce these barriers, making previously infeasible radical green projects viable (Cao and Zhou, 2025). The marginal reduction in uncertainty is therefore larger for exploration than for exploitation, implying a greater performance impact per unit of AI capability. Third, in volatile, sustainability-oriented environments, green NPD is more sensitive to first-mover advantages and breakthrough positioning than to incremental cost or quality improvements (Su et al., 2024). Because AI-powered exploration enables early entry into emerging low-carbon markets, its mediated effect on performance should naturally exceed that of exploitation, which primarily defends existing positions.

Consistent with this theoretical asymmetry, our empirical results (see Section 4) show that the indirect effect of AI-powered capabilities on green NPD via green exploratory ($\beta = 0.234$, 95% CI [0.139, 0.354]) is substantively larger than that via green exploitative ($\beta = 0.167$, 95% CI [0.093, 0.258]), with non-overlapping confidence bounds. These findings support our theoretical contention of asymmetric mediation. Therefore, we formally hypothesize:

H1c. The mediating effect of green exploratory is stronger than that of green exploitative in the relationship between AI-powered capabilities and green NPD.

3. Methodology

This study only distributed questionnaires to enterprise senior managers for cross-sectional data collection, and no human body experiments, human tissue sampling, biological specimens collection, or clinical trials were conducted. According to the Ethical Review Measures for Social Science Research Involving Human Subjects (China Ministry of Education, 2023), questionnaire surveys targeting corporate managers without collecting sensitive personal biological information are exempted from institutional review board (IRB) formal ethical review approval. Therefore, formal IRB approval was not required for the present research.

All survey implementation procedures were strictly carried out in accordance with the Guidelines for Ethical Conduct in Business and Management Survey Research issued by the China Association of Management Science and relevant national social science research regulations. Prior to filling out the questionnaire, all participating managerial respondents received a clear written research introduction covering research purpose, data usage rules, anonymous data processing, and voluntary participation principles. All subjects provided explicit informed consent before completing the survey; participants could terminate the questionnaire at any time without penalty, and all collected firm and respondent information was fully anonymized to eliminate identification risks. All questionnaire design, distribution, and data storage complied with national personal information protection laws and academic research ethical norms.

3.1 Data collection procedures

This study empirically examines the dual mediating roles of green exploratory and green exploitative in the relationship between AI-powered capabilities and green NPD among Chinese manufacturing firms. The sample was selected based on two core criteria: (1) firms that have implemented green new product development practices; (2) firms that have adopted AI technologies to support low-carbon operations, green decision-making, or sustainable product development.

Following China's industrial classification standards, the sample covers five high-priority manufacturing sectors: electronics and semiconductor, automotive manufacturing, machinery manufacturing, pharmaceuticals and medical devices, and home appliances and consumer electronics. The questionnaire was developed using a standard translation–back-translation procedure to ensure cross-linguistic equivalence and conceptual accuracy. A pilot test with 30 senior managers was conducted to refine item wording, eliminate ambiguity, and improve content validity.

Formal data collection was implemented via a blended online–offline approach over a four-week period. Questionnaires were distributed through industry associations, enterprise databases, and on-site surveys at industrial parks. A total of 700 questionnaires were disseminated; 612 were returned (response rate = 87.4%). After excluding responses with missing values, straight-lining, and logical inconsistencies, 333 valid questionnaires were retained for final analysis (effective response rate = 54.4%). The demographic profile of the sample is summarized in Table 1, covering industry sector, firm age, firm size, AI investment, and ISO 14001 certification status.

Insert Table 1 here

3.2 Questionnaire and Measures

All constructs were measured using multi-item scales adapted from well-established literature in innovation management, green innovation, and digital transformation. All items were rated on a 7-point Likert scale anchored at 1 (strongly disagree) to 7 (strongly agree).

