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How Generative AI Applications Drive Green Innovation in Agricultural Enterprises: The Mediating Role of Green Dynamic Capabilities and the Moderating Role of TMT Behavioral Integration

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Abstract

Drawing on dynamic capability theory and upper echelons theory, this study develops a moderated mediation framework that treats green dynamic capabilities as a mediator and top management team (TMT) behavioral integration as a moderator. Empirical tests based on sample data reveal that the application of generative artificial intelligence is positively associated with corporate green innovation. This relationship is partially mediated by green dynamic capabilities. Moreover, TMT behavioral integration not only positively moderates the direct effect of generative AI on green innovation but also strengthens both stages of the indirect path, thereby reinforcing the overall mediated mechanism. The study uncovers a "capability transformation" process and "governance boundary" conditions through which generative AI may facilitate green innovation in agricultural enterprises, extends theoretical research at the nexus of digital technology and green innovation, and offers practical guidance for agri-businesses seeking coordinated digital and green development.

Keywords: generative AI applications; green innovation; agricultural enterprises; green dynamic capabilities; TMT behavioral integration

1. Introduction

Against the dual backdrop of deepening digital transformation and the growing emphasis on sustainable development [1], how to leverage emerging digital technologies to promote green innovation in enterprises has become a key issue of common concern in the fields of management, environmental governance, and agricultural economics [2]. Particularly in the current context of "dual carbon" goals, tightening resource and environmental constraints, and the accelerated advancement of agricultural modernization, agricultural enterprises must not only meet the demands for improved efficiency and market competitiveness but also shoulder the practical pressures of pursuing green, low-carbon development and fulfilling ecological responsibilities [3]. For agricultural technology enterprises, relying solely on traditional inputs of production factors is no longer sufficient to sustain long-term competitive advantages. Promoting green innovation, reshaping resource allocation methods, and optimizing organizational capabilities are gradually becoming key pathways to achieving high-quality development [4]. As a strategic choice that balances environmental and economic performance, green innovation not only helps agricultural enterprises respond to ecological

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regulations but also significantly enhances their responsiveness to changes in green market demand and their sustainable competitive capabilities [5].

With the rapid evolution of artificial intelligence technology, particularly the rise of Generative Artificial Intelligence Applications (GAIA), the logic behind corporate digital applications is shifting from "information processing" toward "knowledge generation" and "solution creation" [6]. Existing research has focused more on the impact of digital transformation, big data, cloud computing, the Internet of Things, platform technologies, or general artificial intelligence on corporate green innovation, while paying insufficient attention to generative artificial intelligence, a technology that has recently spread rapidly [7–9]. Previous research on the relationship between AI and green innovation has primarily focused on the idea that AI indirectly supports innovation by improving data processing efficiency and decision-making accuracy—an approach that essentially falls within the information processing paradigm. The key distinction with generative AI lies in its cognitive-empowering characteristics, which means that generative AI is integrated into the earlier stages of corporate innovation activities [10]. Therefore, continuing to use the broad concept of "digital technology" to encompass different technological forms may obscure the unique mechanisms through which generative AI impacts green innovation [11]. The rapid iteration of AI technologies has opened new pathways for green innovation in agriculture [12]. In other words, generative AI is not merely a tool for improving efficiency, but a new type of cognitive digital technology capable of being deeply embedded in corporate knowledge creation and strategic decision-making processes [13]. In the context of green innovation in agriculture, generative AI's ability to generate knowledge and simulate scenarios can provide direct support for these unstructured decisions, rather than serving merely as a tool for background information processing [14]. Therefore, this study seeks to uncover the unique theoretical mechanisms that distinguish generative AI from traditional digital tools, treating it as a new type of cognitive digital resource capable of triggering the development and renewal of organizational capabilities. At the forefront of the integration of green development and digital technology, the study explores how this new form of digital technology drives green innovation through specific organizational capability mechanisms.

Although existing research has to some extent confirmed that digital technologies can promote corporate green innovation, mechanistic explanations regarding "why and how" this influence occurs remain insufficient, particularly lacking in-depth discussions from the perspectives of capability building and capability transformation. Green innovation in agricultural enterprises is not a direct result of technological investment but rather depends on the enterprise's foundational capacity to continuously identify green opportunities, reorganize green resources, and drive organizational renewal [15]. Therefore, green dynamic capabilities may serve as a crucial mediating mechanism for understanding how generative AI applications influence green innovation. Third, the realization of technological value is not a spontaneous process; it is typically influenced by organizational governance structures and the behavioral characteristics of top-level managers [16]. As the core agents of resource allocation and strategic decision-making within an enterprise, the degree of behavioral integration among executive teams directly influences whether technological resources can be effectively absorbed, transformed, and utilized [17]. However, existing research lacks systematic theoretical analysis and empirical studies on the moderating role of top management team (TMT) behavioral integration in the relationship between generative AI applications and green innovation. Considering this, this paper focuses on three core questions: Can the adoption of generative AI significantly promote green innovation in agricultural enterprises? Is this effect mediated by green dynamic capabilities? And what

role does the alignment of top management team behavior play as a boundary condition in these relationships?

From a theoretical perspective, the theory of dynamic capabilities provides a suitable analytical framework for understanding the relationship between generative AI applications and green innovation [18]. As a new type of digital resource, generative AI can enhance enterprises' ability to perceive changes in the external environment, improve their efficiency in identifying green opportunities, analyzing environmental demands, and adjusting resource allocation strategies [19]. However, technology itself does not automatically translate into innovative outcomes; its effectiveness still depends on the process by which enterprises integrate external knowledge with internal resources to develop sustainable innovation capabilities [20]. Green dynamic capability emphasizes the characteristics of a firm's ability to identify opportunities, integrate resources, and restructure its organization within the context of green development; it provides a sound explanation for how the application of generative AI can be further transformed into green innovation outcomes [21]. Meanwhile, the upper echelons theory suggests that cognitive interactions, information sharing, joint decision-making, and coordinated actions among the top management team significantly influence the efficiency of strategic resource allocation and the quality of strategic execution [22]. The higher the degree of behavioral integration within the top management team, the more likely the enterprise is to effectively embed the knowledge advantages, analytical capabilities, and green dynamic capabilities brought by generative AI into innovation decisions and organizational actions, thereby enhancing the feasibility of green innovation. Based on this, integrating dynamic capabilities theory with the upper echelon's theory can help provide a more systematic explanation of the underlying logic by which generative AI applications drive green innovation in agricultural enterprises, from the perspectives of both "mechanisms of action" and "boundary conditions."

Based on the above analysis, this study focuses on agricultural technology companies as the primary research context and senior and middle managers in agricultural enterprises as the survey subjects. It examines how the application of generative artificial intelligence influences green innovation in agricultural enterprises through green dynamic capabilities and further tests the moderating role of executive team behavioral integration in this process. Centered on this research framework, this study constructs a mediational model comprising "Generative AI Applications–Green Dynamic Capabilities–Green Innovation" and introduces executive team behavioral integration as a moderating variable. Through empirical testing, the study aims to theoretically elucidate the mechanism pathways and boundary conditions through which generative AI applications drive green innovation in agricultural enterprises and to provide practical decision-making references for managers and policymakers in agricultural technology enterprises.

2. Theoretical Analysis and Research Hypotheses

2.1. Generative Artificial Intelligence Applications and Green Innovation in Agricultural Enterprises

Green innovation typically encompasses a range of corporate activities concerning products, processes, management practices, and environmental governance approaches, all aimed at reducing resource consumption and ecological footprints while simultaneously improving both financial and environmental performance [23,24]. For agricultural enterprises, such innovation is not only essential for coping with tightening ecological constraints but also serves as a source of sustained competitive advantage amid rising consumer demand for green products and increasingly strict policy oversight [25]. Prior studies have confirmed that green products and green process innovation are significantly linked to competitive advantage, indicating that green innovation represents not merely a reflection of environmental responsibility but also a strategic choice with tangible economic returns [26].

At the intersection of digitalization and sustainable development, scholars have devoted relatively limited attention to generative AI as a distinct technological category. Although existing research suggests that AI applications more broadly can improve the quantity and quality of corporate green innovation—through mechanisms such as strengthening data-driven decision-making, facilitating human–machine collaboration, and mitigating information asymmetry [27]—generative AI possesses a unique set of features centered on knowledge creation, content reconfiguration, creative assistance, and scenario simulation [28]. Recent innovation management literature further underscores that the true value of generative AI lies in its integration into the front-end stages of ideation, knowledge restructuring, and exploratory innovation, extending far beyond mere efficiency enhancement [29].

