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Assessing the Impacts of New Quality Productivity on Sustainable Agriculture: Structural Mechanisms and Optimization Strategies—Empirical Evidence from China

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Abstract: New quality productivity (N) in China is examined as a key driver for enhancing innovation and promoting sustainable development, with a focus on its structural framework in agriculture across three primary dimensions: New Quality Agricultural Laborers (NQL), New Quality Agricultural Labor Inputs (NQLI), and New Quality Agricultural Production Inputs (NQPI). This study aims to explore the relationship between new quality productivity and sustainable agriculture in China, analyzing its impact mechanisms and optimization strategies using data from 30 provincial-level regions between 2012 and 2021. Initially, Partial Least Squares Structural Equation Modeling (PLS-SEM) is employed to identify the specific structural relationships influencing NQP. The Outer Loadings TOPSIS (OL-TOPSIS) method quantifies the contributions of each construct in NQP research across China's agricultural functional zones. The combined IPMA (cIPMA) model is developed to analyze the necessary conditions, thereby formulating specific optimization strategies. The results indicate that, within the structural framework, the overall NQP construct indicators have a significant impact on promoting sustainable agricultural development. Furthermore, locational analysis reveals that each region exhibits a trend of stability and continuous optimization. In the necessity analysis, both NQL (0.378) and NQLI (0.329) meet the required conditions, and NQPI (0.143) does not satisfy the necessity conditions, necessitating prioritized actions.

Keywords: new quality productivity; sustainable agriculture; PLS-SEM; cIPMA

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1. Introduction

Agriculture, as the foundational industry of the national economy, directly impacts global food security and ecological safety through its sustainable development capabilities. However, against the backdrop of tightening global resource constraints and increasing climate change, the traditional agricultural growth model, which relies on resource consumption and extensive growth, has triggered systemic crises such as land degradation, water resource shortages, and the decline of ecological service functions. According to the Food and Agriculture Organization (FAO) of the United Nations, approximately 33% of global soils have experienced moderate to severe degradation, and agricultural water use accounts for more than 70% of freshwater consumption. This resource-exhausting development model not only accelerates ecological deterioration but also seriously threatens the sustainability of food production. Promoting agricultural transformation and

achieving sustainable development have become urgent global issues that the international community must address. Authoritative institutions like the FAO have clearly stated that promoting sustainable agricultural development is key to addressing global challenges such as climate change, resource shortages, and ensuring food security [1]. In addition, the United Nations 2030 Agenda for Sustainable Development (SDGs) has explicitly set "ending hunger", "sustainable use of natural resources", and "addressing climate change" as core goals [2]. Against this background, developed countries like the United States and the Netherlands have significantly improved agricultural productivity and reduced environmental costs through precision agriculture, smart farming machinery, and big data analysis. For instance, the Netherlands has adopted a "smart agriculture" model, which has reduced water usage by 50% while doubling the yield per unit area [3]. The international academic community has also conducted extensive research on sustainable agricultural development, focusing on technological innovation [4], policy mechanisms [5], and evaluation system construction [6], thereby providing theoretical support for global food security and ecological sustainability. However, there is still a significant imbalance in global agricultural development: data show that the gap in agricultural total factor productivity (TFP) between developing and developed countries continues to widen, with insufficient technology dissemination and resource allocation being key challenges that restrict sustainable agricultural development [7].

As the world's largest developing country and agricultural power, China's agriculture also faces severe constraints related to resources and the environment, ecological system vulnerability, and pressure from traditional growth models that are inadequate for modern transformation. In 2017, the Chinese government identified sustainable agricultural development as one of the core strategies for achieving rural revitalization and promoting high-quality economic growth [8]. Government documents clearly state that high-quality agricultural development is not only a critical cornerstone of China's rural revitalization strategy and the comprehensive building of a socialist modern country but also a key path for advancing rural revitalization, narrowing the urban-rural gap, and achieving common prosperity [9].

However, the existing theoretical frameworks still have limitations in explaining and guiding the practical development of sustainable agriculture in China. Traditional productivity theories focus excessively on factor inputs and output efficiency, making it difficult to fully capture the complexity of agricultural systems. International mainstream development economics theories are often based on the experiences of developed countries, assuming the presence of mature market mechanisms, abundant capital investment, and highly developed technological foundations. However, developing countries generally face the realities of imperfect market mechanisms, insufficient capital and technology investment, and limited resource endowments, making it difficult to directly apply theories centered on capital-intensive growth or technology-driven transformation from developed countries. Against this background, the proposal of new quality productivity (NQP) has provided a new engine for the high-quality development of China's agriculture [10]. In September 2023, General Secretary Xi Jinping emphasized during his inspection of Heilongjiang Province that "integrating technological innovation resources, leading the development of strategic emerging industries and future industries, and accelerating the formation of new quality productivity" is essential [11]. Through the deep integration and innovation of high technology, reshaping production processes, optimizing resource allocation, and stimulating business model innovation [12], NQP can effectively activate the internal development potential of agriculture, promote the efficient allocation and deep integration of production factors, drive agriculture toward more advanced forms, and contribute to high-quality, sustainable agricultural development [13,14]. Therefore,

conducting in-depth academic research on new quality productivity is not only helpful in filling the gaps in existing agricultural development theories but also provides innovative theoretical support for addressing the resource, technology, and ecological bottlenecks that China's agriculture faces during modernization. It also offers valuable experience for the sustainable transformation of agriculture in other developing countries and contributes to the global exploration of agricultural development paths.

Current academic research on new quality productivity mainly revolves around its conceptual definition [15], theoretical framework construction [16], and interdisciplinary applications. The focus is on exploring the specific forms and mechanisms of NQP in sectors such as agriculture [17], manufacturing [18], and services [19] and analyzing its performance in multidimensional contexts, such as digitalization, intelligence, and green sustainable development. However, research on the impact of new quality productivity in agriculture is still insufficient, particularly in terms of its influence structure on agricultural development. Therefore, how to scientifically assess the impact mechanism of new quality productivity on agricultural development, identify the key structural mechanisms, and propose effective optimization strategies is an urgent issue that needs to be addressed in both theory and practice.

This paper aims to explore the intrinsic relationship between New Quality Productivity and China's sustainable agricultural development, conducting a systematic analysis of the impact of new quality productivity on sustainable agriculture from the perspectives of structural mechanisms and optimization strategies. By studying the theoretical connotations of new quality productivity and its mechanisms in sustainable agricultural development, a logical framework for the role of new quality productivity in sustainable agriculture will be constructed, revealing its comprehensive impact on improving agricultural productivity and ecological environmental protection. At the same time, based on the development levels of new quality productivity in different agricultural functional zones, the spatial differentiation characteristics and formation mechanisms will be explored, leading to the proposal of optimization strategies to promote the development of new quality productivity and sustainable agriculture.

This paper is divided into six sections. Section 1 is the introduction, which presents the research background, objectives, and main issues. Section 2 is the literature review, which reviews existing research to provide theoretical support for this study. Section 3 focuses on hypothesis development, where research hypotheses are proposed based on the theoretical framework and literature. Section 4 details the data and research methods, including data sources and processing, as well as the specific steps for model construction. Section 5 presents the research results and discussion, evaluating the reliability and validity of the constructs, displaying the analysis results of the models used, and providing an in-depth discussion. Section 6 is the conclusion, summarizing the research findings, proposing policy recommendations, and highlighting the limitations of this study and directions for future research.

2. Literature Review

With the growth of the global population, the worsening of environmental issues, and the impacts of climate change, sustainable agricultural development has become a core issue of global concern. This issue has evolved from initial resource constraint theories to today's technology-driven and integrated sustainable development frameworks, achieving a transformation from a single production function to the reconstruction of the "production-ecology-livelihood" multidimensional value system [20,21]. Research on sustainable agricultural development in academia has gradually shown a multidimensional

and multi-field trend, covering various aspects ranging from technological innovation to socio-economic factors, policy environments, ecological services, and biodiversity.

Technological innovation is widely regarded as one of the core drivers of productivity improvement and sustainable development. Scholars generally agree that innovation-driven productivity not only relies on traditional inputs such as labor, capital, and resources but also emphasizes the role of non-material factors such as technology, knowledge, and institutions [22]. In the agricultural sector, the global application of technologies such as precision agriculture, digital agriculture, and smart farming has not only improved production efficiency and optimized resource allocation but also effectively reduced negative environmental impacts, significantly boosting agricultural productivity [23]. As important technical supports for precision agriculture, agricultural automation systems and the Internet of Things (IoT) have significantly improved agricultural production efficiency and resource utilization through the synergy of data collection and intelligent execution [24]. Singh et al. [4] pointed out that through sensor networks, intelligent control systems, and automated equipment, farmers can obtain real-time information on soil moisture, meteorological conditions, and crop growth, thereby effectively reducing the use of pesticides and fertilizers and mitigating environmental pollution. Wan S [25]'s research further demonstrated the practical application of IoT monitoring systems based on modular and edge computing in agriculture by designing a hydroponics planting system that enables the intelligent monitoring and precision management of water-plant integrated systems. Froiz-Míguez et al. developed an IoT-enabled intelligent irrigation system based on a Low Power Wide Area Network (LPWAN). This system uses LoRa and LoRaWAN sensor nodes to enable automated environmental monitoring and water resource management in large-scale agricultural scenarios while leveraging meteorological predictions to reduce water consumption by 23% [26]. Additionally, automated equipment, such as drones and smart agricultural machinery, can further reduce labor requirements, optimize operational processes, and help agriculture progress toward sustainability [27]. The Aggregated Farming in the Cloud (AFARCloud) project demonstrates the deep integration of Unmanned Aerial Systems (UAS) with the Farm Management System (FMS), enhancing big data processing and artificial intelligence-based decision support capabilities for precision agriculture through automated operations and connections with other cyber-physical systems [28].