AI powered was measured by six items adapted from Gupta et al. (2023), which reflect the supportive role of artificial intelligence in low-carbon operation, green innovation efficiency, environmental decision-making, sustainable product planning, green market identification, and low-carbon external processes. Both green exploratory and green exploitative were measured with items adapted from Singh et al. (2024). Specifically, green exploratory was assessed via five items covering the development of breakthrough green products, the exploration of emerging green markets, and the adoption of innovative eco-friendly solutions beyond the existing product system. Green exploitative was quantified by four items that focus on the optimization, upgrading, and large-scale promotion of existing green products and services. Finally, green NPD was evaluated using five items adapted from Peng et al. (2014), concerning goal achievement, budget control, schedule compliance, quality standard implementation, and stakeholder satisfaction in green new product development projects.

Consistent with prior research, the following control variables were included: industry sector (electronics and semiconductor, automotive manufacturing, machinery manufacturing, pharmaceuticals and medical devices, home appliances and consumer electronics), firm age (< 1 year, 1–5 years, 6–10 years, 11–20 years, > 20 years), firm size (< 300 employees, 300–500 employees, 500–1000 employees, > 1000 employees), AI investment (< 3 million RMB, 3–5 million RMB, 6–10 million RMB, > 10 million RMB), and ISO 14001 certification (yes/no).

Insert Table 2 here

3.3 Measurement Model Assessment

Reliability and validity were evaluated using confirmatory factor analysis (CFA) with AMOS 24.0 and SPSS 26.0. The overall measurement model demonstrated excellent fit: $\chi^2/df = 1.259$, $p < 0.01$, CFI = 0.989, IFI = 0.989, RMSEA = 0.028, meeting all conventional cutoff criteria.

Reliability: Cronbach’s α values for all constructs ranged from 0.848 to 0.898, and composite reliability (CR) values ranged from 0.849 to 0.898, all above the 0.70 threshold, indicating satisfactory internal consistency.

Convergent validity: All standardized factor loadings were significant at the $p < 0.01$ level and greater than 0.70. Average variance extracted (AVE) values ranged from 0.580 to 0.635, exceeding the 0.50 benchmark.

Discriminant validity: The square root of the AVE for each construct was greater than its correlations with all other constructs, supporting discriminant validity.

Descriptive statistics, correlations, CR, AVE, and Cronbach’s α values are presented in Table 3.

Insert Table 3 here

3.4 Non-response Bias and Common Method Bias Assessment

Non-response bias was assessed by comparing early and late respondents across key firm characteristics. Independent samples t-tests revealed no significant differences ($p > 0.05$), indicating non-response bias was not a concern.

Because all data were collected from a single respondent per firm, common method bias (CMB) was rigorously evaluated. Harman’s single-factor test showed that the first factor accounted for less than 40% of the total variance. CFA comparisons confirmed that the four-factor measurement model fit significantly better than a single-factor model. Together, these tests verified the absence of severe common method bias.

4. Hypotheses Testing Results

Hypothesis testing was performed using hierarchical regression and the bootstrap method (5,000 resamples) via the SPSS PROCESS macro (Model 4). All variables were mean-centered before creating interaction terms to mitigate multicollinearity. Variance inflation factor (VIF) values were below 3, indicating no multicollinearity issues.

4.1 Main and Mediating Effects

Regression results (Table 4) show that AI-powered capabilities were positively and significantly associated with green exploratory ($\beta = 0.624, p < 0.001$) and green exploitative ($\beta = 0.578, p < 0.001$). Both green exploratory ($\beta = 0.375, p < 0.001$) and green exploitative ($\beta = 0.289, p < 0.001$) were positively related to green NPD.

Bootstrap analysis confirmed significant indirect effects:

1. The indirect effect of AI powered on green NPD via green exploratory was 0.234, 95% CI [0.139, 0.354], excluding zero.
2. The indirect effect via green exploitative was 0.167, 95% CI [0.093, 0.258], excluding zero.

These results support the dual mediating roles of green exploratory and green exploitative in the link between AI-powered capabilities and green NPD. The full model explained 54% of the variance in green NPD ($R^2 = 0.540, F = 20.467, p < 0.001$).

5. Discussions

5.1 Theoretical Discussion

This study makes several distinct theoretical contributions to the intersection of artificial intelligence (AI), ambidextrous green innovation, and new product development (NPD) performance in manufacturing firms operating under low-carbon transitions. Below, we elaborate on four key theoretical advancements.