For agri-tech firms, generative AI applications can support green innovation on multiple levels. Green innovation in the agricultural sector often faces simultaneous challenges such as environmental constraints, resource scarcity, uncertain demand, and complex technological pathways; consequently, relying solely on experiential judgment or traditional information systems is often insufficient to support high-quality decision-making [30]. Generative AI applications can help companies identify directions for green technology improvements, detect shifts in green market demand, and predict trends in environmental governance by integrating heterogeneous information and generating alternative solutions [31]. In areas such as R&D, production, supply chain coordination, and customer response, generative AI can assist with problem diagnosis and support rapid trial-and-error processes. This helps enterprises identify green market opportunities more quickly, allocate R&D and operational resources more accurately, and improve the efficiency of developing green innovation solutions [32]. Particularly when agricultural enterprises face multiple pressures—including resource constraints, environmental regulations, and shifting market demands—the cognitive support and knowledge-generation capabilities provided by generative AI can help them drive green innovation more effectively [33].

Previous research also documents a positive correlation between digital innovation and sustainable agricultural development; however, such positive effects are by no means automatic—they depend on firms' ability to translate technological potential into concrete innovative actions [34]. Technological resources alone do not guarantee innovation outcomes; their value realization hinges on whether enterprises can embed technology applications into organizational routines and transform them into new capabilities and actionable initiatives. As an emerging form of digital technology practice, generative AI not only reduces the costs of information search and trial-and-error during innovation but also improves the efficiency and quality of green innovation activities by supporting knowledge recombination and ideation [35].

The application of generative AI in green innovation in agriculture also faces some potential challenges. Generative AI may produce "hallucinated" outputs or unreliable information; data security and privacy concerns may deter businesses from adopting it; and overreliance on AI may hinder an organization's ability to innovate independently [36–38]. In theory, these factors could partially offset the positive impact of generative AI on green innovation. However, in the context of agricultural green innovation, the core challenges faced by enterprises are more closely tied to the complexity of ecological knowledge, the diversity of technological pathways, and the uncertainty of market demand—areas where generative AI can provide unique support through its capabilities in knowledge integration and scenario simulation [39]. As generative AI technology continues to mature and companies gain more experience in its application, these risks are expected to be effectively mitigated through organizational governance and technical management measures. All things considered, this paper still anticipates that the positive effects of generative AI applications on green innovation in agricultural enterprises will predominate.

In summary, agricultural enterprises with higher levels of generative AI adoption also exhibit higher levels of green innovation. Based on this, we propose the following hypothesis:

H1. *Generative AI applications have a significant positive impact on green innovation in agricultural enterprises.*

2.2. The Mediating Role of Green Dynamic Capabilities

Dynamic capabilities theory locates the source of enduring competitive advantage not in the ownership of resources per se, but in a firm's capacity to detect emerging opportunities, amalgamate resources, and restructure the organization when environments shift rapidly [40]. Teece and his colleagues similarly underscored that advantage flows from the ability to coordinate, combine, and reconfigure resources—not from a static resource base [41]. Extending this logic into the green development domain, green dynamic capabilities refer to a firm's capacity to identify green opportunities, allocate and integrate green resources, and renew organizational processes and capability bases in pursuit of green transformation objectives [42]. Contemporary scholarship frames these capabilities as the essential link bridging green-oriented resources with green innovation outcomes: they enable a firm to draw on existing knowledge and assets to continuously upgrade its green organizational abilities amid evolving market conditions [43]. For agri-tech firms, this capability set holds particular significance.

Generative AI applications provide a novel technological foundation for cultivating green dynamic capabilities [44]. Specifically, they can strengthen an enterprise's aptitude for discerning green opportunities within the external environment [45]. With strengths in semantic comprehension, pattern extraction, and solution generation, generative AI helps firms more rapidly capture green signals emanating from policy changes, market preferences, and technological advancements [46]. Moreover, generative AI applications enhance the efficiency of knowledge integration and resource allocation. Their ability to synthesize heterogeneous information and assist in solution development makes it easier for enterprises to improve cross-departmental collaboration and the effectiveness of green resource redeployment [47]. By supporting process optimization and decision-making reconfiguration, generative AI drives enterprises to build a more adaptive green capability system at the organizational level [48].

Thus, the primary function of generative AI is not to directly "produce innovation," but rather to spur the cultivation of green dynamic capabilities. Based on this, we propose that:

H2a. *Generative AI application has a positive impact on the green dynamic capabilities of agricultural enterprises.*

At the same time, green dynamic capabilities themselves act as a key driver of green innovation [49]. Empirical findings indicate that these capabilities significantly enhance green product development performance and facilitate both the adoption and diffusion of green innovations [50]. Green innovation is more accurately viewed as the natural outgrowth of a firm's persistent ability to identify green opportunities, mobilize key resources, and convert green strategies into organizational actions, rather than the direct result of a one-time technological investment [51]. Firms endowed with strong green dynamic capabilities can spot green technology opportunities more swiftly, integrate innovation resources more effectively, and achieve smoother technology transfer and market application [52]. For agricultural enterprises, this means not only responding promptly to green consumption trends and precisely developing environmentally friendly agricultural inputs but also promoting green production technologies more efficiently. Therefore, the stronger the green dynamic capability, the more adept the enterprise becomes at translating external

environmental pressures and internal resource foundations into green products, processes, and management practices [53]. Accordingly, we hypothesize that:

H2b. *Green dynamic capabilities have a positive impact on green innovation in agricultural enterprises.*

Summarizing the above chain of reasoning, the relationship between generative AI applications and green innovation is not a simple linear one. Generative AI exerts its influence through the processes of corporate capability formation and capability transformation [54,55]. Green dynamic capabilities constitute the critical linchpin in this causal chain. Generative AI first promotes the formation of green dynamic capabilities by sharpening enterprises' abilities to identify green opportunities, reorganize knowledge, and integrate resources; in turn, green dynamic capabilities enable enterprises to more effectively translate technological support and green orientation into green innovation practices [56]. Hence, green dynamic capabilities serve as the key transmission mechanism through which generative AI moves from "technological input" to "innovation output." In addition, green dynamic capabilities comprise three sub-dimensions—green environmental adaptability, green resource integration, and organizational learning and absorption—which may play different roles in the "generative AI–green dynamic capabilities–green innovation" pathway. Green environmental adaptability focuses on the perception and anticipation of external green opportunities, which aligns closely with generative AI's strengths in scanning environmental signals and semantic understanding; therefore, it may play a more critical role in the first phase of transforming generative AI into a dynamic green capability. The ability to integrate green resources focuses on the coordination and reorganization of cross-departmental resources. This function is particularly critical when translating organizational capabilities into concrete innovative outcomes; therefore, its role is likely to be most evident in the second stage of the transformation from green dynamic capabilities to green innovation. An organization's capacity for learning and knowledge absorption permeates the entire process of knowledge acquisition, processing, and recreation and may serve as a foundational support for both stages. We thus propose that:

H2c. *Green dynamic capabilities mediate the relationship between generative AI applications and green innovation in agricultural enterprises.*

2.3. The Moderating Role of TMT Behavioral Integration

Behavioral integration of the top management team captures the extent to which TMT members engage in information exchange, collaborative behavior, and joint decision-making throughout strategic formulation and execution [57]. Upper echelons theory argues that TMTs shape not only strategic choices but also the way the firm comprehends, allocates, and deploys critical resources [58]. When confronted with complex technological shifts and green transition imperatives, whether the TMT can attain a high level of collaboration and integration directly determines the firm's capacity to convert novel technology applications and organizational capabilities into innovation outputs [59]. For agri-tech firms, technological complexity and environmental uncertainty render collaborative decision-making within the TMT especially vital [60]. TMT behavioral integration is therefore viewed as a pivotal contextual factor conditioning the value realization of generative AI applications.