In addition, deep learning technology has provided robust technical support for the advancement of precision agriculture and has gradually been applied across key areas, including pest and disease detection, plant health monitoring, yield and quality prediction, irrigation and fertilization optimization, and price forecasting [29]. These applications have significantly contributed to the intelligent and precise development of agricultural production chains. In crop monitoring, studies have shown that Convolutional Neural Networks (CNN) and their variants can automate disease detection and weed identification by efficiently analyzing remote sensing and high-resolution images, thereby greatly improving monitoring accuracy [30]. Mazzia further elaborated that R-CNN enhances the ability to locate and classify diseases through regional extraction, further strengthening disease monitoring capabilities [31]. In yield prediction, Long Short-Term Memory (LSTM) networks leverage their strength in handling non-linear time-series data to model relationships between crop yield and complex variables such as climate, soil conditions, and planting history. This capability allows LSTM to produce long-term trend predictions with improved robustness and accuracy [32,33]. In resource optimization, Generative Adversarial Networks (GANs) have been increasingly applied to climate change simulations and the generation of high-quality remote sensing data, providing ample data support for agricultural decision-making [34]. Additionally, autoencoders have significantly enhanced resource utilization efficiency in the development of precision fertilization and intelligent

irrigation strategies [35]. Overall, deep learning has effectively facilitated the coordinated upgrading of the entire agricultural production chain, injecting new momentum into sustainable agricultural development [36]. At the same time, the development of biotechnology, especially the breeding of drought-resistant and pest-resistant crop varieties, has also significantly enhanced the stability and sustainability of agricultural production [37]. Kim et al. [38] propose that breakthroughs in biotechnology, such as the development of genetically modified and drought-resistant crops, provide technological support for agriculture's adaptation to climate change and improvement of risk resistance.

The promotion and application of technological innovation cannot be separated from appropriate policy innovation and the optimization of institutional environments. Pe'er et al. [39] analyze and point out that government policies play a key role in promoting sustainable agricultural development. By implementing environmental protection laws, providing financial subsidies, and establishing environmental incentive mechanisms, governments can effectively encourage farmers to adopt sustainable agricultural practices. Pham et al. [5] emphasize that a well-developed institutional environment and favorable policies, such as clear land use rights and optimized market access mechanisms, are important drivers for promoting sustainable agricultural development in developing countries. Furthermore, Mazzucato's mission-oriented innovation theory [40] further strengthens the role of policies in driving the combination of technological innovation and ecological goals. Through targeted investment and technological guidance, policy innovation can accelerate agricultural modernization and promote the diffusion of technologies. Therefore, through the collaborative efforts of multiple factors, the integration of technology and policy provides a systematic governance framework for sustainable agricultural development [41].

In addition, there is abundant research focusing on socio-economic factors. Studies show that factors such as farmers' education levels, income structure, rural labor transfer, and the integration of agriculture with other industries help promote rural economic diversification, which in turn has a profound impact on sustainable agricultural development [42]. In this technology- and knowledge-intensive innovation model, farmer participation and improvements in education levels are crucial, especially in promoting farmers' participation in green agriculture and modern farming practices. Agricultural technology education and training can effectively facilitate the dual benefit of improving agricultural productivity and environmental protection [43,44]. At the same time, as consumers' demand for eco-friendly agricultural products continues to rise, market demand is gradually shifting toward sustainability goals, further promoting the dual optimization of ecological value and agricultural production efficiency and pushing agriculture to transition from traditional yield-oriented models to eco-friendly agricultural practices [45,46].

Since classical economics laid the foundation of productivity research with the theory of "division of labor" [47], the study of productivity has undergone multiple theoretical innovations, evolving from a focus on single-factor drivers to system-wide collaborative evolution [48]. Solow's (1956) Total Factor Productivity (TFP) theory established the position of technological progress as the core driving force of long-term economic growth, using "capital-labor-technology" as the main analytical framework for productivity accounting [49]. Subsequently, Arrow's (1962) "learning-by-doing" theory further revealed the important role of knowledge accumulation and dynamic learning effects in enhancing production efficiency, providing a more comprehensive perspective on the endogenous mechanisms of productivity [50]. With the progress of economics and technology, the marginal contributions of labor and capital have gradually shown diminishing returns, and technology, knowledge, and intangible assets have become central to the study of productivity. Romer (1990) [51] and Lucas (1988) [52] respectively proposed models of knowledge spillover and human capital, exploring the roles of knowledge, innovation,

and information technology in the leap in productivity. Brynjolfsson et al. further argue that the synergy of technology, knowledge, and intangible assets is a key driver of modern productivity growth [53]. Haskel and others have systematically reviewed the core contributions of intangible capital (such as intellectual property, brands, and research and development results) to productivity growth, noting that the growth path of modern productivity has shifted from traditional capital-intensive models to knowledge-intensive ones [54]. Scholars widely agree that innovation-driven productivity not only enhances technological efficiency but also holds vast potential for applications in reducing environmental load, optimizing resource utilization, and achieving sustainable development [55]. At the same time, against the backdrop of increasingly severe global climate change, productivity research has gradually integrated new perspectives on sustainable development and ecological economics. Stern's Green Total Factor Productivity (GTFP) and Rockström et al.'s planetary boundary theory refine the balance between ecological constraints and productivity development, promoting the deep integration of productivity research with sustainable development [56,57]. Institutional economics research has also revealed the core role of policy and institutional optimization in enhancing productivity. In recent years, Mazzucato has emphasized that governments can significantly promote the diffusion of frontier technologies and their alignment with social goals through policy guidance and public investment [40]. The integration and progress of theory have given rise to a multipolar development model: the United States relies on the "knowledge economy" to emphasize the driving role of technology-information linkage in productivity, while the European Union uses the "innovation-driven growth" framework to integrate sustainable development and digital transformation [58,59]. Based on its own unique development needs and background, China has inherited the ideas of knowledge spillover and green productivity within the theoretical framework. At the same time, it has developed a new productivity research framework, namely new quality productivity, through innovation-driven approaches, ecological linkage, and institutional optimization.

New Quality Productivity (NQP) is an important supplement to global productivity theory. Compared with traditional productivity, NQP is not only a simple superposition of technological progress; it also emphasizes promoting systematic reconstruction and structural transition of productivity through collaborative innovation of production factors, factor reorganization, and system optimization, representing a "qualitative leap" [60]. For example, traditional agricultural mechanization only achieves quantitative change by improving the efficiency of labor substitution, which falls under "productivity improvement". Unmanned farms achieve full-process independent decision-making through "intelligent agricultural machinery + digital twin" technology, which has given rise to all-factor digital reorganization, thus reconstructing the productivity operation paradigm and representing a qualitative leap. The "newness" of NQP is reflected in its ability to break through the single economic output orientation, emphasizing the dual shift toward value-added ecological services and enhancing social resilience and paying more attention to ecological and environmental protection, social welfare improvement, and the realization of a sustainable development path. It also reflects a transformation from simple economic quantitative growth to an improvement in development quality [61]. These characteristics make NQP particularly advantageous for addressing the needs of developing countries and the agricultural context, offering a novel academic path for the application of existing theories in the agricultural sector. Currently, research on NQP mainly focuses on conceptual definitions [12], logical framework discussions [15], and the construction of evaluation indicator frameworks [16]. Xie F [62] and others argue that NQP is not just a policy slogan. As an emerging concept, it breaks away from traditional economic growth methods and productivity development paths, emphasizing qualitative change and the systematic re-

construction of productivity elements [63,64]. Xu T [65] and others further point out that NQP has higher integration, innovation, and technological content, better aligning with the development requirements of modern productivity. Developing NQP contributes to achieving development goals, enhancing development momentum, improving development structure, expanding development content, and optimizing development elements, thereby empowering high-quality development [66].

As research continues to deepen, some scholars have begun to explore the application of NQP in agriculture. Relevant studies indicate that advancing the construction and application of high-quality NQP is an important prerequisite for achieving high-quality agricultural development and for accelerating the establishment of an agricultural powerhouse [67,68]. Li Yongbin and others [69] used a fixed-effects model to empirically test the positive impact of NQP on high-quality agricultural development and analyzed its mediation effects on agricultural production technology efficiency and moderation effects on agricultural insurance. Li Zicheng and others [17] used a spatial Durbin model and a panel threshold model to explore the driving mechanisms of NQP on high-quality agricultural development.

