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Digital Transformation and Green Agricultural Development: Evidence from Agricultural Value Chain Integration in China

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ABSTRACT

This study examines how digital transformation promotes green agricultural development through value chain integration in China. Using panel data from 31 Chinese provinces during 2013–2023, we employ fixed effects models, mediation analysis, and moderation tests to investigate the underlying mechanisms. Results reveal that digital transformation significantly enhances green agricultural development with a coefficient of 0.298 ($p < 0.01$), and this effect remains robust after IV-2SLS and System GMM estimations. Value chain integration serves as a partial mediator, accounting for 27.5% of the total effect, indicating that digital platforms connect dispersed farmers with markets, standardize green production, and improve resource allocation efficiency. Environmental audit intensity positively moderates this relationship, with the marginal effect rising from 0.187 in low-audit regions to 0.468 in high-audit regions, implying that stricter supervision amplifies the green payoff of digitalization. Placebo permutation tests confirm the causal nature of these relationships, and alternative specifications, such as internet penetration as a proxy for digitalization and agricultural green total factor productivity as the dependent variable, orroborate external validity. These findings contribute to understanding sustainable agricultural transformation in the digital economy era and suggest that realizing digital technology's green potential requires the coordinated advancement of technological innovation, value-chain organization reform, and institutional arrangements. The study provides empirical evidence for policymakers to design integrated strategies promoting agricultural digital-

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ization while strengthening environmental governance mechanisms.
Keywords: Digital Transformation; Green Agricultural Development; Value Chain Integration; Environmental Audit; China

1. Introduction

Global agricultural systems are at an unprecedented critical juncture of transformation. Faced with intensifying climate change, resource depletion, and food security challenges, traditional agricultural production models have become inadequate to meet the demands of sustainable development. In this context, Digital Transformation (DT), as a key driving force for reshaping agricultural production methods, provides new pathways for achieving green agricultural development. Particularly in China, a major agricultural country, how to promote agricultural Value Chain Integration (VCI) through digital technology and thereby advance Green Agricultural Development (GAD) has become a major theoretical and practical issue requiring urgent resolution. According to the latest forecasts, the global agricultural digitalization market will reach $22.5 billion in 2025, with agricultural supply chain finance accounting for 18.7% of total agricultural financing [1]. This trend not only reflects the broad application prospects of digital technology in agriculture but also highlights the central position of VCI in promoting agricultural sustainable development.

DT fundamentally changes the operational model of traditional agricultural value chains by reconstructing information flow mechanisms across agricultural production, circulation, and consumption. This transformation is reflected not only in improved production efficiency but, more importantly, in promoting resource allocation optimization and internalization of environmental negative externalities. Research indicates that digital economic development significantly enhances agricultural net carbon efficiency, with this impact being more pronounced in major grain-producing regions and areas with higher agricultural industry concentration [2]. Simultaneously, digital technology enhances the endogenous momentum of agricultural ecological transformation through two key mechanisms: improving human capital and promoting technological progress. However, it is noteworthy that the impact of digitalization on GAD is not linear but exhibits clear threshold effects. When low-carbon innovation levels are low, digital economic development cannot effectively promote agricultural ecological transformation; only when low-carbon technological innovation exceeds critical values can the digital economy fully exert its driving role, presenting a "U-shaped" relationship [3]. This finding reveals the critical moderating role of technological innovation in the process of digitalization promoting GAD.

VCI, as an important bridge connecting DT and GAD, deserves in-depth exploration of its mechanism. Supported by digital technology, agricultural value chains are evolving from traditional linear structures toward networked and platform-based directions. This evolution not only improves collaborative efficiency among value chain segments but, more importantly, promotes the implementation of green production standards and improvement of environmental performance through mechanisms such as information sharing, quality traceability, and risk management [4]. Particularly in the Chinese context, the digital transformation of agricultural supply chains significantly enhances green productivity, with digitalization in the consumption segment producing the greatest promotional effect [5]. Additionally, digital agricultural solutions enhance agricultural system resilience by reducing crop disaster rates, further promoting green productivity improvement. These findings indicate that VCI is not only an important transmission mechanism for digitalization's impact on green agriculture but also a key pathway for achieving agricultural sustainable development.

The institutional environment plays an important moderating role in the process of digitalization promoting GAD. Environmental Audit (EA), as an important tool of government environmental governance, provides external pressure and incentives for enterprise green innovation by strengthening environmental supervision and accountability mechanisms. Research finds that government EA implementation significantly promotes green innovation in heavily polluting enterprises, with this effect being more pronounced in regions with stronger local official promotion incentives and lower marketization levels [6]. In agriculture, although natural resource audit policies produce energy rebound effects to some extent, they still have positive impacts on agricultural green transformation by improving agricultural energy efficiency [7]. This evidence indicates that EA not only directly affects agricultural producers' environmental behavior but also strengthens the promotional effect of digitalization on GAD through synergy with digital technology.

China, as the world's largest developing country and agricultural power, has agricultural green transformation experiences with important theoretical value and practical significance. Although Chinese agriculture has achieved remarkable success over the past decades, the production-oriented development model has led to coexisting problems of inventory surplus, rapid import growth, and ecological degradation [8]. In this context, exploring how DT promotes GAD through VCI not only helps understand the internal mechanisms of agricultural sustainable development in the digital economy era but also provides valuable experience for other developing countries.

However, while existing studies examine the effects of digital transformation on green agricultural development, they lack systematic analysis of the underlying transmission mechanisms. This study aims to: (1) quantify the total effect of digital transformation on green agricultural development and identify the specific pathways through which this influence operates; (2) decompose this effect to clarify the contribution of value chain integration; and (3) examine how environmental governance institutions heterogeneously shape this relationship across different regions.

This manuscript proceeds as follows: Section 2 reviews relevant literature and develops hypotheses; Section 3 describes methodology and data; Section 4 presents empirical results including mediation and moderation analysis; Section 5 discusses policy implications. Based on panel data from 31 Chinese provinces from 2013 to 2023, this study systematically examines the impact mechanism of DT on GAD, focusing on analyzing the mediating role of VCI and the moderating effect of EA. The research findings not only enrich theoretical research on digital economy and agricultural sustainable development but also provide empirical evidence for policymakers to optimize agricultural digitalization strategies and improve environmental governance mechanisms.

2. Literature Review and Hypotheses

2.1. Conceptual Definition and Theoretical Foundation

2.1.1. Conceptual Evolution and Connotation of Digital Transformation

As the most significant technological paradigm shift of the 21st century, DT has its theoretical foundation rooted in Porter's value chain theory and competitive advantage framework. Porter's [9] proposition that enterprises can achieve competitive advantage through reconfiguring value chain activities laid the theoretical groundwork for the deep application of digital technologies in agriculture. With the rapid development of information and communication technology (ICT), the concept of DT has gradually expanded from manufacturing to agriculture, experiencing a theoretical evolution from precision agriculture to smart agriculture and subsequently to Agriculture 4.0.

As an early manifestation of digital concepts in agriculture, precision agriculture was defined by Zhang et al. [10] as a management strategy that utilizes information technology to collect data and support crop production decisions. This concept was subsequently expanded when Wolfert et al. [11] proposed the concept of smart agriculture, emphasizing the central role of ICT in the cyber-physical farm management cycle. From the perspective of impact mechanisms, Deichmann et al. [12] based on World Bank reports, proposed a theoretical framework indicating that digital technology generates impact through three key pathways: promoting economic inclusiveness, complementing production factors to improve efficiency, and significantly reducing transaction costs to foster innovation. Dayıoğlu and Turker [13] further pointed out that digital transformation has become a key driver for the sustainable future of agriculture.