5.1.1 Unpacking the Dual Mediating Mechanisms in AI-to-green NPD Link

The first major contribution is the identification and empirical validation of *dual mediating pathways*—green exploratory and green exploitative—through which AI-powered capabilities influence green NPD. Prior research on digital transformation and innovation has often treated AI as a direct antecedent of performance outcomes or has focused on a single behavioral mechanism (e.g., knowledge management or process automation) (Zhang and Zhang, 2025, Marion et al., 2025). However, this direct-effects approach obscures the distinct process architectures through which AI generates value in sustainability contexts. By theorizing and testing two parallel mediators, our study responds to recent calls for greater processual granularity in AI-innovation research (Amaya and Holweg, 2024).

Specifically, we demonstrate that AI-powered capabilities enhance green NPD not through a monolithic logic but through two qualitatively different innovation routines: *exploration*—which converts AI-enhanced sensing into breakthrough green products—and *exploitation*—which translates AI-optimized execution into incremental performance gains. This dual-mediation model advances DCT (Teece et al., 1997) by specifying how AI augments each of the three core micro-foundations (sensing, seizing, and transforming) in distinct ways. Sensing is primarily amplified through AI’s pattern-recognition and anomaly-detection functions, enabling exploratory; seizing and transforming are enhanced through AI’s automation and optimization algorithms, supporting exploitative. Thus, our framework provides a more fine-grained account of how AI reconfigures organizational routines for green innovation—a question that prior studies have left largely unanswered.

5.1.2 Asymmetric Mediation: The Primacy of Exploratory Over Exploitative Pathways

A second, and perhaps more provocative, theoretical contribution is the discovery and explanation of asymmetric mediation—that is, the indirect effect of AI on green NPD via green exploratory is significantly stronger than that via green exploitative. While ambidexterity theory traditionally emphasizes the need for balance between exploration and exploitation March (March, 1991), our

findings suggest that in the specific context of AI-enabled green product development, exploration dominates as a transmission mechanism.

We theorize this asymmetry based on three AI-specific characteristics that interact differentially with exploration versus exploitation. First, sensing augmentation—AI’s comparative advantage lies in discovering non-obvious patterns from large-scale, heterogeneous data (Mogaji and Jain, 2024). This capability maps more directly onto exploration (which requires opportunity identification) than onto exploitation (which requires process refinement). Second, uncertainty reduction—generative AI and simulation tools disproportionately lower the experimentation costs and risks inherent in radical green innovation, thereby making previously infeasible exploratory projects viable (Zinoviev et al., 2026). The marginal value of AI is therefore higher for exploration. Third, environmental contingency—in volatile, sustainability-oriented markets, green NPD is more sensitive to first-mover advantages and breakthrough positioning than to incremental efficiency gains (Borah et al., 2021). Because AI-powered exploration enables early entry into emerging low-carbon segments, its mediated effect logically exceeds that of exploitation, which primarily defends existing competitive positions.

This asymmetry finding challenges the “balance assumption” prevalent in ambidexterity research and suggests that firms investing in AI for green innovation should prioritize building exploratory capabilities—especially when facing high technological or regulatory uncertainty. Theoretically, it extends DCT by showing that not all mediated pathways are equally salient; the relative strength of sensing versus seizing/transforming pathways depends on the nature of the capability (AI vs. conventional IT) and the innovation mode (exploration vs. exploitation).

5.1.3 Contextualizing AI Value Creation in Low-Carbon Transitions

Third, this study contributes to the growing literature on sustainable innovation and digitalization by situating AI’s role squarely within the context of low-carbon transitions. Much of existing AI-innovation research has been conducted in general or purely commercial settings, with limited attention to the unique features of green product development—such as regulatory pressure, long payback periods, multi-stakeholder performance criteria, and technological ambiguity about carbon abatement pathways (Zhou et al., 2025, Platania et al., 2025).

Our findings indicate that AI’s value in green NPD is not automatically realized; it depends critically on the firm’s ability to deploy AI outputs through green-specific innovation routines. For example, AI-revealed green market opportunities (e.g., unmet demand for biodegradable packaging or circular economy services) only enhance NPD performance if the firm possesses exploratory routines that are willing to act on such signals. Conversely, AI-driven efficiency gains in green production only translate into superior NPD if exploitative routines can scale and refine those improvements. This contextualization advances the digital sustainability literature by moving beyond techno-centric accounts (AI as a solution in itself) toward a more nuanced *capability-centered* view that emphasizes organizational complements.