Methodologically, Partial Least Squares Structural Equation Modeling (PLS-SEM) is widely used in social science research for multivariate statistical analysis. PLS-SEM has become a powerful tool for exploring the relationships among latent variables due to its ability to handle complex models and its relatively low demand for sample size [70]. It proves particularly effective in analyzing structural mechanisms, as most existing PLS-SEM-based studies rely on cross-sectional data [71], typically obtained via surveys, and are applied extensively in fields such as sustainable agricultural development, technological innovation, and environmental management [72–74]. To investigate new quality productivity (NQP) based on sustainable agriculture, incorporating a time dimension can more effectively reveal the structural mechanisms among the constructs. For instance, Xu et al. innovatively employed panel data to construct path relations for digital agriculture, assessing the impacts of digital technologies on agricultural production efficiency and resource utilization [72]. In evaluating the level of NQP, one of the most frequently used methods is the Entropy Weight Method-TOPSIS (EWM-TOPSIS). Its chief advantage lies in the objective determination of indicator weights via the entropy weight method, thus avoiding potential biases associated with subjective weighting [75]. Xue Xuegong et al. systematically evaluated indicators of agricultural sustainability by dividing regions based on geographical location and quantifying multiple aspects, such as ecological balance, resource use efficiency, agricultural output, and socio-economic development for each region [76]. Additionally, Leite et al. evaluated sustainable agricultural development from the Environmental, Social, and Governance (ESG) perspective, highlighting the vital role of ESG factors in enhancing agricultural sustainability [77]. Huang et al. conducted a detailed measurement of the level of new quality productivity using the EWM-TOPSIS method, revealing the varying contributions of different productivity indicators to sustainable agricultural development [78]. Ma X et al. pioneered the use of panel data alongside factor loadings in a PLS-SEM model to measure forestry levels, identifying the key drivers and impact pathways in sustainable forestry development [79].

Widely used approaches for proposing policy recommendations include the Analytic Hierarchy Process (AHP), the Delphi Method, and Cost-Benefit Analysis (CBA) [80]. These methods are extensively applied in policymaking [81], environmental management [82], public health [83], and other fields. Among them, Importance–Performance Map Analysis (IPMA) is a multi-indicator assessment tool aimed at identifying areas needing priority improvement by evaluating the importance and current performance of each factor. IPMA is closely linked to Partial Least Squares Structural Equation Modeling (PLS-SEM) [84],

wherein PLS-SEM provides a robust statistical foundation for IPMA, enabling the handling of complex multivariate relationships and ensuring the reliability of the analysis results. Hauff et al. (2024) [85] proposed the Combined Importance–Performance Map Analysis (cIPMA), which integrates the traditional IPMA approach with necessary condition analysis (NCA). As an advanced model derived from IPMA, cIPMA currently represents the cutting edge; it conducts necessity analysis on top of the structural equation model, addressing the limitation that the vast majority of existing studies rely solely on sufficiency conditions. Thus, it can reveal inter-factor dependencies under specific conditions, enhancing both the explanatory power and practical value of the model.

This study, based on existing research [86], divides agricultural NQP into new quality laborers (NQL), New Quality Labor Inputs (NQLI), and new quality production inputs (NQPI) using PLS-SEM. Additionally, NQLI is further subdivided into two dimensions: agricultural technology and agricultural ecology, while NQPI is divided into tangible materials and intangible materials. This study attempts to construct their direct and indirect influence structures. Following the approach of Hamid et al. [87], who used outer loadings for horizontal measurement, this study integrates the outer loadings derived from PLS-SEM analysis with the TOPSIS model to analyze the NQP in agricultural functional zones. For optimization strategies, this study employs the cutting-edge social science method, cIPMA, for analysis.

The main innovations of this study are as follows:

1. Grounded in the basic connotations of new quality productivity from a historical materialist perspective, this paper categorizes agricultural new quality productivity from three angles—new quality laborers, new quality production inputs, and new quality labor inputs—thereby further refining its theoretical framework.
2. To gain deeper insights into the multifaceted mechanisms through which new quality productivity influences agricultural development, this study constructs a PLS-SEM system that reveals the relationships among new quality laborers, new quality production inputs, and new quality labor inputs, as well as their sufficiency conditions and overall structural impact on sustainable agricultural development.
3. Leveraging the characteristic of factor loadings within the structural equation model (SEM), this study integrates TOPSIS to conduct a locational analysis of agricultural functional regions, thus providing systematic empirical support for agricultural policymaking.
4. By introducing the advanced cIPMA model, this paper supplements the conventional analysis of each indicator's importance and performance in agricultural development with a necessity analysis. This addition clarifies optimization directions and priorities, effectively enhancing the specificity and efficacy of agricultural policy formulation.

3. Theoretical Analysis and Hypotheses

Since the theory related to sustainable agricultural new quality productivity (NQP) is still in an exploratory stage, the existing theoretical framework is not yet fully developed. Partial Least Squares Structural Equation Modeling (PLS-SEM) is a flexible multivariate statistical analysis method that does not rely on strict theoretical frameworks, making it suitable for analyzing the complex, multidimensional relationships in this study. PLS-SEM can help researchers identify and validate the relationships between key variables, even when the theory is not fully developed [88]. It is particularly appropriate for exploring the mechanisms through which new quality productivity influences sustainable agricultural development. This method not only handles complex multivariate relationships but also adapts to different types of datasets, providing reliable path coefficients and models with strong explanatory power, thereby offering foundational support for subsequent theoretical

refinement and empirical research [89]. Based on this, the following theoretical hypotheses are proposed in this paper:

Marxist productivity theory posits that productivity is "the development of production capacity and its elements" [90], which refers to humanity's ability to utilize and transform nature in the production process. Traditional productivity factor theory [91] holds that it generally includes three elements: laborers, labor materials, and labor objects. The physical and intellectual efforts of laborers, combined with labor materials and labor objects, form the foundation for the realization of productivity. NQP lies in productivity, and its "new" and "quality" characteristics impose higher requirements for high-quality development concerning laborers, labor materials, and labor objects, the three elements of productivity [92]. In the agricultural field, NQP can effectively promote the transformation of agriculture from "resource-dependent" to "innovation-value-added" through three-dimensional innovation involving factor reorganization, process optimization, and value reconstruction. For example, in the Yinchuan Smart Agriculture Demonstration Zone in Ningxia, in response to resource waste and inefficiency in traditional agricultural production models, the government-led wolfberry digital planting project has significantly improved the technical capabilities of workers by providing farmers with precision irrigation and smart equipment training. It also uses the Internet of Things and big data technology to optimize the allocation of water and fertilizer resources, improving crop quality and ecological benefits through drone monitoring and ecological management. This fully proves that NQP can disrupt the traditional agricultural "land-labor-capital" factor combination pattern through a non-linear transition of the productivity system. By integrating the decision support functions of digital agriculture with the efficient execution capabilities of automated systems, it can promote the deep embedding of data, knowledge, and ecological capital, using technological breakthroughs, organizational changes, and the synergy of institutional innovation to achieve simultaneous improvement of economic, ecological, and social values, thereby promoting the sustainable development of agriculture [10,93].

3.1. Impact of New Quality Agricultural Labor Inputs (NQLI) on Sustainable Agricultural Development and Agricultural Output

New Quality Agricultural Labor Inputs (NQLI) are defined as various new types of labor factors in the agricultural production process. Specifically, NQLI can be subdivided into agricultural ecology (ECO) and agricultural technology (TEC) [16].

New quality agricultural ecology focuses on enhancing ecological benefits and sustainable development, emphasizing the integrity of agricultural ecosystems and the optimization of ecosystem services. Its positive impact on sustainable agricultural development is mainly reflected in the optimization of the agricultural production environment, the reduction of resource waste, and the mitigation of environmental pollution, thus promoting sustainable agricultural development. Sustainable Agricultural Development (SUS) is a production model that balances the needs of present and future generations, aiming to enhance agricultural output while ensuring the stability of ecosystems and the sustainable use of resources. It guides agricultural production toward more intensive and intelligent directions, fundamentally improving both economic and ecological efficiencies in agriculture. Ecological protection measures, such as soil conservation and water resource management, not only maintain the stability of agricultural ecosystems but also enhance the long-term sustainability of agricultural production. According to ecosystem service theory, a healthy ecosystem can provide the necessary support and guarantees for agricultural production, thereby enhancing the capacity for sustainable agricultural development [94].