Although generative AI applications can equip enterprises with knowledge support, information synthesis, and solution-generation capacities, these technological advantages may struggle to translate into coherent green innovation initiatives if TMT members lack sufficient information sharing and collaborative decision-making [61]. Conversely, under conditions of high TMT behavioral integration, team members more readily reach consensus on green strategic directions and, through joint decision-making and coordinated action,

accelerate the embedding of generative AI into innovation processes, thereby magnifying its contribution to green innovation [62]. Thus, we propose that:

H3. *TMT behavioral integration positively moderates the relationship between generative AI applications and green innovation in agricultural enterprises.*

The introduction of generative AI typically entails the redesign of organizational processes, demanding that the TMT achieve consensus, coordinate resources, and drive change [63]. At its heart, cultivating green dynamic capabilities is a complex endeavor involving opportunity sensing, resource integration, and organizational restructuring, which depends on the TMT's shared interpretation of external information and coordinated allocation of internal resources [64]. When TMT behavioral integration is high, team members exchange information more thoroughly and engage in joint decision-making more efficiently, thereby more effectively leveraging the analytical support and knowledge outputs provided by generative AI to foster the firm's green dynamic capabilities [65]. In contrast, if TMT behavioral integration is weak, the team may undermine the potency of technological empowerment due to information silos, poor communication, and sluggish decision-making. Even if the enterprise has adopted generative AI, its role in advancing green dynamic capabilities will be weakened by inadequate internal coordination. Hence, we hypothesize that:

H4a. *TMT behavioral integration positively moderates the relationship between generative AI applications and green dynamic capabilities.*

Even when a firm already possesses strong green dynamic capabilities, whether these capabilities genuinely generate green innovation outcomes still hinges on the TMT's ability to effectively embed them into strategic actions and organizational practices. When TMT members exhibit high levels of information sharing, behavioral coordination, and joint decision-making, this helps diminish disagreements among top managers, strengthen execution consistency, and foster a sustained chain of innovation actions linked to green capabilities within the organization [66]. Consequently, this facilitates the streamlined allocation of green resources, the accelerated implementation of green strategies, and the seamless execution of green innovation initiatives, thereby reinforcing the contribution of green dynamic capabilities to green innovation [67]. We therefore propose that:

H4b. *TMT behavioral integration positively moderates the relationship between green dynamic capabilities and green innovation.*

Based on the derivations of the three moderation pathways described above, while TMT behavioral integration moderates all three pathways simultaneously, the logic underlying each pathway has its own distinct focus. First, in the direct pathway, the core function of TMT behavioral integration lies in "strategic consensus": through comprehensive information sharing and joint decision-making, the executive team reaches agreement on how to apply generative AI to green innovation, thereby accelerating the formation and execution of innovation decisions. Second, in the first stage mediating pathway, the core function of TMT behavioral integration lies in "cognitive transformation." Through in-depth communication and shared interpretation, team members transform the knowledge outputs of generative AI into green dynamic capabilities at the organizational level. This process relies heavily on the team's collective understanding of the technology's value and their ability to coordinate resources. Finally, in the second stage mediating pathway, the core function of TMT behavioral integration lies in "execution consistency"; through collaborative action

and mutual support, the team ensures that the established green dynamic capabilities are effectively embedded in innovation practices. Thus, the moderating mechanisms of the three pathways correspond to three distinct organizational processes: strategic consensus, cognitive transformation, and execution consistency. This distinction helps provide a more precise understanding of the multifaceted role of TMT behavioral integration in generative AI-driven green innovation.

2.4. Moderated Mediation

The preceding discussion suggests that green dynamic capabilities function as a central channel through which generative AI applications ultimately shape green innovation. At the same time, TMT behavioral integration separately reinforces two sequential stages: the conversion of generative AI into green dynamic capabilities, and the subsequent translation of those capabilities into innovation outputs—that is, the processes of "capability building" and "capability deployment," respectively. Consequently, the magnitude of the indirect effect running from generative AI through green dynamic capabilities to green innovation should shift in accordance with the degree of TMT behavioral integration.

This moderated mediation framework helps illuminate the intricate mechanisms by which generative AI empowers green innovation in agriculture. Specifically, when TMT behavioral integration is high, firms are better positioned to fully exploit the knowledge-support and resource-coordination functions of generative AI and subsequently translate the resulting green dynamic capabilities into green innovation outcomes more effectively, yielding stronger indirect effects [68]. In agri-tech firms—where cross-departmental collaboration and strategic execution are particularly demanding—this amplification effect may be even more salient. Conversely, when TMT behavioral integration is insufficient, disconnects are likely to emerge between technology application, capability formation, and innovation implementation, thereby attenuating the degree to which generative AI promotes green innovation through green dynamic capabilities [69]. Therefore, TMT behavioral integration functions not merely as a moderator of a single pathway but further influences the strength of the entire mediation mechanism. Accordingly, we propose that:

H5. *TMT behavioral integration moderates the mediating effect of green dynamic capabilities in the relationship between generative AI applications and green innovation in agricultural enterprises.*

2.5. Theoretical Model

Synthesizing the arguments developed above, Figure 1 depicts the conceptual framework guiding this investigation. The model comprises four focal constructs: generative AI applications as the independent variable (X), green dynamic capabilities as the mediator (M), green innovation as the dependent variable (Y), and TMT behavioral integration as the moderator (W). The framework specifies several hypothesized relationships. First, a direct link connects generative AI applications to green innovation (H1). Second, an indirect pathway runs from generative AI through green dynamic capabilities to green innovation (H2a–H2c). Third, TMT behavioral integration is posited to moderate the direct association between generative AI and green innovation (H3), and additionally to moderate both the first-stage and second-stage links of the mediation chain (H4a, H4b), as well as the overall indirect mechanism (H5). Together, these hypothesized pathways provide a systematic account of the mechanisms and boundary conditions through which generative AI applications drive green innovation in agricultural enterprises.

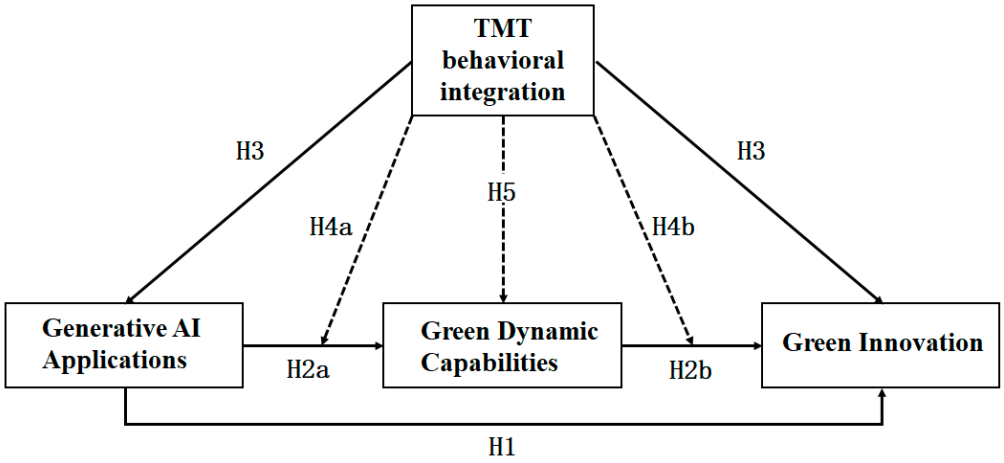


Figure 1. Theoretical Model Diagram.

3. Research Methods

3.1. Research Approach and Methods

This study investigates the processes by which generative AI applications shape green innovation in agricultural enterprises, while also assessing the mediating function of green dynamic capabilities and the moderating influence of TMT behavioral integration. Because the focal constructs capture internal organizational perceptions, capability-building activities, and team-level behavioral dynamics—none of which are readily accessible through publicly available archival data—a survey-based questionnaire was adopted as the primary data collection instrument. The hypothesized relationships were then tested using a combination of multivariate regression, Bootstrap-based mediation analysis, and procedures for examining moderation and moderated mediation.

In terms of research design, this study focuses on agricultural technology enterprises and constructs a measurement model centered on four core variables: generative AI applications, green dynamic capabilities, green innovation, and executive team behavioral integration. The questionnaire items were primarily adapted from established domestic and international scales and revised to align with the agricultural enterprise context, thereby enhancing the content validity of the scales and their suitability for the research setting.

3.2. Research Sample and Data Collection

The sampling frame for this study centered on agricultural technology enterprises located in four provinces: Jiangsu, Zhejiang, Shandong, and Guangdong. The primary reasons for selecting these four provinces are as follows: These four provinces have a high level of agricultural industrialization and digital economic development, with a relatively dense concentration of agricultural technology companies, which facilitates the collection of a sufficient sample size within a reasonable cost range; there are certain differences among the four provinces in terms of agricultural industrial structure, policy environment, and digital infrastructure development, providing the necessary sample variability for the study; and agricultural enterprises in these four provinces are relatively active in digital transformation and green innovation practices, making them suitable for examining the mechanisms through which generative AI applications influence green innovation. Respondents were predominantly recruited from senior and middle-level management, including department heads overseeing digitalization initiatives and managers familiar with their firms' green innovation activities. Questionnaire items were adapted from well-established scales documented in prior literature.