5.1.4 Methodological and Empirical Advancements in Mediation Testing

Finally, although primarily conceptual, our study offers a methodological contribution by demonstrating a rigorous approach to testing dual and asymmetric mediation using the PROCESS macro with bootstrapped confidence intervals (Hayes and Rockwood, 2017). Unlike traditional causal-steps approaches (Baron and Kenny, 1986) or structural equation modeling that only reports average indirect effects, our method allows for direct comparison of the magnitude of two parallel indirect effects and assessment of their confidence intervals for non-overlap. The finding that the 95% CI for green exploratory mediation ([0.139, 0.354]) and for green exploitative mediation ([0.093, 0.258]) exhibit only partial overlap provides statistical support for theoretical asymmetry. This approach offers a replicable template for future research comparing multiple mediators in innovation and strategy contexts, where the theoretical interest lies not merely in *whether* mediation occurs but in which pathway dominates.

5.1.5 Summary of Theoretical Contributions

In sum, this study advances theory in four interrelated ways: (1) by unpacking the black box between AI capabilities and green NPD through dual mediation; (2) by identifying and explaining asymmetric mediation where exploratory dominates over exploitative; (3) by contextualizing AI value creation within the distinctive features of low-carbon transitions; and (4) by providing a rigorous methodological template for testing competing mediation pathways. These contributions collectively extend DCT, ambidexterity theory, and the digital sustainability literature, while opening new avenues for research at the AI-innovation-sustainability nexus.

5.2 Practical Discussion

Beyond theoretical contributions, this study offers several actionable implications for managers, technology vendors, and policymakers engaged in AI-driven green new product development.

5.2.1 Managerial Implications: Prioritizing Exploratory Over Exploitative AI Applications

For senior executives and innovation managers, the most immediate implication is that not all AI-enabled green innovation pathways yield equal returns. Our finding that green exploratory mediates AI's effect on green NPD more strongly than green exploitative suggests that firms should strategically allocate AI resources toward search-oriented rather than optimization-oriented applications. Concretely, this means investing in AI tools that enhance market sensing—such as predictive analytics for emerging low-carbon demand, natural language processing of regulatory signals, and generative design algorithms for radical green concepts—rather than focusing exclusively on AI for production line automation or quality control (Luo and Wang, 2025, Doran et al., 2024).

However, this emphasis on exploration should not be interpreted as a wholesale neglect of exploitation. Our results show that both pathways are statistically significant and practically meaningful; the key insight is one of relative prioritization. A balanced but exploration-skewed ambidexterity—for example, allocating 60–70% of AI innovation budgets to exploratory initiatives and 30–40% to exploitative improvements—may yield superior green NPD outcomes compared to a 50–50 split or a purely exploitation-focused strategy. Managers should also recognize that exploratory AI initiatives often have longer payback periods and higher upfront uncertainty; therefore, performance evaluation systems must tolerate early-stage failures and reward learning from AI-generated green opportunity signals.

5.2.2 Organizational Capability Complements: Building Green Ambidextrous Routines

A second practical insight is that AI alone is insufficient; its value materializes only when firms possess complementary green innovation routines. Our mediation model implies that acquiring advanced AI technologies without simultaneously developing green exploratory or exploitative capabilities will yield disappointing NPD outcomes. Therefore, managers should pursue a co-evolutionary capability building strategy that combines AI infrastructure investments with deliberate organizational changes, including: (1) establishing cross-functional “green AI labs” that integrate data scientists with environmental engineers and product designers; (2) creating incentives and career paths for employees who propose radically new green product concepts based on AI-derived insights; and (3) implementing stage-gate processes that explicitly incorporate AI-generated opportunity assessments into green NPD portfolio decisions.