New quality agricultural technology emphasizes the core role of modern technology in production, especially through the promotion of digital, intelligent, and green technologies, making industrial technological innovation an important driving force for productivity

improvement. Its positive impact on promoting high-quality agricultural development is reflected in enhanced agricultural output. Agricultural Output Value Standards (AgrO) are important indicators for measuring agricultural production outcomes and economic benefits. To account for differences in labor input and avoid data bias caused by varying population sizes, this study exclusively uses AgrO, which is widely recognized in the existing literature as a key indicator for assessing agricultural economic efficiency [95]. Agricultural technology influences agricultural output through two main aspects: optimizing industrial structure and increasing labor productivity. On one hand, new quality technologies drive the transformation of agriculture from traditional models to high value-added and high-tech directions. The widespread adoption of technologies such as precision agriculture, biotechnology, and intelligent management systems not only enhances the efficiency of resource utilization in agriculture but also extends the industrial chain and adds value, enabling agriculture to integrate into the frameworks of the digital and green economies. This significantly boosts market competitiveness and economic benefits [96]. On the other hand, the introduction of intelligent equipment and automated systems reduces dependence on manual labor in traditional agricultural production, increases operational precision, and improves resource usage efficiency, directly enhancing labor output per unit. Additionally, the synergy between technological application and the upgrading of laborers' skills creates a virtuous cycle that not only drives short-term agricultural output growth but also lays a solid technical and human foundation for high-quality agricultural development [97].

Based on the reasoning above, the following hypotheses are proposed:

H1a: *Agricultural ecology has a significant positive impact on sustainable agricultural development.*

H1b: *Agricultural technology has a significant positive impact on Agricultural Output Value Standards.*

3.2. Impact of New Quality Agricultural Production Inputs (NQPI) on Sustainable Agricultural Development and Agricultural Output

New Quality Agricultural Production Inputs (NQPI) are defined as various new types of production factors used in the agricultural production process. Specifically, NQPI can be subdivided into intangible materials (IM) and tangible materials (TM) [16]. Building upon traditional material labor resources, it also encompasses modern technological achievements such as digital platforms and big data, driving the smart, automated, and digital transformation of the production process through the integration of both tangible and intangible elements, thereby achieving a qualitative change in productivity.

Intangible production inputs, as important factors in modern economies, are key elements promoting sustainable agricultural development. Compared to traditional tangible production inputs, new quality intangible materials focus on intangible assets such as knowledge, technology, and information. By driving agricultural technological innovation, optimizing resource allocation, and increasing industrial added value, they inject new vitality into the agricultural economy. More importantly, the application of intangible production inputs fosters an agricultural development model that harmonizes human activities with nature [98]. By integrating modern technology with traditional ecological concepts, such as promoting green agriculture and ecological circular agriculture models, farmers can better practice resource-efficient and environmentally friendly agricultural production methods, reducing the negative impact of agricultural production on natural ecosystems and achieving an organic unity of economic, social, and ecological benefits.

Tangible production inputs, on the other hand, significantly optimize the agricultural production structure through technological advancements, becoming a crucial driver of

efficient agricultural development [99]. For example, high-efficiency fertilizers and soil improvement technologies optimize the structure of soil nutrient supply, significantly enhancing soil fertility and stability, thereby creating favorable conditions for healthy crop growth and achieving a substantial increase in agricultural labor productivity. This greatly boosts per capita agricultural output value [100]. Additionally, by increasing investments in agricultural infrastructure and prioritizing the selection of modern, high value-added production materials, resource waste caused by traditional, low-efficiency, and high-energy-consuming equipment can be significantly reduced. This promotes the mechanization, intelligentization, and refinement of the production process, greatly increasing output per unit area [101]. Supported by efficient capital allocation, agricultural production costs are reduced, and output continues to rise, creating more opportunities for enhancing per capita agricultural output value. This drives the healthy development of green agriculture and enhances the agricultural economy's resilience to risks. Based on the definitions above, the following hypotheses are proposed:

H2a: *New Quality Intangible Production Inputs have a significant positive impact on sustainable agricultural development.*

H2b: *New Quality Tangible Production Inputs have a significant positive impact on Agricultural Output Value Standards.*

3.3. Impact of New Quality Agricultural Laborers (NQL) on Sustainable Agriculture

The core characteristics of New Quality Agricultural Laborers (NQL) are high skill levels and high knowledge density. They play a key role in driving technological progress, optimizing industrial ecology, and accumulating intangible production resources through technological innovation and knowledge sharing, thus providing the core driving force for achieving sustainable agricultural development. Emphasis is placed on human innovation capabilities, technological adaptability, and interdisciplinary collaborative innovation abilities.

The development of sustainable agriculture requires minimizing resource consumption and environmental costs, which not only necessitates technological support but also requires knowledge-intensive laborers to implement advanced concepts in practice. New Quality Agricultural Laborers, with their high levels of innovation and technological adaptability, can drive the transformation from traditional extensive production methods to modern green production models through the promotion and application of precision agriculture technologies [102]. For example, in the application of drone irrigation technology, new quality laborers significantly reduce water resource waste caused by traditional irrigation methods through precise technological operations and scientific water resource management, greatly improving irrigation efficiency. In the field of breeding technology, New Quality Agricultural Laborers accelerate the cultivation of superior varieties through advanced methods such as gene editing, enhancing crop disease resistance and stress tolerance, and significantly increasing yield per unit area. This optimizes the economic efficiency of agricultural production. Such technology-driven transformation, promoted by New Quality Agricultural Laborers, provides a feasible path for sustainable agricultural development while reinforcing the central role of these laborers in sustainable agriculture. Additionally, the technological practices and knowledge sharing of New Quality Agricultural Laborers promote the optimization and development of agricultural ecology. In complex agricultural industrial ecosystems, the interaction of technology, resources, policies, and market factors forms a dynamic balance. New Quality Agricultural Laborers can enhance the synergy of the agricultural industrial chain by promoting the integration of intelligent technologies and ecological management, thereby improving the overall efficiency

of the industry. This not only helps build a resource-sharing, information-exchanging agricultural ecological network but also lays a more solid foundation for the long-term development of agriculture. Furthermore, in the transformation of modern agriculture, New Quality Agricultural Laborers enhance the reserve of agricultural knowledge capital through the creation and accumulation of intangible production inputs [103]. They provide continuous innovative and theoretical support for high-quality agricultural development through technological patent innovations, the integration and utilization of agricultural data, and the dissemination of ecological knowledge.

Based on the reasoning above, the following hypotheses are proposed:

H3a: *New Quality Agricultural Laborers have a significant positive impact on sustainable agricultural development.*

H3b: *New Quality Agricultural Laborers have a significant positive impact on agricultural ecology.*

H3c: *New Quality Agricultural Laborers have a significant positive impact on New Quality Intangible Production Inputs.*

3.4. Impact of Sustainable Agricultural Development on Agricultural Output

Through optimizing resource allocation, improving production efficiency, and promoting technological innovation, sustainable agricultural development can not only improve the agricultural ecological environment but also significantly enhance agricultural output, achieving a win–win situation for economic and environmental benefits. From the perspective of resource utilization, sustainable agriculture employs precision agriculture technologies, biotechnology, and intelligent management systems to effectively increase the efficiency of land and water resource use, reduce resource waste in production processes, and significantly boost yield and economic benefits per unit area [104]. Additionally, sustainable agricultural development emphasizes the protection and restoration of the ecological environment. Implementing measures such as soil improvement and optimized water resource allocation helps maintain the stability of agricultural ecosystems, providing necessary support for the continuous growth of agricultural output [37]. Moreover, sustainable development advocates for green and organic agriculture models, which, through the commercialization of high value-added products, greatly enhance the economic competitiveness of agriculture, achieving an organic unity of ecological and economic benefits.

This paper constructs the basic framework of agricultural new quality productivity (NQP) from three aspects: New Quality Agricultural Laborers (NQL), New Quality Agricultural Labor Inputs (NQLI), and New Quality Agricultural Production Inputs (NQPI). Considering that the ultimate goal of sustainable agricultural development is to increase per capita agricultural output and achieve common development, the following hypothesis is proposed:

H4a: *Sustainable Agricultural Development has a significant positive impact on per capita agricultural output value.*

3.5. Proposed Hypotheses Overview

Due to the large number of hypotheses proposed in this paper, in order to help readers better understand the logical relationships between the hypotheses and their theoretical foundations, we have summarized the development of the hypotheses, as shown in Figure 1. All of our hypotheses are positive, with new quality productivity (NQP) as the core. Starting from the three key elements of new quality laborers, New Quality Agricultural Production Inputs, and new quality labor inputs, we systematically explain

their mechanisms of action on agricultural sustainable development (SUS). By constructing a multi-element coordination and logical interaction framework, this paper will reveal the internal mechanisms and external pathways through which NQP empowers agricultural sustainable development in the coordination and integration of economic, ecological, and social values.