Data collection spanned roughly three months, from December 2025 through mid-February 2026. Survey instruments were administered through a combination of online

and offline channels. For the online component, the research team leveraged WeChat and QQ groups maintained by provincial agricultural enterprise associations and distributed the questionnaire link via email to target firms' official addresses. Additionally, the team contacted mid- to senior-level managers at these companies individually through WeCom to dispatch questionnaires on a one-on-one basis. For the offline component, team members conducted on-site visits to multiple agri-tech firms across the four provinces between December 2025 and February 2026, where paper questionnaires were distributed and collected immediately upon completion. To ensure data quality, the following procedural measures were implemented for this survey. Regarding respondent selection, in principle, only one mid- to senior-level manager from each company was invited to complete the questionnaire to avoid interference among multiple respondents within the same organization; respondents were primarily department heads or higher-level managers responsible for digital transformation, R&D, or green innovation. Regarding survey administration, the questionnaire was completed anonymously. The introductory notes explicitly informed respondents that "this survey is intended solely for academic research and does not involve the identification of personal or corporate information," thereby reducing social desirability bias. For quality control, reverse-scored items were included in the questionnaire to identify careless responses, and invalid questionnaires, completed in an unreasonably short time (less than 3 min) or exhibiting obvious patterns of consistent answers, were excluded.

A total of 643 questionnaires were dispatched, with 459 returned. After screening and removing invalid responses, including those with excessive missing data or patterned answering, the final analytic sample comprised 335 valid questionnaires, yielding an effective response rate of 52.1%. Table 1 presents the demographic and organizational characteristics of the participating enterprises.

Table 1. Descriptive statistical analysis of the enterprises surveyed.

Variable	Feature	No.	%
Enterprise Nature	State-owned enterprise	110	32.84
	Private Enterprise	183	54.63
	Foreign Investment/Other	42	12.54
Years in Business	1–5 years	26	7.76
	6–10 years	106	31.64
	11–20 years	144	42.99
	Over 20 years	59	17.61
Enterprise Scale	1–10 people	39	11.64
	11–50 people	92	27.46
	51–100 people	138	41.19
	100+ people	66	19.7
Field of Application	Agricultural technology research and development companies	75	22.39
	Agricultural production and technology application companies	86	25.67
	Agricultural product processing companies	91	27.16
	Leading agricultural industrialization companies	64	19.1
	Other companies	19	5.67

3.3. Variable Measurement

The principal variables addressed in this study include the independent variable (generative AI applications), the dependent variable (green innovation), the mediating variable (green dynamic capabilities), the moderating variable (TMT behavioral integration), and the control variables (firm age and firm size). To ensure sound reliability and validity, measurement instruments for all substantive variables were based on well-established scales from both domestic and international sources. Each item in the questionnaire was

rated on a five-point Likert scale, with anchors ranging from 1 ("strongly disagree") to 5 ("strongly agree").

Conceptually, each of the four core constructs possesses multidimensional attributes. For the sake of construct completeness, sub-dimension information is retained in the source descriptions of the scales; however, as the research objective is to examine overall causal relationships among generative AI applications, green dynamic capabilities, TMT behavioral integration, and green innovation—rather than to conduct dimension-level comparisons—each variable was modeled as a holistic construct during the empirical analyses. The sources, adaptation processes, and final item distributions for each scale are as follows:

3.3.1. Independent Variable: Generative AI

The generative AI framework primarily draws on the GAIA scale developed by Khatri P et al. [70]. Originally developed in English, the scale consists of 19 items. To adapt it to the context of Chinese agricultural technology companies, we followed the cross-cultural adaptation process outlined by Beaton et al. (2000) [71]: we followed a cross-cultural adaptation process: two researchers in the field of management independently translated the English scale into Chinese, and after discussion and consensus, a preliminary Chinese draft was formulated; three experts in agricultural enterprise management were invited to review the items for content validity, semantic clarity, and situational applicability. Based on the experts' feedback, the generic term "work" in the original scale was refined to "R&D, management, or data tasks related to agricultural production" to better align with the actual work context of agricultural technology enterprises; two ethical items that might induce social desirability bias were removed. Additionally, based on exploratory factor analysis, five items with low loadings or semantic overlap were removed, resulting in a final version of 12 items. Subsequently, a pilot test was conducted with 30 middle and senior managers from agricultural enterprises, and items with unclear wording were further optimized based on their feedback.

Based on the original scale design, the application of generative AI primarily encompasses five dimensions: integrative adoption, adoptive adoption, customization adoption, interface adoption, and ethical adoption. Among these, integrative adoption primarily reflects the extent to which enterprise employees utilize generative AI to solve problems, improve work efficiency, and assist in task completion; adoptive adoption reflects employees' interest in and propensity to use generative AI functions; customization usage reflects the extent to which enterprises adjust, adapt, and update generative AI based on actual business needs; interface usage reflects employees' perceptions of the convenience, user-friendliness, and fluidity of generative AI; and ethical usage reflects the enterprise's understanding of the boundaries of generative AI use and its organizational appropriateness. The generative AI measurement is shown in Table 2. It should be noted that while generative AI encompasses five dimensions, its measurement dimensions do not focus solely on adoption intent or perceived usability. Specifically, the integration dimensions (GAIA1–GAIA3) reflect the substantive use of generative AI within an organization rather than general digital maturity; the customization dimensions (GAIA6–GAIA8) reflect the depth of integration of generative AI capabilities into organizational processes. Consequently, this scale captures the extent to which enterprises apply generative AI—a cognitive digital technology—at the forefront of innovation activities across multiple levels, rather than merely reflecting general technology acceptance. GAIA11 and GAIA12 measure enterprises' awareness of the ethical boundaries of generative AI use. In the context of agricultural enterprises, the application of generative AI may involve sensitive production data, variety information, and farmer privacy. An enterprise's careful assessment of the boundaries of technology use is a critical component of its adoption strategy.

Table 2. Generative AI Assessment Items.

Dimension	N.	Question Item
integrative adoption	GAIA1	Generative AI helps our employees develop problem-solving skills
	GAIA2	Generative AI helps our employees' complete tasks quickly
	GAIA3	Our company trusts the reliability of responses generated by generative AI
adoptive adoption	GAIA4	Our employees are interested in using generative AI features
	GAIA5	Our employees are willing to use generative AI features
customization adoption	GAIA6	Our company proactively seeks updates to ensure the optimal use of generative AI
	GAIA7	Our employees feel comfortable experimenting with different settings for generative AI
	GAIA8	Our company has adjusted daily work practices to leverage the potential of generative AI
interface adoption	GAIA9	Our employees find generative AI user-friendly
	GAIA10	Our employees find the generative AI interface very intuitive
ethical adoption	GAIA11	Our company believes it is acceptable to use technology for the benefit of the organization
	GAIA12	Our company believes it is acceptable to use generative AI even beyond its intended purposes

3.3.2. Dependent Variable: Green Innovation

Green innovation was measured across four dimensions—green technological innovation, green product innovation, green institutional innovation, and green environmental innovation—following the work of Li S et al. [72]. To streamline the scale and make it suitable for agricultural enterprises, the following revisions were made: Based on the results of exploratory factor analysis, the three items with the highest factor loadings for each dimension were retained, resulting in a 12-item scale; the general term "products" was specified as "agricultural products"; and items with weak relevance to agricultural enterprise practices were removed. The revised scale was tested alongside the GAIA scale in the same pilot study (N = 30), and respondents confirmed that the items were clear and easy to understand. Green technological innovation concerns a firm's technical improvements in clean production processes, energy saving, consumption reduction, and pollution prevention. Green product innovation reflects performance in developing green products, obtaining green certifications, and expanding green markets. Green institutional innovation refers to practices in establishing green standards, improving green management mechanisms, and optimizing resource allocation. Green environmental innovation captures activities related to enhancing green services, building green supply chains, and upgrading green marketing performance. Table 3 lists the measurement items.

Table 3. Green Innovation Assessment Items.