Moreover, our asymmetry finding suggests that building exploratory green routines may be more urgent than refining exploitative ones in the AI era. This requires cultural shifts toward greater risk tolerance, longer evaluation horizons, and systematic learning from AI-identified but ultimately unsuccessful green experiments (Srikanth and Ungureanu, 2025). Firms that maintain rigid, efficiency-focused innovation cultures risk underutilizing AI’s most distinctive capability—the discovery of non-obvious, high-potential opportunities.

5.2.3 Implications for AI Vendors and Technology Providers

For AI technology vendors serving the manufacturing sector, our results highlight the importance of task-specific AI solution design. Generic AI platforms that claim to enhance “innovation” broadly are less valuable than solutions tailored to either green exploration or exploitation. Vendors should consider developing two differentiated product families: (1) exploration-oriented AI tools featuring generative design, scenario simulation, and weak signal detection functionalities, marketed to R&D and strategy departments; and (2) exploitation-oriented AI tools emphasizing process optimization, predictive maintenance, and quality control, targeted at operations and production managers. Furthermore, vendors could offer integrated dashboards that help firms visualize their current AI-innovation portfolio

balance and provide recommendations for rebalancing toward exploration given our empirical benchmarks.

5.2.4 Policy and Ecosystem Implications

Finally, for policymakers and industry associations promoting green industrial transformation, our findings suggest that subsidies and technical assistance should be calibrated to support AI-enabled green exploration, which currently may be undersupplied due to its longer time horizons and higher risk profiles. Traditional innovation policies often favor incremental, low-risk exploitation (e.g., tax credits for energy efficiency improvements). While these remain valuable, our evidence indicates that AI-powered exploratory green innovation yields greater performance gains per unit of AI investment. Therefore, policymakers could introduce targeted instruments such as: (1) matching grants for AI-based green market sensing and radical concept development; (2) regulatory sandboxes allowing firms to experiment with AI-generated novel green products under waived compliance requirements for limited periods; and (3) industry-level data cooperatives that pool anonymized low-carbon consumer data to improve AI training for small and medium-sized enterprises lacking sufficient data scale. Additionally, ecosystem-level initiatives—such as AI-powered green innovation platforms connecting manufacturing firms with sustainability research institutes—could lower the fixed costs of exploratory AI adoption.

6. Limitations and Future Research

Despite the theoretical and practical contributions outlined above, this study has several limitations that point to productive avenues for future research.

6.1 Methodological Limitations

Cross-sectional design and causal inference. Our data are cross-sectional, which limits our ability to draw strong causal conclusions about the direction of effects. Although our theoretical model posits AI-powered capabilities as antecedents of green innovation and NPD performance, reciprocal causality is plausible: firms with superior green NPD performance may invest more in AI capabilities, or successful green exploration may generate data that further train AI systems. Future research should employ longitudinal designs, instrumental variable approaches, or natural experiments (e.g., exogenous AI technology shocks or policy interventions) to strengthen causal identification.

Single-respondent and common method bias concerns. Although we conducted Harman's single-factor test and CFA comparisons to rule out severe common method bias, all measures were collected from a single informant per firm. This raises the possibility that unmeasured respondent characteristics (e.g., optimism about digital transformation) could inflate correlations. Future studies should adopt multi-respondent designs (e.g., separating AI capability assessments from NPD performance evaluations) or triangulate survey data with archival performance metrics or AI investment records.

Generalizability beyond Chinese manufacturing. Our sample focuses exclusively on Chinese manufacturing firms in five high-priority sectors. While China represents a critical context for low-carbon innovation and AI adoption, cultural, institutional, and regulatory factors may moderate our observed effects. For instance, state-owned enterprises with strong policy mandates for green innovation might exhibit stronger exploratory mediation, while market-driven economies might show different patterns. Cross-country replication studies—particularly in Europe (with stringent environmental regulations) and emerging economies (with different technology infrastructures)—are essential to establish boundary conditions.

6.2 Conceptual and Measurement Limitations

Operationalization of AI-powered capabilities. Our measure captures general AI applications for green operations and decision-making but does not distinguish between different AI architectures (e.g., machine learning vs. rule-based systems vs. generative AI) or levels of AI maturity (e.g., pilot vs. scaled deployment). Given the rapid evolution of generative AI and foundation models (Zhang & Zhang, 2025), future research should develop more fine-grained taxonomies of AI capabilities and examine whether different AI types differentially affect exploration versus exploitation. For example, generative AI for concept creation may be particularly conducive to exploration, whereas reinforcement learning for production scheduling may primarily serve exploitation.