In the process of agricultural digital transformation, digital financial services play a fundamental pivotal role. China's practical data fully demonstrates this point. As of 2024, through technological innovations such as remote sensing intelligent interpretation and multi-source data modeling, digital financial platforms have served over 6 million farmers with cumulative credit of nearly 100 billion yuan, of which nearly 80% are small-scale farmers with planting areas of less than 10 acres. At the industrial chain level, digital finance has unified capital flow, information flow, and logistics through supply chain finance models, covering major agricultural industries in 31 provinces across the country. As of 2023, leading non-traditional financial institutions alone have cumulatively issued over 100 billion yuan in loans to farmers in 100,000 villages, forming a comprehensive service system of "finance + technology + industry".

Through service forms such as mobile payments, online credit, and digital insurance, digital finance provides convenient financial support for agricultural operators, effectively addressing the problems of narrow coverage, high costs, and low efficiency of traditional agricultural financial services. This financial innovation based on digital technology not only lowers the threshold for agricultural operators to access financial services but also enhances the precision of financial services through big data analysis and risk assessment technologies. More importantly, while providing financial services, digital financial platforms have embedded functions such as agricultural technology promotion, market information, and supply chain management, substantially promoting the digital transformation of the entire agricultural industry chain.

Based on the comprehensive analysis of the above literature, this study defines digital transformation as: an agricultural digitalization process primarily driven by digital financial services, which enhances the convenience and accessibility of financial services for agricultural operators through fintech means such as digital payments, online credit, and digital insurance, thereby promoting systematic reform in agricultural production efficiency improvement and green development through technology diffusion effects, data sharing mechanisms, and platform ecosystem effects.

2.1.2. Theoretical Foundation and Evolution of Green Agricultural Development

The concept of GAD is rooted in the deepened application of sustainable development theory. The development philosophy systematically articulated by the World Commission on Environment and Development (1987) in "Our Common Future" report—meeting the needs of the present without compromising the ability of future generations to meet their own needs—established the fundamental theoretical foundation for GAD. The theoretical framework of environment-economy relationships refined by Pearce and Turner [14] in environmental economics research proposed the important idea of internalizing environmental factors into economic decision-making.

Since the 21st century, GAD theory has been further deepened. Research published in Nature indicated that the doubling of global food demand over the next 50 years poses enormous challenges to the sustainability of food production, establishing the core agenda for agricultural sustainable development research [15]. Pretty et al. [16] demonstrated through empirical research on 286 sustainable agriculture projects covering 12.9 million hectares that resource-conserving agriculture could significantly increase yields in developing countries. Analysis of ecological economics development trends showed that interdisciplinarity, sustainable development orientation, and systems thinking have become important theoretical foundations for GAD research [17]. Agriculture 4.0 research emphasized that sustainable intensification should follow the triple principles of people, production, and planet [18]. Current research indicates that the core of GAD lies in achieving continuous improvement in resource utilization efficiency and effective control of environmental burden. Digital economy empowers sustainable agricultural development by enhancing farmers' willingness to adopt ecological agricultural technologies [19].

From measurement and assessment perspectives, GAD is primarily manifested in two dimensions: environmental efficiency and resource efficiency of agricultural production. Environmental efficiency is mainly measured by agricultural carbon productivity, which reflects the low-carbon level of agricultural production as the agricultural output value generated per unit of carbon emissions. Resource efficiency is measured through indicators such as fertilizer efficiency, pesticide efficiency, and water resource efficiency, reflecting the utilization efficiency of agricultural inputs. Additionally, indicators such as agricultural waste recycling rates reflect the circular economy characteristics of agricultural production.

Based on these theoretical developments, this study defines GAD as: a sustainable development model with the core objective of improving agricultural environmental efficiency and resource utilization efficiency, achieving enhanced agricultural carbon productivity, input reduction and efficiency improvement, and waste resource utilization through technological innovation and management optimization, while maintaining agricultural production capacity while reducing environmental burden.

2.1.3. Research Gaps and Documentary Contributions

Recent studies have documented multiple transmission mechanisms for digital technology's impact on green agricultural development. Wu and Lin [20] found that digital inclusive finance promotes inclusive green growth through green technology innovation, industrial upgrading, and employment quality as mediating factors. Shen et al. [21] demonstrated that digital financial inclusion improves agricultural green total factor productivity, with the effect operating through land transfer facilitation and strengthened by green credit policies. However, three research gaps remain. First, the role of value chain integration as a mediating mechanism has received limited empirical attention despite its theoretical importance. Second, institutional factors such as environmental governance intensity in moderating this relationship remain largely unexplored in agriculture. Third, existing studies lack precise quantification of each mechanism's relative contribution.

This study bridges these gaps by: (1) systematically examining value chain integration as a mediating pathway and quantifying its magnitude; (2) analyzing how environmental audit intensity heterogeneously moderates the relationship; and (3) providing rigorous causal identification for policy guidance.

2.2. Impact Mechanisms of Digital Transformation on Green Agricultural Development

2.2.1. Theoretical Mechanism Analysis

The impact mechanisms of digital transformation on green agricultural development operate through transaction cost reduction and information asymmetry mitigation. According to transaction cost economics [22], digital platforms reduce information search costs, verification costs, and monitoring costs in agricultural value chains, lowering barriers to green technology adoption. From information economics perspective [23], digital platforms enable transparent data sharing, which improves decision quality and resource allocation efficiency.

Digital finance reshapes farmers' decision-making environment by requiring detailed production plans and input budgets when applying for credit, promoting more scientific agricultural practices. Satellite remote sensing technology employed by platforms such as MYbank, originally designed for loan risk assessment, simultaneously provides farmers with planting monitoring and fertilization recommendations. This integration of financial services with technical guidance reduces resource waste inherent in traditional extensive production. Additionally, digital insurance and accessible credit alter farmers' risk expectations. In traditional agriculture, inadequate risk protection mechanisms drive excessive fertilizer and pesticide application as defensive strategies. By mitigating information gaps about risk and financing options, digital platforms enable farmers to adopt more environmentally friendly production methods previously perceived as too risky.

Supply chain integration through digital platforms further reduces transaction costs. By connecting dispersed farmers into coordinated systems through models such as order-based agriculture and contract farming, platforms achieve centralized procurement and standardized input management. This institutional arrangement enables economies of scale in green input adoption while ensuring input quality and promoting widespread use of green inputs such as biological pesticides and organic fertilizers. Finally, accumulated production and transaction data, after processing, become personalized decision-support recommendations. Farmers can optimize resource applications for water, fertilizers, and pesticides based on market demand, weather patterns, and soil conditions, thereby improving resource utilization efficiency.

2.2.2. Empirical Research Evidence

Extensive empirical studies both domestically and internationally provide strong empirical evidence for DT promoting GAD. From international experience, analysis of the economy-wide impacts of climate-smart agriculture in India based on social accounting matrix frameworks indicated that rice-wheat intensification systems provided the highest economic impact when considering lower greenhouse gas emissions and water footprints, demonstrating that digital technology-supported smart agriculture has significant economic and environmental dual benefits in developing countries [24].

From Chinese practical experience, empirical analysis based on panel data from 30 Chinese provinces from 2015 to 2021 indicated that agricultural DT can significantly reduce agricultural carbon emissions through three pathways: expanding agricultural production scale, optimizing agricultural industrial structure, and promoting agricultural technological progress [25]. Research on the impact of digital economy development on farmers' enthusiasm for adopting ecological agricultural technologies showed that this positive influence is more pronounced in regions with stronger environmental regulations. A questionnaire survey of 1500 farmers in Hubei Province showed that the existence of digital divides significantly affects farmers' agricultural practice motivations, with usage gaps showing the strongest inhibitory effects [26]. Systematic literature reviews indicated that the application of data envelopment analysis (DEA) in agricultural sustainability assessment can provide stakeholders with more interpretable feasible solutions [27].