Dimension	N.	Question Item
green technological innovation	GI1	Our company adopts waste treatment and recycling processes that meet environmental standards.
	GI2	The production technologies we utilize lead to significant reductions in energy use.
	GI3	This company's production process effectively prevents and reduces pollution.
green product innovation	GI4	All this company's agricultural products have obtained green/organic certification.
	GI5	Our company prioritizes investment in green agricultural products.
	GI6	Our company's market share for green agricultural products has increased.
green institutional innovation	GI7	The rate at which our company commercializes green technological advances has risen.
	GI8	Formal standards for green production technologies have been put in place by our firm.
	GI9	Our company implements coordinated planning to optimize its energy structure.
green environmental innovation	GI10	Continuous improvement in the quality of our green services is a firm commitment.
	GI11	Establishing an environmentally responsible supply chain is a central focus for our company.
	GI12	We dedicate substantial effort to enhancing the effectiveness of our green marketing initiatives.

3.3.3. Mediating Variable: Green Dynamic Capabilities

Green dynamic capabilities were measured primarily based on research by Cao Cuizhen et al. [73] and Dong Baobao et al. [74]. The scale has been validated in a Chinese

context, and no revisions were made in this study. In the pilot test (N = 30), participants reported that the items were clear and required no adjustments. The construct encompasses three core dimensions: green environmental adaptability, green resource integration capability, and organizational learning adaptability. Specifically, green environmental adaptability reflects an enterprise's ability to sense market shifts, capture green opportunities, and respond to external environmental uncertainties. Green resource integration capability captures the ability to develop, allocate, share, and collaboratively utilize green resources. Organizational learning adaptability refers to the firm's capacity to advance green learning through internal communication, knowledge sharing, knowledge processing, and knowledge recreation. The measurement items are shown in Table 4.

Table 4. Items for Measuring Green Dynamic Competence.

Dimension	N.	Question Item
green environmental adaptability	GDC1	The ability to accurately analyze the market and allocate resources appropriately
	GDC2	The ability to engage with stakeholders and gather useful information
	GDC3	The ability to anticipate changes in the environment and prepare in advance
	GDC4	The ability to identify, develop, and capitalize on opportunities within the industrial chain
	GDC5	A deep understanding of the operational patterns and development trends of the industry
green resource integration capability	GDC6	The company is continuously improving its resource capabilities
	GDC7	The company is satisfied with its resource development and expansion
	GDC8	The company has utilized resources to complete cross-departmental tasks
	GDC9	The company is satisfied with resource sharing among departments
	GDC10	The company has enhanced its overall efficiency and effectiveness through resource integration
organizational learning and absorption capability	GDC11	The company is continuously learning through strategic alliances
	GDC12	Internal communication channels within the company are smooth and effective
	GDC13	Knowledge sharing has been achieved both internally and with strategic partners
	GDC14	The company can process and utilize new knowledge
	GDC15	The company can create new knowledge

3.3.4. Moderating Variable: Behavioral Integration of the Top Management Team

The measurement of behavioral integration of the TMT was primarily based on the scale developed by Yao Zhenhua et al. [75]. This scale is widely used in domestic research on executive teams; this study adopted the original wording directly without modification. During the pilot test, respondents indicated that they understood the items correctly. Based on the adopted scale, TMT behavioral integration primarily comprises three dimensions: decision-making participation, open communication, and teamwork. Among these, decision-making participation reflects the extent to which team members express their opinions, engage in discussions, and participate in joint decision-making regarding major corporate decisions; open communication reflects the adequacy of information sharing, interaction, and feedback among team members; and teamwork primarily reflects members' behavioral performance in task advancement, mutual support, and collaborative action. The measurement of executive team behavioral integration is shown in Table 5.

3.3.5. Control Variables

Given that firm age and size may influence agricultural enterprises' green innovation through their impact on generative AI application, both were incorporated as control variables in the analysis. The decision to select firm age and firm size as control variables is primarily based on the following considerations: First, firm age and size are the most commonly used control variables in innovation research, making it easier to compare our findings with those of existing studies; second, firm age and size are typically closely related to a firm's resource endowment, investment in technological innovation, and organizational maturity, and may simultaneously influence both the level of generative AI adoption and

green innovation performance. To mitigate the potential interference of heteroscedasticity on regression estimates, the raw data for these variables were log-transformed. This approach helps improve the robustness of estimation results and facilitates a clearer interpretation of relationships among the core constructs.

Table 5. Items for Measuring Behavioral Integration in Top Management Team.

Dimension	N.	Question Item
decision-making participation	TMT1	The company encourages everyone to voice their differing opinions.
	TMT2	All differing opinions from team members are taken seriously.
	TMT3	Team members can engage in constructive debate when they have differing opinions.
open communication	TMT4	Relevant information is fully shared when team members make decisions.
	TMT5	Team members frequently engage in informal communication.
	TMT6	Team members regularly discuss their mutual expectations and requirements.
teamwork	TMT7	When a team member is busy, other members help share the workload.
	TMT8	Team members frequently support each other in their work. When coordination issues
	TMT9	arise between team members' areas of responsibility, they often inform one another.

3.3.6. Common Method Bias Test

Because the data were collected from a single respondent pool, common method variance could potentially be a concern. To evaluate this risk, we performed Harman's single-factor test by entering all measurement items into an unrotated exploratory factor analysis. The results revealed that the first factor extracted without rotation explained 38.14% of the total variance, which is below the widely accepted benchmark of 40%. This finding indicates that common method bias does not pose a serious threat to the present study. In addition, confirmatory factor analysis was conducted using AMOS 29.0, and the model fit results are presented in Table 6. All fit indices for the four-factor model were excellent: $\chi^2/df = 1.078$, CFI = 0.993, TLI = 0.992, and RMSEA = 0.015. This indicates that the discriminant validity of the core constructs is good and that common method bias does not pose a serious threat.

Table 6. Results of confirmatory factor analysis.

Models	Variables	χ^2/df	TLI	CFI	IFI	RMSEA
Four-factor model	GAIA, GDC, GI, TMT	1.078	0.992	0.993	0.993	0.015
Three-factor model	GAIA, GDC, GI + TMT	2.442	0.862	0.868	0.868	0.066
Two-factor model	GAIA, GDC + GI + TMT	4.285	0.685	0.698	0.7	0.099
One-factor model	GAIA + GDC + GI + TMT	6.063	0.514	0.535	0.536	0.123

4. Testing and Analysis of Research Hypotheses

4.1. Validity and Reliability Testing

To ascertain the reliability and validity of the measurement instruments, systematic tests were performed on the four core constructs. The outcomes are summarized in Table 7. Cronbach's α coefficients for Generative AI Applications, Green Innovation, Green Dynamic Capabilities, and TMT Behavioral Integration reached 0.95, 0.949, 0.962, and 0.936, respectively—each value substantially exceeding the widely accepted benchmark of 0.7. These figures demonstrate that every scale exhibits outstanding internal consistency, and the measurement results are stable and dependable.

Table 7. Reliability and Validity Testing.

V.	N.	Factor Load	KMO	Cronbach's α	AVE	CR
Generative AI Applications	GAIA1	0.762	0.974	0.95	0.581	0.943
	GAIA2	0.746				
	GAIA3	0.767				
	GAIA4	0.781				
	GAIA5	0.773				
	GAIA6	0.758				
	GAIA7	0.774				
	GAIA8	0.79				
	GAIA9	0.724				
	GAIA10	0.77				
	GAIA11	0.759				
	GAIA12	0.742				
Green Innovation	GI1	0.729	0.973	0.949	0.57	0.941
	GI2	0.75				
	GI3	0.767				
	GI4	0.754				
	GI5	0.768				
	GI6	0.776				
	GI7	0.747				
	GI8	0.737				
	GI9	0.782				
	GI10	0.759				
	GI11	0.742				
	GI12	0.744				
Green Dynamic Capabilities	GDC1	0.733	0.978	0.962	0.58	0.954
	GDC2	0.749				
	GDC3	0.763				
	GDC4	0.777				
	GDC5	0.787				
	GDC6	0.748				
	GDC7	0.757				
	GDC8	0.771				
	GDC9	0.763				
	GDC10	0.769				
	GDC11	0.752				
	GDC12	0.763				
	GDC13	0.802				
	GDC14	0.748				
	GDC15	0.736				
TMT behavioral integration	TMT1	0.767	0.958	0.936	0.696	0.953
	TMT2	0.755				
	TMT3	0.766				
	TMT4	0.73				
	TMT5	0.741				
	TMT6	0.77				
	TMT7	0.742				
	TMT8	0.758				
	TMT9	0.766				

Measuring instruments drew on well-established scales from both domestic and international research, with targeted adaptations to capture the specificities of agricultural technology firms. Before the main survey was administered, the phrasing of items was iteratively refined through expert panels and pilot testing, verifying that each indicator faithfully reflected the intended construct. The Kaiser–Meyer–Olkin (KMO) statistics for the scales spanned from 0.958 to 0.978, comfortably exceeding the 0.7 threshold, while Bartlett's sphericity tests produced significant results ($p < 0.001$), confirming that the data were amenable to factor analysis. When principal component analysis with varimax rotation

was conducted, all items within each scale loaded cleanly on a single factor. Individual factor loadings fell between 0.724 and 0.802, all beyond the recommended benchmark of 0.5, thus supporting acceptable construct validity. The average variance extracted (AVE) estimates for the latent variables ranged from 0.570 to 0.696, all above the critical 0.5 cutoff, and composite reliability (CR) coefficients ranged from 0.941 to 0.954, well surpassing the 0.7 standard. Collectively, these diagnostics supported the convergent validity of the scales. Moreover, the square root of the AVE for each construct (ranging from 0.755 to 0.834) exceeded any of the inter-construct correlations (the largest being 0.472), thereby corroborating satisfactory discriminant validity.