Dimensions of green NPD performance. We measured green NPD performance as a composite of goal attainment, budget adherence, schedule compliance, quality standards, and stakeholder satisfaction. However, green products often have multi-dimensional performance criteria—including life-cycle carbon reduction, circularity metrics, and regulatory compliance—that may not all load onto a single factor. Future studies could decompose green NPD into sub-dimensions (e.g., environmental impact, cost efficiency, market acceptance) and examine whether AI-mediated pathways differentially predict each sub-dimension.

Absence of contingency moderators in the current model. While our central focus was on dual mediation, the theoretical framework in Fig. 1 also proposes technology uncertainty as a moderator (H3a, H3b, H4a, H4b). The current manuscript reports main and mediating effects, leaving the full moderated-mediation model for subsequent analysis. Future research should test whether technology uncertainty weakens or strengthens the AI-exploration/exploitation relationships and whether the asymmetry of mediation changes under high versus low uncertainty.

6.3 Avenues for Future Research

Dynamic and reciprocal effects. Beyond cross-sectional mediation, future research could model feedback loops between AI capabilities and green innovation. For instance, does successful green exploration generate data that enhances AI prediction accuracy, creating a virtuous cycle? Alternatively, does over-emphasis on AI-driven exploitation lead to competency traps that reduce future exploration? Longitudinal panel data with three or more waves would allow researchers to estimate cross-lagged panel models or dynamic panel regressions to disentangle such reciprocal dynamics.

Behavioral micro-foundations. Our study operates at the firm level, but AI-enabled green innovation ultimately involves individual managers' decisions, attention allocation, and risk perceptions. Future research could employ experimental or quasi-experimental designs to examine how AI-generated green opportunity recommendations affect managers' willingness to fund exploratory versus exploitative projects, and whether AI explanations (e.g., feature attribution or confidence scores) moderate these effects.

Integration with other digital technologies. AI often co-evolves with other Industry 4.0 technologies—such as Internet of Things (IoT), digital twins, and blockchain—which may have complementary or substitutive effects on green NPD. For example, IoT provides real-time environmental data that feed AI models; blockchain ensures traceability of green claims verified by AI. Future research should examine technology configurations rather than isolated AI effects, using methods such as fuzzy-set qualitative comparative analysis (fsQCA) or machine learning-based interaction detection.

Unintended consequences and ethical considerations. Finally, the darker side of AI in green NPD deserves attention. AI applications may inadvertently lock firms into certain technological trajectories, create new forms of environmental burden (e.g., energy consumption of large AI models), or generate greenwashing risks where AI-optimized reporting masks poor environmental performance. Future research should adopt a critical perspective, investigating when and why AI-powered green exploration and exploitation produce negative outcomes for sustainability or stakeholders.

7. Conclusions

This study set out to investigate the mechanisms through which AI-powered capabilities influence green NPD in manufacturing firms navigating low-carbon transitions. Moving beyond direct-effects models, we theorized and empirically tested a dual mediation framework grounded in DCT, distinguishing green exploratory (search for novel green technologies and markets) from green exploitative (refinement and scaling of existing green solutions).

Analyzing survey data from 333 Chinese manufacturing firms across five high-priority sectors, we found robust support for both mediating pathways: AI-powered capabilities enhanced green NPD through green exploratory (indirect effect = 0.234, 95% CI [0.139, 0.354]) and through green exploitative (indirect effect = 0.167, 95% CI [0.093, 0.258]). Critically, we identified and explained an asymmetric mediation effect: the exploratory pathway was significantly stronger than the exploitative pathway, a finding theoretically grounded in AI's comparative advantage in sensing augmentation, its disproportionate reduction of exploration uncertainty, and the first-mover advantages inherent in volatile green markets.