H1. *Digital transformation has a significantly positive impact on green agricultural development.*

2.3. Mediating Mechanism of Value Chain Integration

2.3.1. Agricultural Value Chain Theory Development and Digital Reconstruction

The agricultural value chain (AVC) concept originates from Porter's value chain theory, which proposed that value chains are collections of interrelated activities that create value for enterprises, and sustainable competitive advantages can be achieved through systematic optimization of value chain configurations. Since the beginning of the millennium, the AVC concept has been widely applied in agricultural development fields, primarily adopted by researchers and practitioners engaged in agricultural development work in developing countries.

Under the digital era background, traditional AVCs are undergoing profound structural transformations. Agricultural social networks, as the core of AVC management and sustainability, consist of complex interdependent participant networks including farmers, distributors, processors, and retailers, providing user scenario backgrounds for AVC digitalization and digital solution development [28]. The AVC financing ecosystem approach can effectively reduce transaction costs and utilize social and trade capital to mitigate quality, price, and market-related risks through constructing financial platforms for value chain transaction records, implementing value chain bundled services, and evolving from value chains to value networks [29].

The core mechanisms of digitalized VCI are manifested in three levels: information integration mechanisms, standard transmission mechanisms, and risk-sharing mechanisms. Regarding information integration mechanisms, digital platforms break down information barriers in traditional value chains, enabling real-time information sharing among production, processing, circulation, and consumption stages; regarding standard transmission mechanisms, green demands from the consumption end can be effectively transmitted to the production end through digitalized traceability systems; regarding risk-sharing mechanisms, digital platforms can more accurately assess and distribute various risks through big data analytics and artificial intelligence technologies.

2.3.2. Pathways of Value Chain Integration Promoting Green Agricultural Development

The mechanisms through which VCI promotes GAD are primarily realized through three key pathways. First, reducing green conversion costs by improving information transparency. VCI can provide farmers with accurate and timely market price signals and consumer preference information through constructing digitalized information platforms, significantly reducing uncertainty and risks in the green conversion process. Second, achieving economic feasibility of green technologies through scaled operations. Many green agricultural technologies have high fixed investment costs and can only achieve economic feasibility when reaching certain scales. The resilience of AVCs in developing country contexts is an important guarantee for ensuring food security and achieving sustainable food systems [30]. VCI helps small farmers achieve economies of scale through cooperation and coordination by improving the organizational level of agricultural production, thereby reducing the unit costs of green technology adoption.

Finally, achieving win-win situations for multiple parties through value co-creation mechanisms. In integrated value chains, entities at various stages are no longer in simple buyer-seller relationships but co-create value-added services and products through deep collaboration. The combination of global value chains (GVCs) and digitalization has positive impacts on green growth, with increased digitalization enabling the impact of GVC positions on green productivity to shift from negative to positive, while digitalization also promotes the green technological progress effects of GVC positions and backward participation [31]. This value co-creation model makes green development not a unilateral cost burden but a value enhancement process for the entire value chain. Fintech significantly promotes agricultural green development through two key mechanisms: rural human capital and agricultural industrial agglomeration, with this impact showing obvious heterogeneity among different types of agricultural business entities [32].

H2. *Value chain integration plays a mediating role in the process of digital transformation affecting green agricultural development.*

2.4. Moderating Mechanism of Environmental Auditing

2.4.1. Theoretical Foundation and Institutional Functions of Environmental Auditing

As an important component of government environmental governance systems, EA has theoretical foundations covering multiple disciplines including public administration, environmental economics, and auditing. Analysis from the public administration perspective indicates that EA is an important institutional tool for governments to fulfill environmental regulatory functions, improving the execution effects and governance performance of environmental policies through establishing scientific accountability mechanisms. The environmental economics perspective shows that EA can effectively correct market failure problems by internalizing environmental externalities into economic decision-making processes, guiding economic entities to adopt more environmentally friendly behavioral patterns.

The positive contributions of EA to sustainable development of green economy are increasingly prominent, particularly in natural resource management fields such as forestry, where comprehensive performance assessment of economic, environmental, social, information, and organizational subsystems can optimize cost structures and ensure accuracy of production cost accounting [33]. China's natural resource asset audit upon departure system represents an important institutional innovation in the EA field. Analysis based on Chinese empirical data indicated that natural resource accountability auditing, as an institutional innovation, can significantly improve green total factor productivity (GTFP) in heavily polluting industries through two mechanisms: resource allocation optimization and technological innovation drive, with this impact showing obvious differences across different regions, industries, and individual characteristics [34].

From the institutional function perspective, the mechanisms through which EA exerts moderating effects are primarily manifested in four aspects: constraint mechanisms, incentive mechanisms, capacity enhancement mechanisms, and institutional improvement mechanisms. Constraint mechanisms constrain environmental misconduct of agricultural business entities by increasing expected costs of polluting behaviors, creating objective demand for digital technology applications in environmental governance; incentive mechanisms guide agricultural business entities to actively adopt environmentally friendly technologies through establishing positive incentive systems; capacity enhancement mechanisms promote the popularization and deep application of digitalized environmental monitoring technologies; institutional improvement mechanisms provide more optimized institutional environments for widespread digital technology applications by promptly identifying loopholes and implementation deviations in environmental governance systems.

2.4.2. Moderating Effects of Environmental Auditing on Digital Green Transformation

The moderating effect of environmental auditing on digital transformation's promotion of green agricultural development is primarily achieved through changing the institutional environment and incentive structure in which digital finance operates. This moderation does not directly act on digital technology itself but rather guides digital financial resources to be more effectively allocated to green agricultural projects through strengthening environmental constraints, improving information transparency, and innovating incentive mechanisms.

From the perspective of institutional constraints, the compliance pressure created by environmental auditing directly changes the resource allocation orientation of digital finance. Strict environmental auditing exposes agricultural operators to higher violation costs, and this pressure transmits to the financial demand side, prompting them to more actively seek green transformation funds. To reduce their own risks, digital financial platforms pay greater attention to borrowers' environmental performance in loan approval. As Meemken et al. [35] pointed out, while sustainability standards, as rule systems for supply chain participants to demonstrate their commitment to social equity and environmental protection, can improve the sustainability of production processes under specific circumstances, they remain insufficient to ensure the sustainability of large-scale food systems. Environmental auditing serves as an important institutional arrangement to address this insufficiency, ensuring that projects supported by digital finance truly meet green standards through mandatory supervision and inspection.

The synergy between environmental auditing and digital finance is also reflected in data sharing and technology application. The detailed production records and emission data required by environmental auditing promote the digital management of agricultural production, which naturally aligns with the data requirements of digital financial platforms. Gerber et al. [36], in their assessment study of environmental, social and governance (ESG) reporting in the agricultural sector, indicated that although there are obvious coordination problems in current information disclosure in the agri-food sector, the implementation of the new Global Reporting Initiative (GRI) 13 industry standard provides opportunities for improving transparency and gaining strategic advantages. In this context, the standardized data collection promoted by environmental auditing not only meets regulatory requirements but also provides a data foundation for risk assessment and product innovation by digital financial platforms. Platforms can develop differentiated financial products based on environmental audit data, such as green loans and carbon finance, achieving a win-win situation for both environmental and economic benefits.

However, the moderating effect of environmental auditing exhibits clear threshold effects and regional differences. Only when environmental auditing reaches a certain intensity and enforcement level can it effectively guide digital financial resources toward green projects. In regions with weak environmental regulation, even with advanced digital financial services, the green transformation effect is significantly diminished. This indicates that achieving the green effects of digital transformation requires coordinated advancement of technological innovation and institutional development; relying solely on market mechanisms or technological progress is insufficient to achieve ideal results.