4.2. Descriptive Statistics and Correlation Analysis

Descriptive statistics and Pearson correlation coefficients were computed for the main variables to provide a preliminary view of the data distribution and the interrelationships among constructs. The results are displayed in Table 8. The means of the core variables fell within the range of 3.33 to 3.44, while standard deviations clustered around 0.93, suggesting that sample enterprises perceived these constructs at a moderately above-average level, with a fair degree of dispersion.

Table 8. Descriptive Statistics and Correlation Matrix.

	Mean	SD	1	2	3	4	5	6
1. Firm Age	2.7	0.847	1					
2. Firm Size	2.69	0.918	−0.011	1				
3. GAIA	3.3328	0.93265	−0.02	−0.056	1			
4. GI	3.3766	0.92818	−0.017	−0.106	0.423 ***	1		
5. GDC	3.4382	0.93553	−0.026	−0.001	0.437 ***	0.452 ***	1	
6. TMT	3.4116	0.94715	0.065	−0.055	0.403 ***	0.457 ***	0.472 ***	1

Note: $N = 335$; *** $p < 0.001$; GI = Green Innovation, GDC = Green Dynamic Capabilities, GAIA = Generative AI Applications, TMT = Top Management Team Behavioral Integration.

Regarding bivariate correlations, generative AI applications showed a significant positive association with green innovation (r = 0.437, $p < 0.001$) and with green dynamic capabilities (r = 0.403, $p < 0.001$). Green dynamic capabilities were also significantly and positively correlated with green innovation (r = 0.452, $p < 0.001$). TMT behavioral integration exhibited significant positive correlations with green innovation, green dynamic capabilities, and generative AI applications (r = 0.457, 0.472, and 0.403, respectively; all $p < 0.001$). These bivariate results offer preliminary support for the theoretical model. Moreover, all correlation coefficients among the core constructs remained below 0.50, indicating no serious concerns about multicollinearity.

4.3. Hypothesis Testing

4.3.1. Main Effects and Mediating Effects

The direct association between generative AI applications and green innovation (H1), together with the mediating function of green dynamic capabilities (H2a, H2b, H2c), was examined through a hierarchical regression design, complemented by PROCESS Model 4 (5000 bootstrap samples) to gauge the significance of the indirect paths. Model 4 is a specialized template within the PROCESS macro developed by Hayes (2017) [76] for testing simple mediation models; its output includes total effects, direct effects, and indirect effects estimated using the Bootstrap method. Tables 9 and 10 summarize these results.

Table 9. Regression Analysis of Main Effects and Mediating Effects.

		GI		GDC
	Model 1	Model 2	Model 3	Model 4
1. Firm Age	−0.019	−0.01	−0.004	−0.019
2. Firm Size	−0.107	−0.083	−0.091	0.024
3. GAIA		0.416 ***	0.271 ***	0.439 ***
4.GAC			0.330 ***	
R^2	0.012	0.186	0.275	0.192
Adjusted R^2	0.006	0.179	0.266	0.184
F	1.938	25.191 ***	31.334 ***	26.177 ***

Note: $N = 335$; *** $p < 0.001$. The coefficients in the table are unstandardized regression coefficients (B).

Table 10. Testing the Mediating Effect of Green Dynamic Capabilities.

		Effect Size	BOOTSE	BOOT LLCI	BOOT ULCI
Total effect	AI→GI	0.4163	0.0494	0.319	0.5135
Direct effect	AI→GI	0.2714	0.052	0.1692	0.3736
Mediating effect	AI→GDC→GI	0.1449	0.0259	0.0956	0.197

Note: 5000 bootstrap samples were drawn, with a 95% confidence interval. The fact that the confidence interval for the indirect effect does not include 0 indicates that the mediating effect is significant.

Hierarchical regression was first applied to estimate the direct influence of generative AI applications on green innovation. Control variables (firm age and firm size) were entered in Model 1, after which the independent variable GAIA was introduced in Model 2. As reported in Table 9, the unstandardized coefficient for GAIA in Model 2 was 0.416 ($p < 0.001$), confirming that generative AI exerts a significant and positive influence on green innovation in agricultural enterprises. Hypothesis H1 thus receives support.

Model 4 examines the first segment of the mediation pathway. The estimates indicate that generative AI has a significant positive effect on green dynamic capabilities (B = 0.439, $p < 0.001$), lending empirical backing to Hypothesis H2a. To test the second segment of the mediation path, green dynamic capability was added to Model 2, forming Model 3. The coefficient for green dynamic capability on green innovation was 0.330 ($p < 0.001$), suggesting that green dynamic capability partially transmits the effect of generative AI to green innovation. Accordingly, Hypothesis H2b is supported.

To further verify the mediating role of green dynamic capabilities in the generative AI–green innovation relationship, PROCESS Model 4 was applied with 5000 bootstrap iterations. As reported in Table 10, the indirect effect of generative AI on green innovation transmitted through green dynamic capabilities was estimated at 0.1449, with a 95% bias-corrected bootstrap confidence interval of [0.0956, 0.1956]. Because this interval does not contain zero, the indirect pathway is considered statistically significant. These findings support Hypothesis H2c, demonstrating that green dynamic capabilities act as a partial mediator in the link between generative AI applications and green innovation within agricultural enterprises.

4.3.2. Moderating Effect

To test whether TMT behavioral integration moderates the direct association between generative AI and green innovation (H3), a hierarchical regression analysis was performed. Prior to estimation, the independent variable (generative AI) and the moderator (TMT behavioral integration) were mean-centered, and their product term was constructed as the interaction term to reduce potential multicollinearity concerns. The results are displayed in Table 11.

Table 11. Results of the moderating effects regression analysis.

	GI		
	Model 1	Model 2	Model 3
1. Firm Age	−0.019	−0.037	−0.016
2. Firm Size	−0.107	−0.073	−0.057
GAIA		0.279 ***	0.254 ***
TMT		0.335 ***	0.304 ***
GAIA × TMT			0.248 ***
R^2	0.012	0.283	0.333
Adjusted R^2	0.006	0.274	0.323
F	1.938	32.571 ***	32.837 ***

Note: N = 335; *** $p < 0.001$. The table shows unstandardized coefficients (B); all continuous variables were mean-centered; N = 335.

Both generative AI (B = 0.279, $p < 0.001$) and TMT behavioral integration (B = 0.335, $p < 0.001$) had significant positive direct effects on corporate green innovation. When the interaction term between generative AI and TMT behavioral integration was added to the equation, its regression coefficient reached 0.248 ($p < 0.001$). This finding indicates that TMT behavioral integration positively moderates the generative AI–green innovation relationship, thereby lending support to H3.

To more clearly illustrate the nature of this moderating effect, a simple slope analysis was carried out. As depicted in Figure 2, at high levels of TMT behavioral integration, the positive impact of generative AI on green innovation was markedly stronger (slope = 0.489, $p < 0.001$, 95% CI [0.362, 0.616]). Conversely, at low levels of TMT behavioral integration, this positive impact became much weaker and statistically non-significant (slope = 0.019, $p = 0.788$, 95% CI [–0.122, 0.161]). The contrast between the two slope lines provides direct and compelling evidence that the promoting effect of generative AI on green innovation intensifies as the degree of TMT behavioral integration increases, thereby offering the most intuitive confirmation of H3.