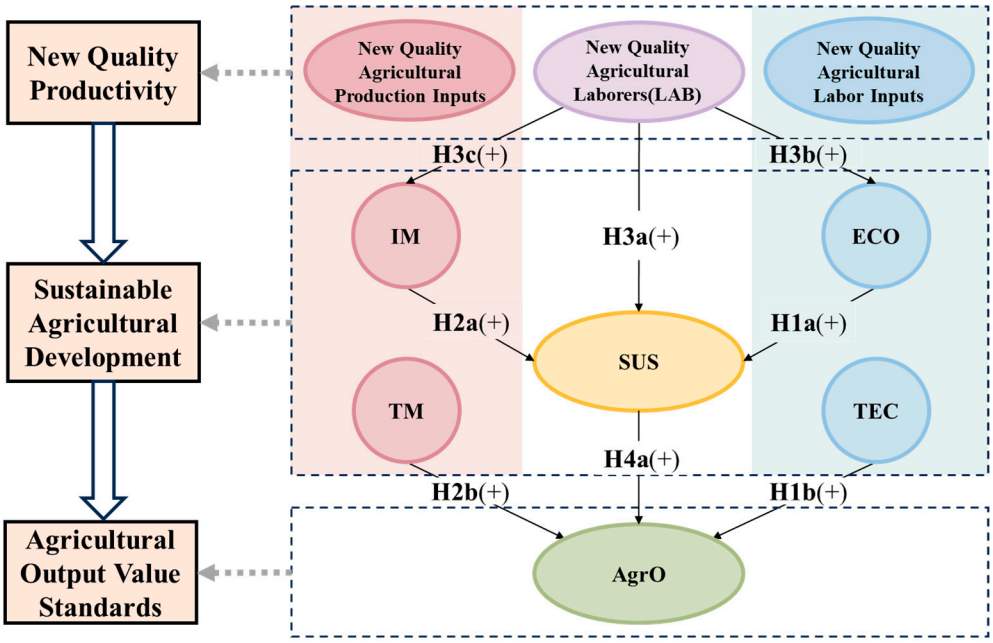


Figure 1. Theoretical analysis framework of new agricultural productivity.

4. Data and Research Method

In the section on model construction and research methods, this paper conducts a systematic analysis and exploration based on the research flow illustrated in Figure 2. This approach ensures the rigor and logical coherence of the research methods, serving as the framework for the subsequent empirical analysis.

In the structural mechanisms section, Partial Least Squares Structural Equation Modeling (PLS-SEM) is employed to deeply analyze the interrelationships among various influencing factors and their pathways affecting sustainable agricultural development. The PLS-SEM method allows for the precise capture of latent connections among multiple variables and the quantification of their impacts on sustainability goals within agricultural development. This approach not only reveals the significant relationships between individual factors but also models the latent variables, thereby providing a comprehensive theoretical framework for sustainable agricultural development. During this process, sufficiency assessment is utilized to evaluate the contribution of each construct, particularly those key factors that may directly influence sustainability goals, further supporting a systematic understanding of the sustainable agricultural development process.

In the Optimization Strategies section, this paper adopts the Outer Loadings TOPSIS (OL-TOPSIS) and Combined Importance–Performance Map Analysis (cIPMA) methods to thoroughly explore the optimization of agricultural functional zoning and the identification and improvement of necessary factors. OL-TOPSIS integrates structural equation modeling with a weighted comprehensive evaluation method, enabling the assessment of the relative strengths and weaknesses among different regions based on their functional characteristics and inherent relationships. This provides a scientific basis for optimizing agricultural functional zones. By evaluating the comprehensive performance of each region, this method offers specific recommendations for policymakers regarding regional functional

optimization. Meanwhile, cIPMA, as an enhanced version of Importance–Performance Matrix Analysis (IPMA), combines necessary condition analysis (NCA) to classify and prioritize key factors in sustainable agricultural development [85]. By identifying factors that do not meet necessary conditions within the four quadrants, cIPMA provides more precise decision support. This is particularly useful in the process of sustainable agricultural development, as it allows for the prioritization of addressing bottleneck factors that have not met necessary standards, thereby effectively promoting systematic improvements. Through this method, the paper is able to offer more targeted and systematic optimization strategies for sustainable agricultural development, ensuring the optimal configuration and continuous improvement of different factors in agricultural development.

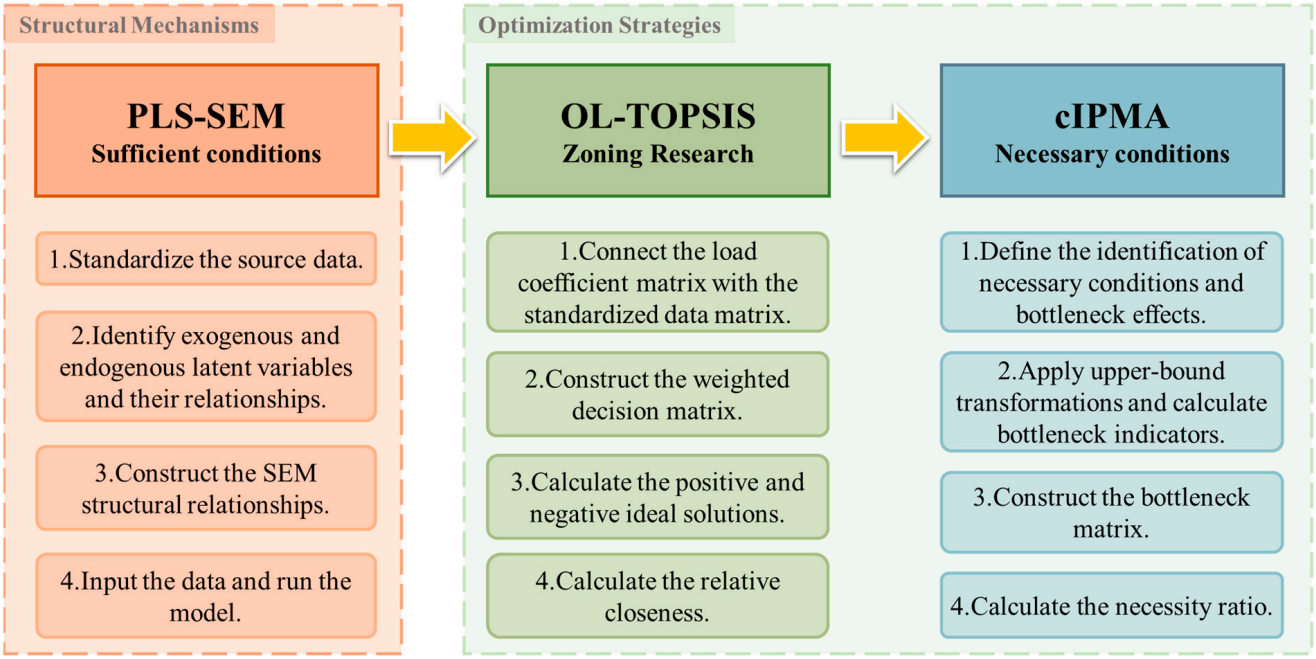


Figure 2. Research flowchart.

4.1. Data Source and Processing

To accommodate the exploratory objectives of this study and the model's requirements for small samples, empirical analysis was conducted using panel data from 30 provinces (including autonomous regions and municipalities directly under the central government, excluding Tibet) in mainland China over a relatively short period from 2012 to 2021. Starting from the five dimensions of new quality productivity (NQP), this study selected data that are all designed as positive indicators. The primary data sources include the official website of the National Bureau of Statistics, various provincial statistical yearbooks, the *China Statistical Yearbook*, and the *China Rural Statistical Yearbook*. Additionally, some data were obtained from the China National Knowledge Infrastructure (CNKI) patent database and Peking University's Digital Inclusive Finance Index. For detailed information on the specific data used, please refer to Table 1.

Table 1. Basic data information.

Variable Name (Code)	Description	Source
New Quality Agricultural Laborers		
Internet penetration rate (LAB1)	Number of Internet users in a region/regional population	*China Statistical Yearbook*
Education (LAB2)	Average years of education for rural labor force	
Labor Productivity (LAB3)	Total output value of agriculture, forestry, animal husbandry, and fishery/number of employees in the primary industry	
New Quality Agricultural Labor Inputs		
Agricultural mechanization level (TEC1)	Total power of rural mechanization	*China Rural Statistical Yearbook*
Production environment testing level (TEC2)	Number of environmental and agricultural meteorological observation stations	*China Statistical Yearbook*
Proportion of leisure agriculture demonstration counties (ECO1)	Total number of counties/regions with demonstration of leisure agriculture	
Agricultural film usage per unit area (ECO2)	Total power of rural mechanization agricultural plastic film usage (tons)/total sown area of crops (thousand hectares)	*China Rural Statistical Yearbook*
Land productivity (ECO3)	Total agricultural output value/crop sowing area	
Rural land transfer rate (ECO4)	The proportion of household contracted land transfer in agricultural land	
New Quality Agricultural Production Inputs		
Proportion of agricultural fiscal investment (TM1)	Fiscal expenditure on agriculture, forestry and water resources/fiscal expenditure	*China Statistical Yearbook*
Tangible Agricultural Equipment Resources (TM2)	Number of large and medium-sized agricultural tractors	
Electrification level (TM3)	Added value of agriculture, forestry, animal husbandry and fishery/total rural electricity consumption	
Number of agricultural technology patents (IM1)	Direct data	*CNKI Patent Database*
Digital Base (IM2)	Number of Taobao Villages	*Alibaba Research Institute Report*
Sustainable Agriculture development		
Agricultural R&D Investment Intensity (SUS1)	Agricultural Research and Development (R&D) funding	*China Statistical Yearbook*
Rural Optical Fiber Deployment Scale (SUS2)	Total length of rural optical fiber lines	
Per Capita Rural Consumption Level (SUS3)	Per capita rural household consumption expenditure	*China Rural Statistical Yearbook*
Digital Infrastructure Distribution (SUS4)	Direct data	*China Statistical Yearbook*
Green Investment Level (SUS5)	Environmental pollution control investment/GDP	
Agricultural Output Value Standards		
Agricultural Output Value Standards (AgrO)	Total agricultural output value/total rural population	*China Statistical Yearbook*

Note: If the data source is not filled in, it is the same as above.