H3. *Environmental auditing intensity positively moderates the impact of digital transformation on green agricultural development.*

Figure 1 presents the theoretical framework and hypothetical relationships of this study. DT, as the core explanatory variable, affects GAD through two pathways: first, a direct promotional effect (Hypothesis 1), reflecting digital technology's direct contribution to improving resource utilization efficiency and reducing environmental pollution; second, an indirect pathway through VCI (Hypothesis 2), embodying the mechanism by which digitalization reshapes industrial organizational forms and thereby promotes green transformation. EA, as an important institutional variable, produces moderating effects on the relationship between DT and GAD (Hypothesis 3), strengthening or weakening digital technology's green empowerment effects. Control variables cover multiple dimensions including economic development, industrial structure, and human capital to exclude interference from other factors. The entire framework reflects the interactive effects of technological progress, industrial organization, and institutional environment, providing a clear logical foundation for empirical analysis.

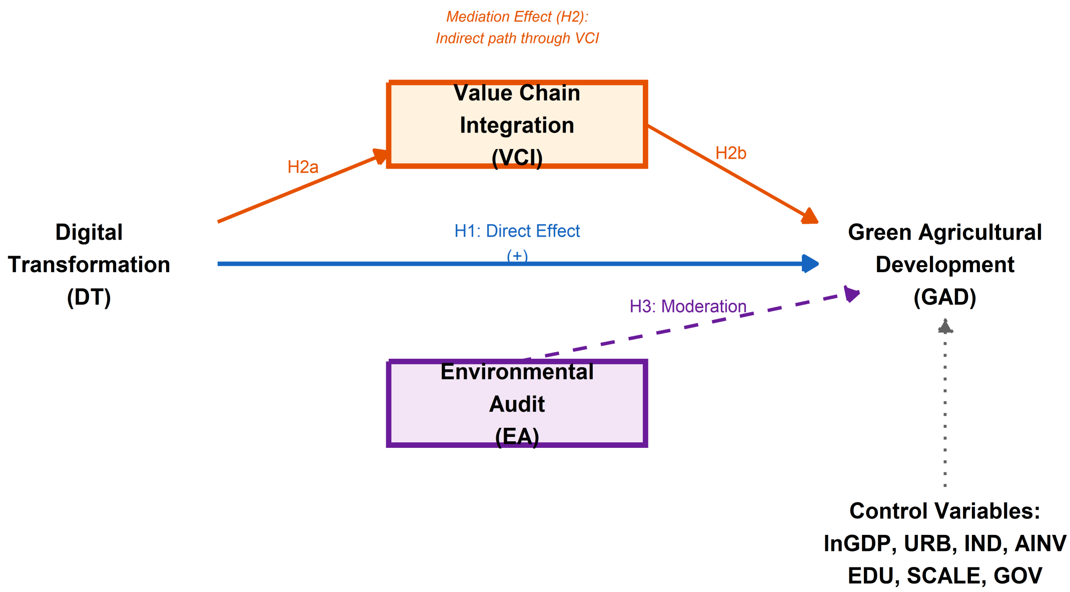

Figure 1. Research Hypothesis Framework.

3. Methodology

3.1. Data and Sample

This study employs panel data from 31 Chinese provinces (excluding Hong Kong, Macao, and Taiwan) spanning 2013–2023 for empirical analysis. The selection of the sample period's starting point has important policy background justification: In August 2013, the State Council issued the "Broadband China Strategy and Implementation Plan" (State Council Document [2013] No. 31), marking the formal elevation of broadband network construction to national strategic status and laying the infrastructure foundation for digital economy development. In November of the same year, the Third Plenary Session of the 18th Central Committee of the Communist Party of China first proposed implementing Natural Resource Asset (NRA) departure audits for leading officials, initiating a new phase of institutionalized construction of EA systems. The implementation of these two major policies provides clear institutional change nodes for this study.

Data sources include: (1) GAD-related indicators from the China Agricultural Statistical Yearbook, China Rural Statistical Yearbook, China Environmental Statistics Annual Report, and the National Bureau of Statistics database; (2) DT indicators using the Digital Financial Inclusion Index (PKU-DFIIC) released by the Digital Finance Research Center of Peking University, which covers digital finance development in 31 provinces nationwide from 2011 to 2023; (3) VCI data based on China's Input-Output Tables (2012, 2015, 2017, 2020 editions) published by the National Bureau of Statistics, with interpolation methods used to complete data for intermediate years; (4) EA data sourced from the China Audit Yearbook and audit announcements publicly released by provincial audit departments. Through multi-source data matching and cleaning, 341 valid observations were ultimately obtained, constructing a complete balanced panel dataset.

3.2. Variable Measurement

Table 1 provides detailed presentation of definitions, measurement methods, and data sources for all variables involved in this study. The construction of the variable system follows the principle of combining theoretical drive with data availability, ensuring that each variable both accurately reflects theoretical concepts and possesses good operability and comparability. The measurement of core explanatory and dependent variables adopts internationally recognized composite indicator methods, while the selection of control variables is based on widely validated influencing factors in existing literature to maximize control of potential omitted variable bias.

Table 1. Variable Definitions and Measurements.

Variable	Symbol	Measurement Method	Data Source
Green Agricultural Development	GAD	Composite index using entropy method with 5 dimensions: (1) Agricultural carbon productivity = Agricultural output value (10^8 CNY)/Agricultural carbon emissions (10^4 tons CO_2), where agricultural carbon emissions are calculated using the emission coefficient method: $ACE = \sum (Input_i \times Coefficient_i)$, encompassing chemical fertilizer, pesticide, plastic film, and diesel consumption weighted by emission coefficients aligned with IPCC guidelines and China's agricultural carbon accounting standards; (2) Chemical fertilizer efficiency = Agricultural output value/Fertilizer consumption (10^4 tons); (3) Pesticide efficiency = Agricultural output value/Pesticide usage (10^4 tons); (4) Water resource efficiency = Agricultural output value/Agricultural water consumption (10^8 m^3); (5) Agricultural waste recycling rate (%)	China Agricultural Statistical Yearbook, China Environmental Statistical Yearbook, China Environmental Statistics Annual Report, Provincial Environmental Statistical Reports, and IPCC/national agricultural carbon accounting guidelines
Digital Transformation	DT	PKU Digital Financial Inclusion Index (0–100 scale), comprising: (1) Coverage breadth sub-index; (2) Usage depth sub-index; (3) Digitalization level sub-index. The index is based on transaction data from Ant Group covering payment, credit, insurance, investment and other financial services	Peking University Digital Finance Research Center Database
Value Chain Integration	VCI	Forward and backward linkage coefficients calculated from Input-Output Tables: $VCI = 0.5 \times (FL_i + BL_i)$ where $FL_i = \sum_{j=1}^{n} a_{ij}/\bar{a}$ (forward linkage), $BL_i = \sum_{i=1}^{n} a_{ij}/\bar{a}$ (backward linkage), a_{ij} represents direct consumption coefficien, $\bar{a}$ is the average of all coefficients	China Input-Output Table (2012, 2015, 2017, 2020)
Environmental Audit	EA	Provincial environmental audit intensity = Number of environmental audit cases/Provincial area (10^4 km^2). Cases include natural resource audits, environmental protection fund audits, and ecological project audits	China Audit Yearbook, Provincial Audit Reports
Economic Development	lnGDP	Natural logarithm of real per capita GDP (2013 constant prices, CNY)	China Statistical Yearbook
Urbanization Rate	URB	Urban population/Total population × 100 (%)	China Statistical Yearbook
Industrial Structure	IND	Secondary industry value added/GDP × 100 (%)	China Statistical Yearbook
Agricultural Investment	AINV	Agricultural fixed asset investment/Total fixed asset investment × 100 (%)	China Fixed Asset Investment Statistical Yearbook
Education Level	EDU	Average years of schooling = Σ(Population at education level i × Years of education i)/Total population aged 6+	China Education Statistical Yearbook