These results advance theory in four ways: (1) unpacking the black box between AI and green NPD by specifying distinct process architectures; (2) challenging the "balance assumption" of ambidexterity theory by demonstrating the primacy of exploration; (3) contextualizing AI's value creation within the unique features of low-carbon transitions; and (4) providing a rigorous methodological template for dual and asymmetric mediation testing. Practically, the findings guide managers toward exploration-skewed

AI investments, inform AI vendors' product differentiation strategies, and suggest policy recalibrations to support higher-risk exploratory green innovation.

Nevertheless, these conclusions must be tempered by the study's limitations—cross-sectional design, single-respondent data, sectoral and geographic scope—which collectively call for longitudinal, multi-method, and cross-cultural replication. Future research should also explore dynamic feedback loops, behavioral micro-foundations, technology configurations, and unintended consequences to develop a more complete understanding of AI's evolving role in sustainable innovation.

In an era where both digital transformation and climate imperatives demand urgent action, understanding how firms can harness AI to accelerate green product development is not merely an academic exercise—it is a practical necessity. This study offers an initial roadmap, but much remains to be discovered at the intersection of artificial intelligence, ambidextrous innovation, and environmental sustainability.

Declarations

No competing interests; No funding; No AI tools used.

Data availability

The datasets used in this study can be obtained from the corresponding author on reasonable request.

The authors declare no competing interests.

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Tables

Tables 1 to 4 are available in the supplementary files section

Figures

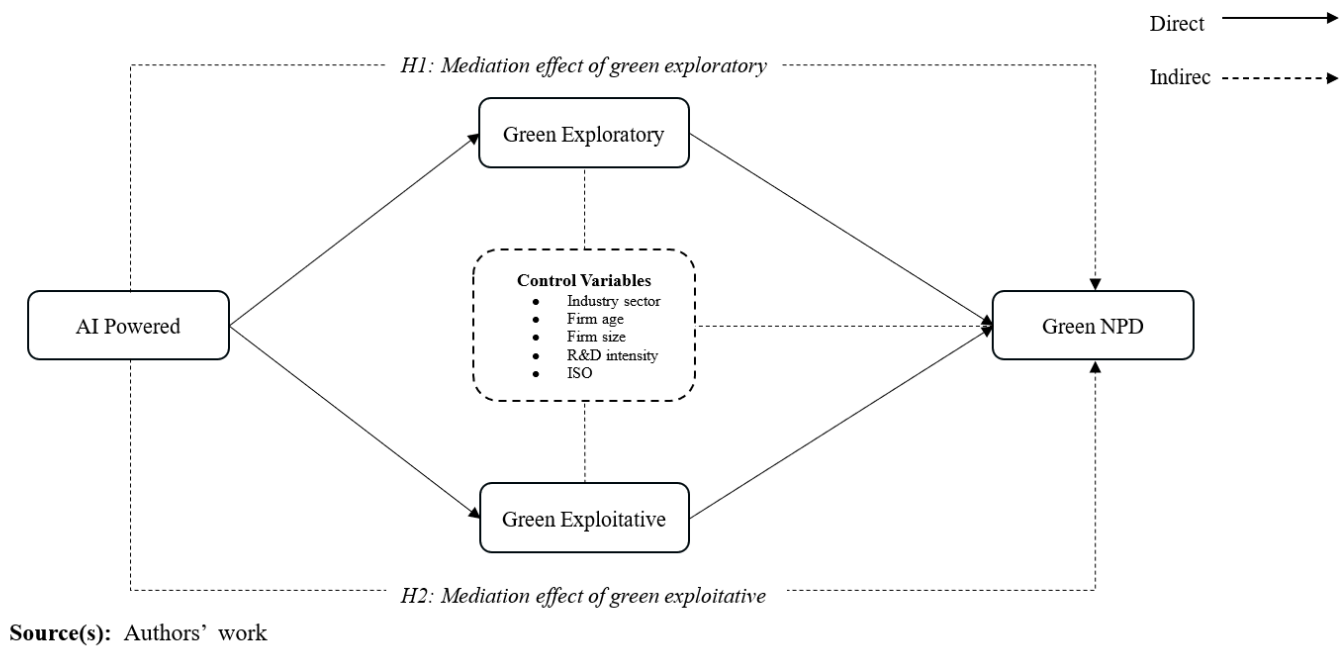


Figure 1

Research framework

Supplementary Files

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