In selecting variables, this study fully considers the characteristics and connotations of NQP and constructs an evaluation system that scientifically reflects its multidimensional mechanisms through comprehensive coverage of economic, social, and environmental

dimensions [15,16]. On the one hand, traditional variables, such as labor productivity and internet penetration rate, are given new analytical perspectives within the NQP framework, more comprehensively reflecting the characteristics of resource optimization and quality improvement in agricultural production. On the other hand, this study introduces emerging variables, such as digital bases and leisure agriculture demonstration counties, to reflect the innovative value-added and ecological synergy emphasized by NQP in agriculture. Additionally, in line with the requirements for sustainable agricultural development, indicators such as green investment and per capita rural consumption are incorporated to reflect the integrated effects of NQP on resource efficiency, ecological friendliness, and social welfare improvement comprehensively [18].

4.2. Partial Least Squares Structural Equation Modeling (PLS-SEM)

New quality productivity (NQP), as a transformative form of productivity, does not develop in a linear and gradual manner; rather, it may undergo abrupt, leap-like transitions. This non-linear leap characteristic makes it necessary to capture and analyze complex causal pathways when studying its causal relationships. PLS-SEM, as a path analysis method, is capable of effectively handling and identifying these non-linear relationships and multiple causal paths [105], making it an ideal tool for analyzing the impact mechanisms of transformative productivity. Path analysis methods can reveal the causal paths between different factors and analyze how these paths, through multi-level interactive effects, jointly drive the enhancement of transformative productivity. PLS-SEM can handle the complex relationships among multiple latent variables, helping researchers accurately capture the non-linear causal relationships between these variables [105], which are key features required in the study of transformative productivity. Additionally, research on NQP often faces challenges such as immature theoretical frameworks and data distribution biases. PLS-SEM, as a highly adaptable path analysis method, can effectively handle complex causal relationships and provide robust results, even under non-ideal data conditions.

Due to the highly exploratory nature of NQP's development, traditional quantitative methods, such as panel data regression [106], Covariance-Based structural equation modeling (CB-SEM) [107], and Observed Variable Stepwise Regression [108], due to their reliance on linear assumptions, strict normality requirements, and the independence of observed variables, make it difficult to uncover the underlying causal mechanisms of transformative productivity. Specifically, panel data regression suffers from model specification bias when handling latent variable interactions [109]; CB-SEM faces parameter estimation distortion due to its rigid constraints on sample size (usually requiring $n > 400$) and multivariate normality, especially when dealing with limited provincial panel data ($n = 300$) and asymmetric distributions (Kline, 2023) [107]; and stepwise regression ignores the systematic relationships of latent constructs, often resulting in spurious correlations and local optima traps [108]. In contrast, PLS-SEM, through composite-based modeling and iterative component estimation [110], can stably capture multiple mediating and asymmetric causal paths, even under conditions of small samples, multicollinearity, and non-normal data, thus offering the possibility for the theoretical reconstruction of the non-linear structure of transformative productivity's leap mechanisms.

Furthermore, for provincial panel data with limited sample sizes and non-normal distribution characteristics, PLS-SEM reduces the model's degrees of freedom requirements through component-based algorithms. Its non-parametric nature allows for parameter estimation using Bootstrap resampling (5000 iterations), effectively overcoming the strict constraints of traditional covariance-based structural equation models (CB-SEM) regarding sample size and normal distribution [111].

The SEM model primarily consists of two components: The measurement model and the Structural Model. The measurement model further includes Reflective Models and Formative Models. In this study, a Reflective Model is adopted for the measurement model construction. Specifically, observed variables are considered reflections or manifestations of latent variables, which are represented by a set of related observed variables. In this paper, ξ and η are used as observed variables for exogenous and endogenous latent variables, respectively. The specific construction is as follows:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{nm} \end{bmatrix}_{m \times n} \tag{1}$$

$$Y = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1n} \\ y_{21} & y_{22} & \cdots & y_{2n} \\ \vdots & \vdots & & \vdots \\ y_{m1} & y_{m2} & \cdots & y_{nm} \end{bmatrix}_{m \times n} \tag{2}$$

Exogenous Latent Variables ($x_j \rightarrow \xi$): These are independent and are not explained by other variables in the model. They are used to explain other latent variables. Endogenous Latent Variables ($y_j \rightarrow \eta$): These are dependent and are explained or predicted by other latent variables within the model. x_j and y_j are the most basic input data, representing the data presentation form in Table 1. X and Y are their matrix representations.

$$Z_x = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{3}$$

$$Z_y = \frac{y_{ij}}{\sum_{i=1}^{m} y_{ij}} \tag{4}$$

Perform dimensionless standardization on the data to eliminate the influence of units. The core expression of the SEM model is as follows:

$$Z_x = \Lambda_x \xi + \delta \tag{5}$$

$$Z_y = \Lambda_y \eta + \epsilon \tag{6}$$

Z_x, Z_y: The matrix composed of observed variables of the latent variables, that is, the standardized input source data. Λ_x, Λ_y: The matrix of load coefficients that represents the relationships between latent variables and observed variables. ξ, η: The vector matrix composed of latent variables. δ, ϵ: The matrix of residual terms with a mean of 0 and mutual independence.

The structural model represents the structural relationships between endogenous and exogenous latent variables and can be expressed using the following regression model (7):

$$\eta = B\eta + \Gamma\xi + \zeta \tag{7}$$

B: The path coefficient matrix among endogenous latent variables. Γ: The path coefficient matrix from exogenous latent variables to endogenous latent variables. ζ: The matrix of residual terms that have a mean of 0 and are mutually independent from each other. From this, it can be inferred that $B\eta$ is the influence matrix among endogenous latent variables. If η_1 influences η_2, then there will be a path coefficient at the corresponding position in the matrix, B; $\Gamma\xi$ is the influence matrix from exogenous latent variables to

endogenous latent variables. If ξ_1 influences ξ_2, then there will be a path coefficient at the corresponding position in the matrix, Γ.

In this study, the endogenous latent variables are sustainable agricultural development (SUS) and Agricultural Output Value Standards (AgrO). The exogenous latent variables are New Quality Agricultural Laborers (NQL), New Quality Agricultural Labor Inputs (TEC, ECO), and New Quality Agricultural Production Inputs (IM, TM). The observed variables, X, are the five specific indicator systems for evaluating New Quality Agricultural Productivity; the observed variables, Y, are the specific indicator systems for evaluating sustainable agricultural development. The load coefficients, Λ_x and Λ_y, represent the explanatory power of each observed variable for the latent variables. By examining the magnitude and significance of the path coefficients, B and Γ, in the observed structural model, the influence pathways of New Quality Agricultural Productivity on sustainable agricultural development can be determined.

The PLS method, as a path modeling analysis approach, is renowned for its excellent mathematical foundation and unique iterative algorithms. It gradually approximates the optimal estimates of all parameters through multiple iterations. Unlike traditional regression methods, the PLS method simultaneously considers the variance of both independent and dependent variables during modeling, thereby maximizing the covariance among explanatory variables. It exhibits strong robustness in the presence of multicollinearity, high-dimensional data, and small sample sizes [112].

In structural equation modeling (SEM), the main advantage of PLS is its ability to handle models that include multiple causal relationships and complex path structures. Specifically, the PLS method first extracts principal components from subsets of observed variables for different latent variables and incorporates them into the regression model for estimation. By continuously adjusting the weights of these principal components, PLS maximizes the predictive capability of the model. Therefore, PLS in SEM is particularly suitable for prediction-oriented studies and for handling complex multivariate relationships, performing excellently in exploratory research [70,113]. Consequently, this study adopts the PLS estimation method for SEM model analysis with an exploratory purpose, fully leveraging its unique advantages in handling small samples and complex data.

4.3. Outer Loadings TOPSIS (OL-TOPSIS)

In the impact mechanism analysis, we further subdivide New Quality Agricultural Labor Inputs (NQLI) into agricultural technology (TEC) and agricultural ecology (ECO), and New Quality Agricultural Production Inputs (NQPI) into tangible materials (TM) and intangible materials (IM) in order to explore their micro-mechanisms. During the analysis process, PLS-SEM is applied to the underlying analysis, using fine-grained indicators for latent variable modeling. At the same time, in order to conduct a macro-level analysis, we introduce the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), which aims to integrate the indicators and use coarse-grained indicators in top-level decision-making. According to the information filtering principle [114], Decision-makers are constrained by limited cognitive abilities when processing information and must effectively filter and combine this information to improve decision efficiency. Therefore, the introduction of the TOPSIS method is based on this principle, optimizing indicator integration to help decision-makers make reasonable judgments and choices in a complex multi-indicator environment. This method not only compensates for the limitations of PLS-SEM in handling time-series data but also further integrates the indicators of NQPI and NQLI, providing more comprehensive decision support and laying the foundation for the subsequent cIPMA impact analysis based on latent variable scores.