Table 1. *Cont.*

Variable	Symbol	Measurement Method	Data Source
Agricultural Scale	SCALE	Average cultivated area per agricultural labor force (hectares/person)	China Rural Statistical Yearbook
Government Support	GOV	Agricultural fiscal expenditure/Total fiscal expenditure × 100 (%)	China Financial Statistical Yearbook
Agricultural Green Total Factor Productivity	GTFP	Estimated using the DEA-Malmquist productivity index with agricultural output value (10^8 CNY) as the desired output and agricultural carbon emissions (10^4 tons CO_2) as the undesired output. Inputs include labor, capital, fertilizer, pesticide, water, and land use. GTFP measures productivity growth while accounting for environmental degradation, where values greater than 1 indicate green productivity improvement.	China Agricultural Statistical Yearbook, China Rural Statistical Yearbook, China Environmental Statistics Annual Report

As shown in **Table 1**, the Green Agricultural Development (GAD) index serves as the dependent variable, employing the entropy method to comprehensively measure five dimensions. These five dimensions comprehensively assess the environmental efficiency of agricultural production from perspectives of carbon emissions, fertilizer use, pesticide use, water resource consumption, and waste recycling. The advantage of the entropy method lies in its ability to objectively determine weights based on the degree of data dispersion itself, avoiding bias that may result from subjective weighting. The Digital Transformation (DT) variable adopts the Peking University Digital Financial Inclusion Index, which is compiled based on massive transaction data from Ant Group, covering three dimensions of coverage breadth, usage depth, and digitalization degree with 33 specific indicators, representing the most authoritative and comprehensive measurement indicator of digital finance development in China. The Value Chain Integration (VCI) variable is derived by calculating the average of forward and backward linkage coefficients, accurately reflecting the degree of embedding and intensity of economic and technological connections of the agricultural sector within the entire industrial system. The Environmental Audit (EA) variable is measured by the number of environmental audit cases per unit area, considering both the absolute quantity of audit activities and eliminating the impact of provincial scale differences through area standardization. The selection of control variables is based on classical practices in existing literature, covering multiple dimensions including economic development level, urbanization process, industrial structure, agricultural investment, human capital, production scale, and government support, ensuring the robustness and reliability of model estimation.

3.3. Econometric Models

To systematically examine the impact mechanism of DT on GAD, this study constructs an econometric model system encompassing direct effects, mediating effects, and moderating effects.

First, a baseline regression model is constructed to test Hypothesis 1:

$$GAD_{it} = \beta_0 + \beta_1 DT_{it} + \sum_{k=1}^{K} \beta_k Control_{kit} + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

Where i represents province, t represents year, $Control_{kit}$ is the set of control variables, μ_i is province fixed effects, λ_t is year fixed effects, and ε_{it} is the random disturbance term.

Second, the stepwise testing method by Baron and Kenny (1986) and the Sobel test are employed to verify the mediating effect of VCI (Hypothesis 2):

$$VCI_{it} = \alpha_0 + \alpha_1 DT_{it} + \sum_{k=1}^{K} \alpha_k \, Control_{\,kit} + \mu_i + \lambda_t + \varepsilon_{it} \tag{2}$$

$$GAD_{it} = \gamma_0 + \gamma_1 DT_{it} + \gamma_2 VCI_{it} + \sum_{k=1}^{K} \gamma_k Control_{kit} + \mu_i + \lambda_i + \varepsilon_{it} \tag{3}$$

The magnitude of the mediating effect is $\alpha_1 \times \gamma_2$, with the Bootstrap method (1000 repeated samples) used to construct confidence intervals for significance testing.

Finally, a moderating effect model is constructed to test Hypothesis 3:

$$GAD_{it} = \delta_0 + \delta_1 DT_{it} + \delta_2 EA_{it} + \delta_3 (DT \times EA)it + \sum k = 1^K \delta_k Control_{ixt} + \mu_i + \lambda_i + \varepsilon_{it} \quad (4)$$

To avoid multicollinearity problems, the interaction term is centered:

$$(DT \times EA)it = (DTit - \overline{DT}) \times (EA_{it} - \overline{EA}).$$

Considering potential endogeneity issues, the following strategies are employed for treatment: (1) adopting the System Generalized Method of Moments (GMM) to address endogeneity in dynamic panel models; (2) using provincial-level clustered robust standard errors to address potential heteroskedasticity and serial correlation problems. For robustness checks, we employ an alternative specification using agricultural green total factor productivity (GTFP) as the dependent variable in place of GAD. In this specification, we adopt two-way fixed effects (TWFE) estimation with province and year fixed effects to maintain consistency with the baseline model framework.

4. Results

4.1. Descriptive Statistics

Table 2 reports descriptive statistics for the main variables. The GAD index has a mean of 42.68 and standard deviation of 15.23, indicating substantial differences in GAD levels across Chinese provinces. From a temporal perspective, GAD increased from 35.42 in 2013 to 51.36 in 2023, with an average annual growth rate of 3.8%, reflecting positive progress in China's agricultural green transformation. The DT index has a mean of 48.75, with minimum and maximum values of 8.92 and 89.67 respectively, showing even more significant inter-provincial differences, with eastern coastal provinces' digitalization levels significantly higher than those in central and western regions. The VCI degree has a mean of 0.782, indicating that the connection between the agricultural sector and other industries requires further enhancement. The EA intensity has a mean of 2.34 and shows an increasing trend year by year, reflecting the government's continuously strengthening emphasis on environmental governance.

Table 2. Descriptive Statistics.

Variable	Obs	Mean	Std.Dev	Min	Max	P25	P50	P75
GAD	341	42.68	15.23	12.35	78.92	31.24	41.58	53.67
DT	341	48.75	21.34	8.92	89.67	32.16	47.83	64.29
VCI	341	0.782	0.156	0.423	1.234	0.678	0.775	0.891
EA	341	2.34	1.87	0.12	8.95	0.98	1.95	3.42
lnGDP	341	10.82	0.43	9.87	11.96	10.51	10.79	11.12
URB	341	58.42	12.67	35.28	89.60	48.95	57.83	66.74
IND	341	41.23	8.45	19.76	58.94	35.68	41.92	47.31
AINV	341	3.45	1.92	0.87	9.84	2.13	3.21	4.56
EDU	341	9.23	1.34	6.82	12.87	8.34	9.15	10.08
SCALE	341	0.68	0.42	0.21	2.35	0.41	0.59	0.84
GOV	341	10.34	3.21	4.56	19.87	8.12	9.98	12.34

From a temporal dimension (see **Figure 2**), the main variables all exhibit upward trends but with different growth rates. The DT index grows most rapidly, with an average annual growth rate of 9.3%, reflecting the rapid development of China's digital economy. The GAD index steadily improves with an average annual growth of 3.8%, indicating that although agricultural green transformation has made progress, acceleration is still needed. The improvement in VCI and EA intensity is relatively moderate, suggesting considerable room for improvement in industrial integration and environmental regulation. This differentiated growth pattern provides favorable identification conditions for studying DT driving GAD.