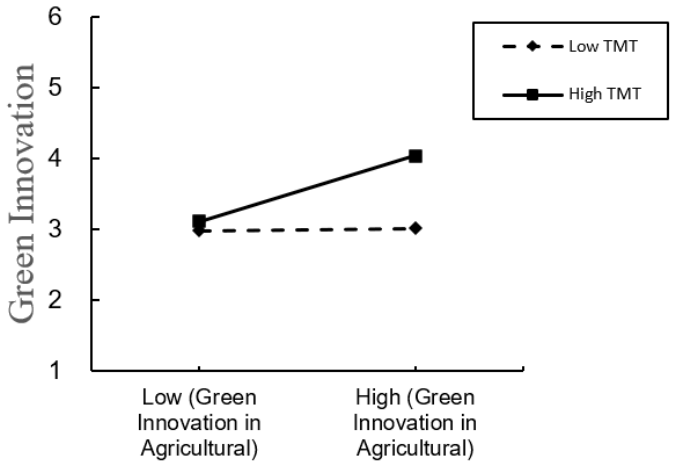


Figure 2. The Moderating Effect of TMT Behavioral Integration on the Relationship between Generative AI and Green Innovation.

4.3.3. Moderated Mediation Effect

To examine how TMT behavioral integration moderates' different segments of the mediation pathway, this study applied Hayes's (2017) PROCESS macro (Model 58) to evaluate the moderated mediation framework (see Figure 3) [76]. The theoretical framework of this study posits that TMT behavioral integration moderates both the "GAIA→GDC" and "GDC→GI" pathways simultaneously. This model allows for the simultaneous testing

of first-order moderation (X × W→M) and second-order moderation (M × W→Y), as well as the calculation of conditional indirect effects across different levels of the moderating variables. The outputs are presented in Table 12.

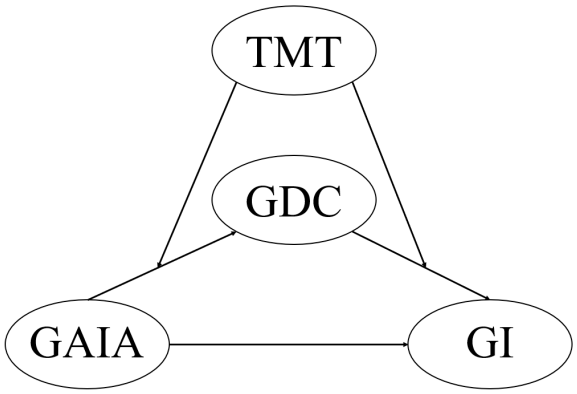


Figure 3. The Modified Green Dynamic Capabilities Model.

Table 12. Results of the moderated mediation analysis (PROCESS Model 58).

	GDC	**GI**
	Model 2	Model 4
Years in Business	−0.034	−0.023
Business Size	0.045	−0.075
GAIA	0.278 ***	0.173 **
TMT	0.335 ***	0.248 ***
GDC		0.22 ***
GAIA*TMT	0.157 ** [0.057, 0.258]	
GDC*TMT		0.193 *** [0.093, 0.294]
R^2	0.319	0.351
F	30.775 ***	29.579 ***

Note: N = 335; The table shows unstandardized coefficients (B); the values in square brackets represent 95% Bootstrap confidence intervals; *** $p < 0.001$, ** $p < 0.01$.

First-stage moderation effect (H4a): In the equation predicting green dynamic capabilities, the interaction between generative AI and TMT behavioral integration (X × W) yielded a significant positive coefficient (B = 0.157, SE = 0.051, $p = 0.002$), with a 95% Bootstrap confidence interval of [0.057, 0.258] that excludes zero. This interaction term contributed an additional ΔR^2 of 0.020 (F (1, 329) = 9.558, $p = 0.002$). These results demonstrate that TMT behavioral integration strengthens the effect of generative AI on green dynamic capabilities, thus supporting H4a.

Second-stage moderation effect (H4b): When green innovation was treated as the outcome variable, the product term capturing the interaction between green dynamic capabilities and TMT behavioral integration (M × W) carried a significant positive coefficient (B = 0.193, SE = 0.051, $p < 0.001$), accompanied by a bootstrap-based 95% confidence interval of [0.093, 0.294] that excludes zero. The inclusion of this interaction produced an incremental ΔR^2 of 0.028 (F (1, 328) = 14.351, $p < 0.001$). This pattern confirms that TMT behavioral integration strengthens the contribution of green dynamic capabilities to green innovation, thereby providing support for H4b.

Combining the results of H4a and H4b, executive team behavioral integration not only enhances the facilitative effect of generative AI on green dynamic capabilities but also strengthens the translation of green dynamic capabilities into green innovation, laying the foundation for subsequent tests of moderated mediation effects.

To examine whether the behavioral integration of the executive team moderates the mediating path of "generative AI–green dynamic capabilities–green innovation" (H5), we calculated the conditional indirect effects at different levels of executive integration based on the output of the PROCESS Model58 and compared differences across groups. The results are shown in Table 13.

Table 13. Conditional Indirect Effects and Between-Group Differences Across Levels of TMT Behavioral Integration.

Level of TMT Integration	Indirect Effects	Boot SE	95% Bootstrap CI
Low level (−1 SD)	0.005	0.011	[−0.018, 0.027]
Mean	0.061	0.018	[0.028, 0.100]
High level (+1 SD)	0.172	0.039	[0.102, 0.258]
Difference between groups (high vs. low)	0.168	0.04	[0.0960, 0.255]

Note: N = 335; The table shows unstandardized coefficients (B).

Under conditions of low TMT integration, the indirect effect transmitted through green dynamic capabilities was negligible and statistically indistinguishable from zero (estimate = 0.005, 95% CI [–0.018, 0.027]). At the mean level of the moderator, this indirect effect rose to 0.061 (95% CI [0.028, 0.100]), reaching significance. When TMT integration was high, the indirect effect increased further to 0.172 (95% CI [0.102, 0.258]). Moreover, the contrast between the high- and low-integration conditions yielded a difference of 0.168, whose 95% confidence interval [0.096, 0.255] excludes zero. This graded pattern reveals that the mediating pathway from generative AI through green dynamic capabilities to green innovation gains strength in tandem with rising TMT behavioral integration, lending clear empirical support to H5.

4.3.4. Robustness Test

To verify the reliability of the above conclusions, we conducted robustness tests using random sampling, following the method described by Wu et al. [77]. Simple random sampling was performed using SPSS 27.0 software, with approximately 50% of the sample randomly selected on two occasions. The results are shown in Table 14. The directions and significance levels of the path coefficients remained entirely consistent, and all hypotheses (H1–H5) were supported. These results indicate that the main conclusions are not driven by specific sample characteristics and demonstrate good robustness.

Table 14. Random Sampling Test Results.

	Green Transformation	
	First subsample (N = 187)	Second subsample (N =164)
H1: GAIA→GI	0.471 ***	0.414 ***
H2: Indirect effect: GAIA→GDC→GI	0.155 [0.090, 0.232]	0.152 [0.083, 0.233]
H3: GAIA*TMT→GI	0.231 ***	0.212 **
H4a: GAIA*TMT→GDC	0.122 *	0.239 **
H4b: GDC*TMT→GI	0.303 ***	0.165 *
Conditional indirect effects		
Low TMT (−1 SD)	−0.153 [−0.377, 0.071]	−0.0001 [−0.027, 0.027]
Mean TMT	0.218 [0.071, 0.365]	0.049 [0.008, 0.104]
High TMT (+1 SD)	0.521 [0.326, 0.717]	0.215 [0.087, 0.375]

Note: All coefficients are unstandardized (B). Values in brackets are 95% bias-corrected bootstrap confidence intervals. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

5. Discussion

5.1. Discussion of Results

Grounded in dynamic capabilities theory and upper echelons theory, this research formulates a moderate mediation model that links generative AI applications to green innovation in agricultural enterprises. Drawing on survey data from 335 agri-technology firms, the study empirically evaluates the mediating function of green dynamic capabilities along with the moderating role of TMT behavioral integration. The empirical findings provide support for every proposed hypothesis, illuminating both the underlying mechanisms and the boundary conditions that shape how generative AI may contribute to green innovation in agricultural settings.

The results indicate that generative AI applications have a significant and positive association with green innovation in agricultural enterprises. This suggests that the value of generative AI extends beyond enhancing information utilization efficiency; more critically, it supplies a novel knowledge base and cognitive support for green product development, process improvement, and management innovation through capabilities such as knowledge creation, creative assistance, and scenario simulation. Such cognitive empowerment is especially relevant for agri-technology firms, given that agricultural green innovation frequently entails complex ecological knowledge, the evaluation of alternative technology pathways, and the anticipation of market dynamics. Generative AI can substantially alleviate the cognitive load and trial-and-error costs inherent in the innovation process.