TOPSIS is a widely used tool for multi-attribute decision analysis that is especially suitable for building various evaluation systems. In practical applications, TOPSIS helps decision-makers conduct comprehensive evaluations of different alternatives based on multiple indicators, especially in complex multidimensional, multi-indicator systems, effectively extracting information, eliminating subjectivity, and improving the scientific nature of the decision-making process [115–117]. The TOPSIS method has been widely used in agricultural zoning to enhance decision-making and optimization capabilities. For example, Shujuan and her colleagues utilized the entropy-weighted TOPSIS model to evaluate the level of green agricultural development in Henan Province. They comprehensively considered multiple indicators, such as resource utilization, environmental protection, and economic benefits, thereby optimizing agricultural functional zoning and improving the efficiency of the rational allocation of cultivated land resources [75]. Furthermore, the TOPSIS method has also been applied to the multifunctional positioning of rural landscapes in urban suburbs. By integrating gray relational analysis (GRA), researchers have comprehensively evaluated the ecological, production, and living functions of rural landscapes to support scientific decision-making [118]. In the field of cultivated land security management, Yanjun and her team employed the DPSIR-TOPSIS model to assess the security status of cultivated land and diagnose obstacle factors in Shandong Province, providing a scientific basis for decision-making regarding agricultural function zoning [119].

Meanwhile, in practical applications, it is often necessary to assign weights to the indicators in TOPSIS. Common methods for assigning weights include the entropy weight method (EWM), the Analytic Hierarchy Process (AHP), and Criteria Importance Through Intercriteria Correlation (CRITIC). These methods each have strengths and weaknesses. For example, although EWM can reflect the amount of information in the indicators, it relies too heavily on data variability and tends to ignore the relative importance of the indicators [120]. AHP, while allowing experts to assign weights, may lead to uneven weight distribution in the presence of strong subjectivity or uncertainty in expert opinions [121]. The CRITIC method, based on data standard deviation and covariance, may lead to oversimplification when dealing with high-dimensional data, leading to the underestimation of some important dimensions [122]. Therefore, these traditional methods often suffer from excessive simplification of information, subjective bias, and a high dependence on data.

This study further refines the advantages of SEM and TOPSIS by constructing the OL-TOPSIS empirical analysis framework. By using the outer loadings from PLS-SEM as weights for TOPSIS [123,124], the OL-TOPSIS model maximizes latent variable explanatory variance and optimizes constrained covariance (see Appendix A), transitioning the weights from purely data-driven to theory-based data-driven. This not only effectively reduces the sensitivity of common weight-assignment methods to data distribution but also integrates domain knowledge guidance, fully considering the interrelationships between evaluation indicators [109,111]. For China's grain functional zoning, which involves multiple regions, levels, and indicators, the OL-TOPSIS model can flexibly meet these practical needs. By capturing latent relationships between regions using the structural equation model and using TOPSIS for comprehensive ranking, the OL-TOPSIS model can provide scientific decision-making support for policymakers, helping to optimize the overall strategy for the development of new quality agricultural development in China's grain functional zoning.

(Step 1) After conducting PLS-SEM modeling, obtain the outer loading matrices for each observed variable in relation to the exogenous latent variables and endogenous latent variables. Next, perform a concatenation operation to obtain a comprehensive load coefficient matrix, Λ. Then, concatenate the standardized matrices, Z_x and Z_y, of the

exogenous latent variables and endogenous latent variables to form an overall standardized matrix, Z.

$$(\lambda_j) = \Lambda = [\Lambda_x || \Lambda_y] \tag{8}$$

$$(z_j) = Z = [Z_x || Z_y] \tag{9}$$

On this basis, introduce λ_j and z_j as the column vectors of the comprehensive load coefficient matrix, Λ, and the specific elements of the overall standardized matrix, Z, respectively.

(Step 2) Subsequently, construct the weighted decision matrix, V.

$$V = (v_{ij})_{m \times n} = (\lambda_j z_j)_{m \times n} \tag{10}$$

Weighting is performed using load factors as weights. Since load factors reflect the degree of contribution of each observed variable to the latent variables in the PLS-SEM model, this weighting method effectively reduces the sensitivity of the entropy weight method (EWM) to data distribution through the process of structural equation modeling [125]. Specifically, PLS-SEM, when estimating load factors, comprehensively considers the latent relationships and structures among variables, thereby smoothing the weight fluctuations caused by abnormal data distributions [70]. Moreover, the construction of the PLS-SEM model is usually based on theoretical frameworks and domain knowledge, which allows load factors to naturally incorporate expert experience and theoretical guidance in weight allocation, overcoming the limitation of EWM in weight allocation that lacks domain knowledge guidance [125]. At the same time, the application of load factors, through the modeling process of latent variables, fully considers the interrelationships among various indicators, capturing the latent dependencies between indicators. This compensates for EWM's shortcomings in neglecting the interrelationships among indicators, enhances the objectivity and scientific nature of the evaluation system, and improves the stability and reliability of the comprehensive evaluation results [124].

(Step 3) Based on the positive and negative ideal solutions, calculate the degree of closeness of each evaluation object to the ideal solution. The evaluation object that is closer to the positive ideal solution is considered the optimal evaluation object. Therefore, we obtain the following equations:

$$L_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^+\right)^2} \tag{11}$$

$$L_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^-\right)^2} \tag{12}$$

Since all the indicators we use are benefit-type indicators, only the positive ideal solution is discussed. Here, v_j^+ is $\max(x_{ij})$ and v_j^- is $\min(x_{ij})$.

(Step 4) Calculate the relative closeness.

$$d_i^* = \frac{L_i^-}{L_i^- + L_i^+} \tag{13}$$

d_i^* represents the relative closeness of each evaluation object to the positive ideal solution. The larger the value of the relative closeness, the closer the candidate object is to the ideal solution, and the final solution obtained is the optimal solution. Since the input data have already been standardized in the earlier stage, the calculation results will lie between 0 and 1. Because the data are already on a unified scale after standardization

and we need to observe the gap between the optimal and the ideal states, no additional normalization is performed on the results.

4.4. Combined Importance–Performance Map Analysis (cIPMA)

Combined IPMA (cIPMA) is a cutting-edge multi-attribute decision analysis method proposed by Hauff et al. [85]. It combines IPMA with necessary condition analysis (NCA) to provide a more comprehensive and detailed evaluation perspective. The choice of the cIPMA method is rooted in the alignment between its technical characteristics and the needs of agricultural policy decision-making. Compared with traditional multi-attribute decision-making methods such as AHP or fuzzy logic, cIPMA is based on the PLS-SEM framework, which quantifies indirect effects in complex causal chains through path coefficient and latent variable analysis. This approach avoids the subjectivity inherent in AHP's reliance on weighting assignment [126] and the simplification bias caused by preset rules in fuzzy logic [127]. More importantly, cIPMA innovatively integrates necessary condition analysis (NCA), enabling it to identify threshold-type conditions in agricultural systems that "must be met but are not sufficient", such as minimum irrigation coverage and soil nutrient thresholds. Traditional methods focus solely on weight optimization under sufficient conditions, often overlooking the "one-vote veto" risk. This means that policies that ignore necessary conditions may fail, even if their comprehensive scores are high.

In agricultural policy scenarios, this capability significantly enhances decision-making robustness. On one hand, cIPMA employs a "performance-necessity" matrix to identify low-performance yet necessary indicators, such as insurance penetration rates, that require priority improvement, thereby avoiding resource mismatches caused by deviations in weight allocation under traditional MCDA methods [128]. On the other hand, its data-driven, non-linear analytical capabilities adapt effectively to the strong coupling and irreversibility of agricultural systems, addressing the blind spots of traditional methods in threshold effects and long-term planning [88,129]. Consequently, cIPMA not only integrates the dual logic of linear sufficient conditions and non-linear necessary conditions at the methodological level but also achieves a paradigm shift at the application level—from "pursuing static optimal solutions" to "preventing and controlling systemic risks". This approach provides an analytical framework that is both predictive and adaptive for agricultural policies in high levels of uncertainty.

Traditional IPMA is a widely used multi-attribute decision-making tool in the field of management, employed to compare the importance and current performance of various attributes in achieving specific outcomes [130]. IPMA typically uses a two-dimensional chart to display the high and low importance alongside the high and low performance of each attribute, categorizing them into four quadrants to help managers identify areas that require focused improvement [131–133]. IPMA is especially prevalent within the PLS-SEM framework because it can integrate path coefficients with performance scores to provide a comprehensive evaluation of the antecedent variables of constructs [70,134,135]. The specific calculation process is as follows:

$$TE = DE_{i \to Y} + \sum \left(DE_{i \to M_j} \times TE_{M_j \to Y} \right) \tag{14}$$

$$Importance_i = TE_i \tag{15}$$

TE_i is the total effect of the factor on the target variable, Y. $DE_{i \to Y}$ is the direct effect of factor on the target variable, Y. $DE_{i \to M_j}$ is the direct effect of the factor, i, on the mediator variable, M_j. $TE_{M_j \to Y}$ is the total effect of the mediator variable, M_j, on the target variable, Y.