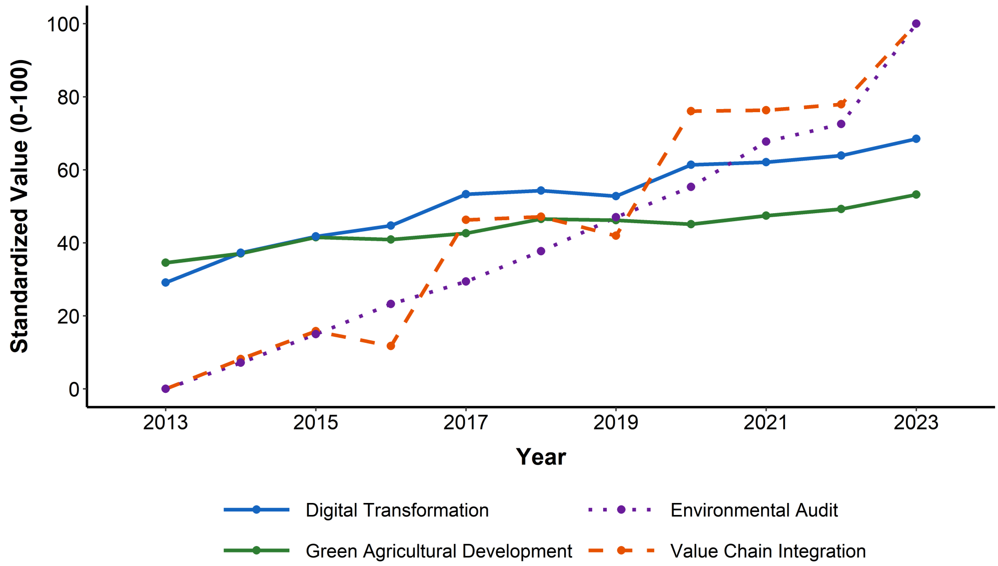

Figure 2. Time Trends of Main Variables.

Note: To facilitate comparison of variables with different dimensions, all variables are standardized to the 0–100 interval.

4.2. Direct Effects Results

Model specification tests show that the Hausman test results (χ^2 = 45.32, p < 0.01) strongly reject the random effects hypothesis, supporting the choice of fixed effects models. Variance Inflation Factor (VIF) tests indicate that all variables have VIF values below 5, confirming no serious multicollinearity problems. **Table 3** presents the baseline regression results of DT's impact on GAD. Column (1) includes only the core explanatory variable, with the DT coefficient of 0.324 (p < 0.01), indicating that DT significantly promotes GAD. As control variables are gradually added (columns 2–4), the coefficient slightly decreases but remains highly significant, finally stabilizing around 0.298. Column (5) shows 2SLS estimation using first-lagged DT as an instrumental variable, with a coefficient of 0.386, higher than the Ordinary Least Squares (OLS) estimate, suggesting that potential endogeneity bias led to underestimation. The first-stage F-statistic of 45.67 far exceeds the empirical critical value of 10, confirming the validity of the instrumental variable.

Table 3. Direct Effect Regression Results.

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5) IV-2SLS**
DT	0.324*** (0.045)	0.312*** (0.043)	0.305*** (0.042)	0.298*** (0.041)	0.386*** (0.058)
lnGDP		4.567*** (1.234)	4.423*** (1.198)	4.386*** (1.176)	4.298*** (1.213)
URB		0.087 (0.056)	0.092 (0.055)	0.095* (0.054)	0.089 (0.057)
IND			−0.234*** (0.078)	−0.228*** (0.076)	−0.242*** (0.081)
AINV			0.456** (0.198)	0.442** (0.195)	0.468** (0.203)
EDU				1.234*** (0.342)	1.187*** (0.356)
SCALE				2.876** (1.234)	2.798** (1.267)
GOV				0.542*** (0.167)	0.556*** (0.172)
Constant	23.45*** (2.34)	−21.34** (9.87)	−19.87** (9.56)	−24.56*** (9.23)	−26.78*** (9.67)

Table 3. *Cont.*

Variables	(1)	(2)	(3)	(4)	(5) IV-2SLS
Province FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	341	341	341	341	341
R-squared	0.612	0.634	0.647	0.668	0.659
First-stage F					45.67

Note: Figures in parentheses are clustered robust standard errors; ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

The estimation results for control variables conform to theoretical expectations. The coefficient of economic development level (lnGDP) is significantly positive, indicating that economic development provides a material foundation for agricultural green transformation. Education level (EDU) and agricultural scale degree (SCALE) both significantly promote GAD, reflecting the important roles of human capital and economies of scale. The positive impact of government support (GOV) highlights the guiding role of fiscal policy. The coefficient of industrial proportion (IND) is negative, possibly reflecting the crowding-out effect of industrialization on agricultural resources.

4.3. Mediation Effect Results

Table 4 presents the mediation effect test results for VCI. Column (1) indicates that DT significantly enhances agricultural VCI levels, with a DT coefficient of 0.0042 ($p < 0.01$). Column (2) includes both DT and VCI simultaneously, showing that the direct effect of DT decreases to 0.216 but remains significant, while the VCI coefficient reaches 18.762 ($p < 0.01$), confirming the partial mediating role of VCI. The Sobel test Z-value is 3.876 ($p < 0.01$), and the 95% confidence interval constructed by the Bootstrap method is [0.042, 0.126], which does not include zero, further verifying the statistical significance of the mediation effect. Calculations show that the mediation effect accounts for 27.5% of the total effect, indicating that DT has an important impact on GAD through the pathway of promoting VCI.

4.4. Moderating Effect Results

The test results for EA's moderating role are shown in **Table 5**. The interaction term DT×EA coefficient is 0.087 ($p < 0.05$), confirming the positive moderating effect of EA on DT effects. Group regression results more clearly demonstrate this moderating effect: the DT coefficient in the high EA intensity group reaches 0.468, the medium intensity group shows 0.312, and the low intensity group only 0.187, presenting a clear gradient decline pattern. This indicates that strict environmental regulation can strengthen the green empowerment effect of digital technology, prompting enterprises to more fully utilize digital means to achieve green transformation.

Table 4. Mediation Effect Test Results.

Variables	(1) VCI	(2) GAD
DT	0.0042***	0.216***
	(0.0008)	(0.039)
VCI		18.762***
		(4.234)
Control Variables	Yes	Yes
Province FE	Yes	Yes
Year FE	Yes	Yes
Observations	341	341
R-squared	0.542	0.698
Sobel Test Z-value		3.876***
Bootstrap 95% CI		[0.042, 0.126]
Mediation Effect		0.079***
Proportion of Mediation		27.5%

Note: *** indicates significance at the 1%.

Table 5. Moderation Effect Test Results.

Variables	(1) Full Sample	(2) High EA	(3) Medium EA	(4) Low EA
DT	0.289***	0.468***	0.312***	0.187**
	(0.042)	(0.067)	(0.051)	(0.089)
EA	2.345***			
	(0.567)			
DT×EA	0.087**			
	(0.034)			
Control Variables	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	341	114	113	114
R-squared	0.687	0.712	0.668	0.634

Note: *** and ** indicate significance at the 1% and 5% levels, respectively.

Figure 3 further reveals the economic significance of the moderating effect. As shown in the figure, when DT levels are low (DT < 30), the differences in GAD under different EA intensities are relatively small; however, as digitalization levels increase, these differences gradually expand. When DT reaches 80, GAD values in high EA regions are approximately 17 units higher than in low EA regions, equivalent to 40% of the average level. This "scissors gap" phenomenon indicates that EA's moderating role has cumulative and amplifying characteristics—the higher the digitalization degree in a region, the more pronounced the enhancing effect of EA. Additionally, all three regression lines maintain positive slopes and do not intersect, indicating that even under low EA intensity, DT can still promote GAD, but supporting strict environmental regulation will significantly enhance the realization of this effect.

4.5. Robustness Tests

Table 6 summarizes multiple robustness test results. We employ principal component analysis to reconstruct the dependent variable, adopt System GMM estimation to address endogeneity concerns, replace the core explanatory variables with alternative measures of digital transformation, and replace the dependent variable with agricultural green total factor productivity estimated via two-way fixed effects (TWFE). The core conclusions remain robust across all specifications. The AR(2) test (p = 0.342) and Hansen test (p = 0.456) for System GMM estimation both pass, confirming the reasonableness of model specification.