The analysis further reveals that green dynamic capabilities serve as an important mediating mechanism: roughly 34.8% of the total effect of generative AI on green innovation is routed through this capability-building pathway, underscoring its role as a core conversion channel that translates technological potential into tangible green outcomes, consistent with the logic of dynamic capabilities theory.

In addition, the strength of both the direct effect and the mediated pathway is contingent on the degree of behavioral integration within the TMT. Specifically, greater integration amplifies these relationships, aligning with a key premise of upper echelons theory—namely, that the extent of cognitive collaboration, mutual information exchange, and joint decision-making among senior executives fundamentally shapes how firms perceive, channel, and deploy strategically important resources for green innovation.

5.2. Theoretical Contributions

The present research addresses three interconnected issues: whether generative AI applications can substantially elevate the level of green innovation in agricultural enterprises, whether green dynamic capabilities function as a mediating mechanism in this relationship, and whether TMT behavioral integration reinforces these effects. The theoretical contributions that emerge from this inquiry can be delineated along several lines.

A primary contribution lies in extending the scholarly conversation on digital technology and green innovation into the more contemporary domain of generative AI applications. The evidence presented here suggests that generative AI ought to be understood not as a mere information-processing instrument that boosts efficiency, but rather as a distinctive form of cognitive digital technology endowed with the capacity for knowledge creation and solution generation. This conceptual reframing broadens the technological boundaries within which antecedents of green innovation are examined.

A second contribution stems from the adoption of a green dynamic capabilities perspective, which makes it possible to disentangle the mechanism linking generative AI applications to green innovation in agricultural enterprises. In doing so, the study speaks to an important lacuna in the extant literature—namely, the question of how digital tech-

nologies are converted into green innovation outcomes—and offers a richer perspective on the "technology-capability-performance" transformation sequence.

A further contribution lies in positioning TMT behavioral integration as an important contextual variable and tracing its moderating influence across multiple pathways. The findings indicate that TMT behavioral integration governs not only the immediate effects of technology adoption but also the broader process through which technological resources are converted into capabilities and, subsequently, into innovation outcomes, thus serving to either strengthen or weaken the entire empowerment pathway. This insight advances a more nuanced understanding of the boundary conditions under which TMT behavioral integration shapes the innovation returns from generative AI and contributes to the broader literature on how upper-echelon governance factors relate to green innovation.

5.3. Management Insights

This study enables agri-technology firms to develop a fuller appreciation of the strategic value of generative AI, steering them away from mere technology deployment and toward capability cultivation and innovation conversion, thereby facilitating digitally driven green transformation. For example, generative AI can be leveraged to analyze market demand for green solutions, simulate the ecological benefits of different green technology options, and optimize resource allocation in agricultural production processes, thereby improving the efficiency and quality of green innovation. In parallel, the research suggests that enterprises should focus on cultivating dynamic green capabilities and building a bridge from technology application to innovative outcomes. Specifically, enterprises can establish cross-departmental green innovation teams, strengthen environmental data monitoring and analysis, and promote green knowledge sharing and training, thereby effectively translating the advantages of generative AI into green innovation. Notably, the study confirms that agricultural technology companies should focus on enhancing the level of behavioral integration within their Top Management Teams to fully leverage the amplifying effects of organizational governance. To this end, companies can establish regular high-level communication mechanisms to encourage open discussion and information sharing, ensuring that differing viewpoints are fully expressed during the decision-making process for green strategies. Second, they should foster a spirit of teamwork to promote collaborative action among members in green innovation projects and reduce coordination barriers between departments. Only when a high level of behavioral integration is achieved within the TMT can the value of technology applications be fully realized.

6. Conclusions

6.1. Key Findings of the Study

This research centers on agricultural technology enterprises. Drawing upon dynamic capabilities theory and upper echelons theory, it constructs a moderate mediation model investigating the relationship between generative AI applications and green innovation in agricultural enterprises. The empirical analysis yields several key conclusions.

The findings reveal that generative AI applications are positively associated with green innovation in agricultural enterprises, indicating that this emerging cognitive digital technology may effectively advance green product development, green process improvements, and green management innovation within these firms. Furthermore, green dynamic capabilities partially mediate the generative AI–green innovation relationship. Specifically, generative AI facilitates the formation and strengthening of green dynamic capabilities by sharpening an enterprise's capacity to identify green opportunities, integrate green resources, and absorb organizational learning, thereby indirectly contributing to green innovation. In addition, TMT behavioral integration positively moderates the direct link

between generative AI and green innovation, while simultaneously moderating both segments of the indirect pathway—generative AI → green dynamic capabilities and green dynamic capabilities → green innovation—and further moderates the overall mediated mechanism. When TMT behavioral integration is at a high level, the positive association between generative AI and green innovation tends to be more pronounced, and the mediating function of green dynamic capabilities becomes stronger.

6.2. Limitations of the Study and Future Prospects

Several limitations of the present research warrant acknowledgment and point to promising directions for future inquiry. One noteworthy constraint is the reliance on cross-sectional survey data, meaning all constructs were captured at a single time point. Although the hypothesized causal ordering is grounded in theoretical reasoning, the possibility of reverse causality or common method variance cannot be definitively excluded. To address this concern, subsequent research could adopt longitudinal tracking designs or quasi-experimental approaches to more rigorously examine the dynamic relationships among generative AI applications, green dynamic capabilities, and green innovation, thereby revealing how the patterns associated with technology adoption unfold over time. Furthermore, this study controlled only two variables: firm age and firm size. Other factors that may influence green innovations, such as ownership type, industry sector, R&D intensity, and regulatory pressure, were not included in the analysis. Future research could further test the robustness of the findings by utilizing a broader range of objective firm-level data.

A second consideration relates to the geographic scope of the sample. The research sample consists primarily of agricultural technology firms from four provinces: Jiangsu, Zhejiang, Shandong, and Guangdong. All four provinces are in the eastern coastal region and generally possess a strong foundation in agricultural industrialization and digitalization; as such, the sample may not fully represent the developmental characteristics of agricultural technology firms in central and western China. Although there are certain internal differences among these four provinces in terms of industrial structure, policy environment, and level of digitalization, caution should still be exercised when generalizing the study's conclusions to central and western regions as well as areas with lower levels of agricultural industrialization. Furthermore, as the study's sample is entirely drawn from the Chinese context—where the agricultural policy framework, market environment, and stage of digital development differ from those of other countries and regions—the generalizability of these conclusions to other economies and institutional contexts requires further testing. Expanding the sampling frame to encompass agricultural enterprises from central and western provinces, or undertaking cross-regional comparative research, would help verify the robustness and broader applicability of the findings.

A further limitation lies in the scope of the theoretical model itself. The current framework concentrates on green dynamic capabilities as a mediating mechanism and TMT behavioral integration as a moderating condition, yet other intervening pathways and boundary conditions likely exist within the generative AI–green innovation nexus. Although the core constructs in this study are multidimensional, the main model treats them as holistic constructs. For example, the specific mechanisms through which the sub-dimensions of green dynamic capabilities differentially mediate the relationship between generative AI and green innovation, as well as the potential differential effects of generative AI's sub-dimensions on the sub-dimensions of green innovation, remain to be elucidated by future research through empirical designs at the dimensional level. Future research could further expand the theoretical model by introducing additional mediating and moderating variables and by subdividing the core constructs into specific dimensions, thereby providing

a more comprehensive understanding of the mechanisms through which generative AI may contribute to green innovation in agricultural enterprises.

While this study examines the role of generative AI in relation to green innovation among agricultural enterprises, it has not yet fully accounted for the inherent limitations and potential risks of generative AI technology itself. For example, these include reliance on the quality of input data, the risk of generating unreliable outputs, and data security concerns; these factors may, to some extent, constrain the effectiveness of generative AI in supporting green innovation. Regarding these technical limitations, future research could further investigate the moderating or inhibitory effects of these risk factors on the relationship between generative AI and green innovation.

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Institutional Review Board Statement: This study was conducted in accordance with the ethical principles of the Declaration of Helsinki and its subsequent amendments. Ethical approval was obtained from the Ethics Committee of Anhui Science and Technology University (Approval No.: ECE-AHSTU20251104; Date: 4 November 2025). All participants were fully informed of the study's purpose and procedures prior to their participation, and informed consent was obtained from each individual. The survey was designed to be risk-free, with no anticipated physical, psychological, or economic harm. All collected data were anonymized to ensure confidentiality and were used solely for academic and statistical purposes.

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