To further verify the authenticity of causal relationships, this study implements placebo tests. Specifically, keeping other variables unchanged, the DT data of 31 provinces are randomly shuffled and the model is re-estimated, repeating this process 1000 times. **Figure 4** shows the distribution of these 1000 "pseudo" regression coefficients. Three key characteristics can be clearly observed from the figure: First, placebo coefficients present a standard normal distribution with a mean of 0.003, close to zero, indicating that randomization treatment successfully eliminates systematic associations; Second, only 42 coefficients (4.2%) are significant at the 10% level, lower than the statistical expectation of 10%, and these significant coefficients are randomly distributed on both positive and negative sides; Finally and most importantly, the true estimated value of 0.298 is located at the extreme right end of the distribution, far exceeding the 99.5th percentile, with an occurrence probability close to zero. This extreme position powerfully demonstrates that DT's promotional effect on GAD is not caused by data mining or chance factors, but reflects a true causal relationship. The blue dashed normal distribution curve overlay further verifies the effectiveness of randomization, providing strong support for the internal validity of research conclusions.

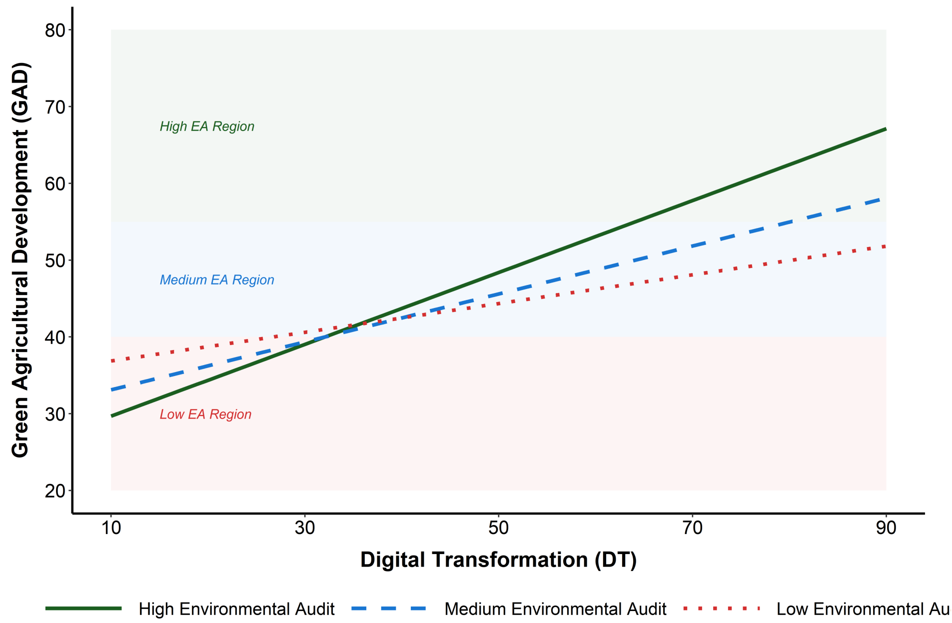

Figure 3. Moderating Effect of Environmental Audit.

Note: High, medium, and low EA intensities are divided based on sample mean plus or minus one standard deviation.

Table 6. Robustness Test Results.

Test Method	DT Coefficient	VCI Mediation	DT×EA Interaction	Observations	Notes
(1) PCA for GAD	0.316*** (0.044)	0.082*** (0.021)	0.091** (0.038)	341	Alternative GAD measurement
(2) System GMM	0.342*** (0.051)	0.086*** (0.023)	0.094** (0.041)	341	AR(2): p = 0.342; Hansen: p = 0.456
(3) Alternative DT Measure	0.453*** (0.087)	0.112*** (0.034)	0.126** (0.052)	341	Internet penetration rate
(4) TWFE with Agricultural Green TFP	0.298*** (0.045)	0.075*** (0.022)	0.088** (0.039)	341	Dependent variable: agricultural green TFP

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are reported in parentheses. AR(2) and Hansen tests are specification tests for System GMM estimation. Agricultural green TFP is estimated using the DEA-Malmquist index.

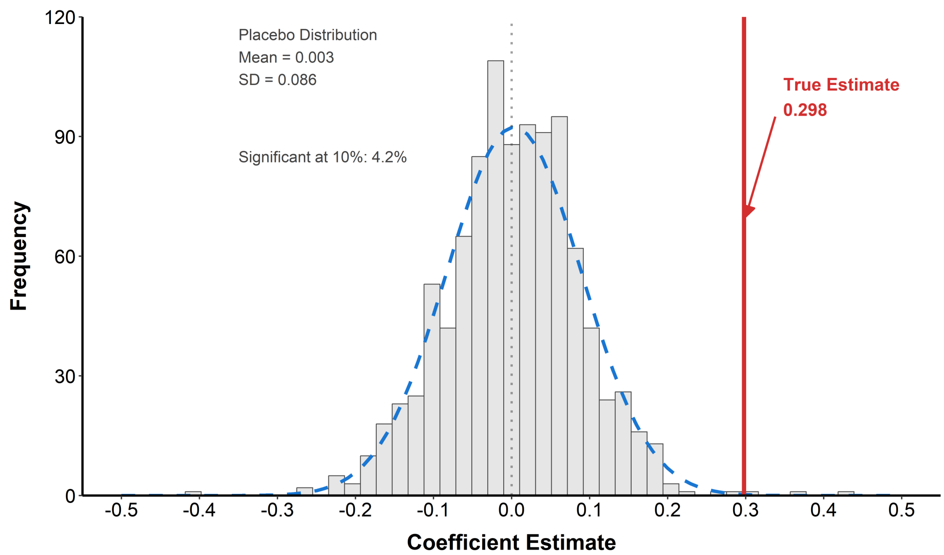

Figure 4. Distribution of Placebo Test Results.

Note: Based on 1000 random permutation tests. Gray histogram shows coefficient distribution after randomization, blue dashed line is the fitted normal distribution curve, red solid line marks the true estimated value (0.298).

5. Discussion

5.1. Research Contributions and Theoretical Implications

This study makes significant contributions to understanding agricultural sustainable transformation in the digital economy era. Theoretically, the research constructs a comprehensive framework revealing how digital transformation promotes green agricultural development through value chain integration mechanisms moderated by environmental audit intensity. The direct effect coefficient of 0.298 demonstrates digital technology's potential as a General Purpose Technology (GPT) for agricultural systems, involving systematic reconstruction rather than simple technological substitution. This advances agricultural economics beyond traditional production efficiency focus to incorporate environmental and social dimensions into multi-objective optimization models [37].

The mediating role of value chain integration provides new insights into how digital platforms break traditional agricultural value chains' linear structure and information asymmetry, enabling ecological agricultural products' true value realization in markets [38]. Digital platforms create market forces driving industrial chain greening through demand transmission from consumption end. Research shows digitalization-enabled transparency and traceability systems effectively correct market failures in valuing ecological products [39], particularly important for China's smallholder-dominated agriculture.

The positive moderating effect of environmental audit validates that digital technology's environmental impact depends on users' objectives and constraints. Strict environmental regulation guides enterprises toward pollution reduction and resource efficiency improvement by changing cost-benefit structures. This echoes recent findings that sustainable agricultural transformation requires government intervention beyond market mechanisms to correct externalities [40,41].

Practically, this research provides empirical evidence for policy formulation. China's Sustainable Agricultural Development Plan achieved positive results through comprehensive technology promotion, fiscal support, and institutional innovation, with obvious effects in major grain-producing and cotton-producing regions [42]. The regional heterogeneity reflects differences in resource endowments and implementation capabilities, informing differentiated policy design.

5.2. Policy Recommendations

Based on the research findings, this study proposes specific, actionable recommendations for different stakeholders.

For Government Agencies: Establish provincial-level digital agriculture development funds with annual budgets of at least 2% of agricultural GDP. Create integrated digital infrastructure covering broadband connectivity, IoT networks, and data centers in rural areas. Eastern provinces should invest in AI and precision agriculture technologies, while central and western regions should prioritize basic digital infrastructure and farmer digital literacy programs. Strengthen environmental audit systems by increasing audit frequency from annual to bi-annual reviews and establishing real-time monitoring systems using satellite data and IoT sensors. Implement tax incentives (15–20% reduction) for enterprises adopting certified green digital technologies.

For Agricultural Enterprises: Invest minimum 5% of annual revenue in digital transformation, focusing on integrated platforms combining financial services, supply chain management, and environmental monitoring. Establish "company + farmers" partnerships with at least 100 smallholder farmers per enterprise, providing free digital training and technical support. Implement blockchain-based traceability systems covering seed-to-consumer tracking within 24 months. Leading enterprises should create technology demonstration bases showcasing digital precision agriculture techniques and providing hands-on training for 500+ farmers annually.

For Financial Institutions: Develop specialized agricultural digital financial products including mobile payment systems with transaction fees below 0.5%, online credit services with approval times under 48 hours, and crop insurance products covering climate risks. Establish agricultural credit scoring systems using satellite data, IoT sensors, and transaction histories. Create value chain financing platforms supporting green certification and environmental compliance, offering 2–3% interest rate reductions for verified sustainable practices.

For Farmers and Cooperatives: Form cooperatives with minimum 50 members to achieve economies of scale for digital technology adoption. Participate in certified digital literacy programs (40+ hours annually) covering precision agriculture, financial services, and environmental monitoring. Adopt precision fertilizer and pesticide application systems reducing input use by 20–30% while maintaining yields. Implement soil health monitoring using digital tools and maintain electronic records for environmental audit compliance.

5.3. Research Limitations and Future Directions

Despite making important contributions, this study has certain limitations, which also point to important directions for future research. While provincial-level macro data can reveal overall trends, it is difficult to capture behavioral differences and decision-making processes of micro-level entities such as individual farmers and enterprises. The aggregated nature of provincial data may obscure important heterogeneity within regions and among different types of agricultural producers. This limitation suggests that future research should combine macro-level analysis with micro-surveys and case studies to provide more comprehensive insights into digital transformation mechanisms. Additionally, although the ten-year observation period (2013–2023) covers a critical period of China's digital agriculture development, it may still be insufficient for evaluating the long-term impacts of digitalization as an emerging and rapidly evolving phenomenon, as the full environmental and economic effects of digital transformation may require decades to fully manifest and be accurately measured.

The measurement of digital transformation relies primarily on the Digital Financial Inclusion Index, which focuses on the digitalization of financial services and may not fully capture other dimensions of agricultural digitalization, such as precision agriculture technologies, Internet of Things (IoT) applications, and artificial intelligence-driven decision support systems. However, this measurement choice has its rationality: first, in the Chinese context, digital finance serves as the infrastructure for agricultural digitalization, with farmers typically accessing digital services through financial platforms; second, the Peking University Digital Financial Inclusion Index, based on actual transaction records of over 200 million users, provides comprehensive and reliable provincial panel data. Most importantly, the robustness test using internet penetration rate as an alternative indicator yielded consistent results (coefficient = 0.453, $p < 0.01$). This measurement limitation may underestimate the full scope of digital transformation impacts but does not compromise the validity of the identified relationships. Meanwhile, this study's focus on the Chinese experience may limit the generalizability of the findings to other countries with different institutional frameworks, development stages, and agricultural systems.

Based on these limitations, future research should deepen in several key directions. Solutions require industry-academia-research collaboration, core technology development, and interdisciplinary talent cultivation. Bibliometric analysis shows that sustainable agriculture research exhibits a trend of interdisciplinary integration, requiring further integration of theories and methods from agronomy, ecology, information science, and social sciences [43]. The relationship between digital transformation and green agricultural development will continue to deepen through technological progress and institutional evolution, with next-generation technologies including blockchain, artificial intelligence, and digital twins enhancing agricultural precision and sustainability. However, technological deepening also brings challenges including data security, privacy protection, and technological monopoly, requiring improved governance mechanisms. Eastern developed regions should focus on frontier technology applications of artificial intelligence and IoT in precision agriculture, while central and western regions should prioritize popularizing digital infrastructure to narrow the digital divides.

Future research should particularly focus on technology integration mechanisms, institutional framework optimization, and cross-regional comparative studies. The digital era provides new tools for measuring environmental impacts, identifying sustainability constraints, and designing policy interventions through big data and artificial intelligence technologies. Special attention should be paid to scaling up successful pilot projects, measuring long-term environmental impacts, and developing inclusive digital transformation models that benefit all agricultural stakeholders. Digital and green transformation practices in different countries provide useful references, with successful models offering lessons for other developing countries. Through systematic cross-national comparisons and long-term tracking studies, it is possible to better understand the universal patterns and contextual factors of digital transformation in promoting sustainable agricultural development.

6. Conclusion

Through empirical analysis of Chinese provincial panel data from 2013 to 2023, this study confirms the positive impact of DT on GAD and finds that this impact is strengthened through VCI while being significantly moderated by EA intensity. Research results indicate that the application of digital technology in agriculture is not simply tool substitution but promotes the transformation of agricultural production toward environmentally friendly directions by reshaping industrial organizational forms and optimizing resource allocation mechanisms. The partial mediating role of VCI indicates that digital platforms connecting dispersed agricultural producers with markets not only improve transaction efficiency but also create favorable conditions for promoting green production standards. The positive moderating effect of EA reminds us that technological progress needs to be combined with institutional innovation to fully realize its green empowerment potential. These findings are significant for China in coordinating economic growth and environmental protection while advancing agricultural modernization and also provide experience for other developing countries exploring sustainable agricultural development paths.

Of course, this study still has areas that need improvement. Provincial macro data, while revealing overall trends, have difficulty capturing behavioral differences and decision-making processes of micro entities. The ten-year observation period may not be sufficient for evaluating the long-term impacts of digitalization, an emerging phenomenon. Future research can deepen these findings through more granular data and longer time series. Additionally, as new technologies such as AI and blockchain continue to deepen their applications in agriculture, the relationship between digitalization and green agriculture may present new characteristics and patterns, providing broad space for subsequent research. Overall, in the era of rapid digital economy development and deep advancement of ecological civilization construction, how to fully realize the green potential of digital technology and construct sustainable agricultural production systems remains an important topic worthy of continued exploration.

Author Contributions

Conceptualization, D.W. and G.H.; methodology, D.W.; software, D.W.; validation, D.W., O.R.S. and G.H.; formal analysis, D.W.; investigation, D.W.; resources, G.H.; data curation, D.W.; writing—original draft preparation, D.W.; writing—review and editing, O.R.S. and G.H.; visualization, D.W.; supervision, G.H.; project administration, G.H.; funding acquisition, G.H. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

The data supporting this study are publicly available from national statistical yearbooks and databases, including the China Agricultural Statistical Yearbook, China Rural Statistical Yearbook, China Environmental Statistics Annual Report, the National Bureau of Statistics database, the China Audit Yearbook, and the PKU Digital Financial Inclusion Index (DFIIC). Processed panel datasets and code used for analysis are available from the corresponding author upon reasonable request.

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Conflicts of Interest

The authors declare no conflict of interest.

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