The importance score is directly taken as the value of TE.

$$Performace_i = \frac{1}{N}\sum_{k=1}^{N} \text{Score}_{i,k} \tag{16}$$

Here, N is the total number of samples, and $\text{Score}_{i,k}$ is the score of the k-th sample on latent variable, i, which is directly calculated using PLS-SEM.

However, traditional IPMA has some significant drawbacks, including its reliance on average scores to understand importance and performance, which may not accurately reflect complex causal relationships and threshold effects. Moreover, it is mainly based on linear relationships and fails to identify necessary conditions that are indispensable for achieving specific outcomes, relying instead on sufficient conditions of the model, leading to the neglect of some key attributes [101,102].

To overcome these deficiencies of traditional IPMA, Hauff et al. (2024) [85] introduced cIPMA, which combines the advantages of IPMA and necessary condition analysis (NCA). Specifically, by integrating NCA, cIPMA can identify necessary conditions that must be satisfied to achieve the goals, even if these conditions show low importance in traditional IPMA. This approach not only enhances the comprehensiveness and accuracy of the evaluation but also ensures that key but low-importance attributes are not overlooked in the decision-making process [85]. Additionally, cIPMA combines linear and non-linear analyses, providing more detailed and multidimensional evaluation results and offering more scientific and comprehensive support for managers to develop optimization strategies. Therefore, cIPMA exhibits stronger applicability and practicality in multi-attribute decision analysis, especially in complex management scenarios, providing deeper and more reliable insights [85]. In contrast, by combining NCA, cIPMA not only retains IPMA's linear analysis of importance and performance but also identifies necessary conditions that must meet specific thresholds to achieve the goals, thereby compensating for the shortcomings of traditional IPMA, which is especially important for the exploratory research in this paper.

Necessary Condition Analysis (NCA) is a method used to identify and quantify the conditions that must be met to achieve specific outcomes [129,136]. Unlike traditional sufficient condition analysis, NCA focuses on whether a particular condition is a necessary prerequisite for the occurrence of a result. The specific analysis process is as follows:

Necessary Condition: For a given outcome variable, Y, and condition variable, X, if $X \geq x$ must be satisfied when $Y \geq y$, then X is considered a necessary condition for Y. Formally, it can be expressed as follows:

$$Y \geq y^* \Rightarrow X \geq x^* \tag{17}$$

where y^* is the specific threshold for Y, and x^* is the necessary threshold for X.

Necessity Logic: NCA is based on logical implication and aims to determine to what extent the condition variable, X, is a necessary prerequisite for the outcome variable, Y, to reach or exceed a specific threshold, y^*. Necessity logic emphasizes that when Y reaches or exceeds y^*, X must satisfy $X \geq x^*$. The core of NCA is to identify and quantify the necessity of the condition variable for the outcome variable. Its mathematical framework includes the following key steps:

(Step 1) Define the identification of necessity conditions and bottleneck effects. First, determine the target level y^* of the outcome variable, Y, and the necessary level x^* of the condition variable, X. The Bottleneck Effect refers to the minimum value, x_{min}, that the

condition variable, X, must reach for the outcome variable, Y, to meet the specific target level, y^*. Mathematically, the bottleneck point, x_{min}, can be expressed as follows:

$$x_{min} = \min\{X_i | Y_i \geq y^*\} \tag{18}$$

(Step 2) Upper bound transformation and bottleneck index calculation. To quantify the strength of the necessity condition, an upper bound transformation (Ceiling Transformation) is introduced. The bottleneck index, $\hat{X}_i$, for each observation is defined as the minimum value of X_j that satisfies $Y_j \geq Y_i$ as follows:

$$\hat{X}_i = min\{X_j | Y_j \geq Y_i\}, \forall i \in \{1, 2, ..., n\} \tag{19}$$

(Step 3) Construction of the Bottleneck Matrix. Based on the bottleneck index, the Bottleneck Matrix, B, is constructed, where its elements, B_{ij}, are defined as follows:

$$f(x) = \begin{cases} 1, & \text{if } X_{ij} \geq \hat{X}_{ij} \\ 0, & \text{else} \end{cases} \tag{20}$$

(Step 4) Calculation of the Proportion of Necessity. By calculating the proportion of observation points that meet the necessary conditions, define the Proportion of Non-Bottleneck Points (PNBP) as follows:

$$PNBP = \frac{1}{n}\sum_{i=1}^{n} B_i \tag{21}$$

where n is the sample size. The $PNBP$ value ranges between 0 and 1, indicating the strength of the condition variable, X, as a necessary condition for the outcome variable Y. Subsequently, perform a statistical significance test for $PNBP$. To ensure the reliability of the NCA results, a Permutation Test is used to assess the statistical significance of $PNBP$.

In traditional IPMA plots, each latent variable is represented by a coordinate point composed of its $importance_i$ and $performance_i$, thus forming a scatter plot. In cIPMA, each construct is represented by a three-dimensional coordinate consisting of its importance, performance, and the Proportion of Non-Bottleneck Points, $PNBP_i$, forming a bubble chart. By analyzing the cIPMA chart, decision-makers can identify constructs that are dominant in importance but have low performance, which need to be prioritized for optimization. Additionally, the cIPMA chart can reveal constructs that, although of relatively low importance, are necessary conditions for achieving the goals and must meet certain thresholds, enabling decision-makers to develop more systematic and precise optimization strategies [85].

Hauff S. et al. [85] detailed the algorithmic process of cIPMA in their paper and released the plotting framework of their paper on the SmartPLS website, ensuring the transparency and reproducibility of the method. In terms of scoring, we adopted the integrated TOPSIS scores, achieving a comprehensive measurement of new quality productivity across different regions through multi-criteria evaluation. To further enhance data comparability and analysis accuracy, this study also employed the rescaled trick mentioned in the paper to normalize the data, standardizing the scores of each indicator to a range of 0 to 100 while considering both the maximum and minimum values, thereby enhancing the depth and breadth of the cIPMA analysis.

5. Results and Discussion

Due to the extensive number of measurement indicators, we have provided a consolidated explanation of the reliability and validity assessment indicators, as shown in Table 2.

Detailed interpretations and relevant literature references are presented in the subsequent analysis of the experimental results.

Table 2. Term descriptions.

Terms	Descriptions
PLS-SEM Model Section	
Outer Loadings	Outer loadings reflect the degree of correlation between observed variables and latent variables and are important indicators for measuring the explanatory power of observed variables within the latent structure.
Variance Inflation Factor (VIF)	Variance Inflation Factor (VIF) is a measurement indicator; the larger the VIF value, the more severe the collinearity problem.
Cronbach's Alpha	The closer Cronbach's Alpha is to 1, the higher the reliability, the lower the measurement error, and the better the stability.
Composite Reliability (CR)	CR in PLS-SEM assesses the internal consistency of the measurement model, indicating the reliability of the indicators reflecting the latent variable. CR values are typically expected to be above 0.7.
Average Variance Extracted (AVE)	Convergent validity is usually judged through the Average Variance Extracted (AVE) value, which measures the shared variance among the measurement variables within a latent variable.
Heterotrait–Monotrait ratio (HTMT)	HTMT is determined by comparing the correlations between different latent variables with the correlations among indicators within the same latent variable.
R^2 (coefficient of determination)	The R^2 (R-square) of the observed model is one of the key indicators for measuring the goodness of fit of the model.
Variance Accounted For (VAF)	VAF measures the mediation effect size, showing the proportion of the total effect of the independent variable on the dependent variable, as explained by the mediator. A higher VAF indicates a stronger mediation effect.
cIPMA Model section	
Conditional Efficiency Free Disposable Hull model (CE-FDH)	A model that incorporates conditional variables to assess efficiency while accounting for external factors.
Conditional Robust Free Disposable Hull (CR-FDH)	An extension of CE-FDH that improves robustness against data noise and uncertainty.
Bottleneck table	A tool to identify bottlenecks in production and optimize efficiency.

5.1. Construct Reliability and Validity

Reliability and validity are essential elements for ensuring the scientific rigor and credibility of research. Reliability measures the consistency and stability of results, serving as the foundation for the replicability and reliability of research findings. Validity assesses whether the measurement tools accurately capture the target constructs, directly determining the explanatory power and theoretical significance of the results. Both are indispensable, working together to ensure the rigor of the research process and the credibility of its findings. Below is a detailed explanation of the reliability and validity assessment results of the experiment.

5.1.1. Reliability Indicators Testing Analysis

Outer loadings reflect the degree of correlation between observed variables and latent variables and are important indicators for measuring the explanatory power of observed variables within the latent structure. In this study, the outer loadings of observed variables for each latent variable mostly meet the requirements, and the model fits well, as shown in Table 3. Specifically, the outer loadings of the measurement variables for each dimension of sustainable agricultural development mostly exceed 0.7, indicating that the selected

measurement variables are reasonable. Only TEC1 and SUS5 in intangible materials have outer loadings between 0.6 and 0.7, which are acceptable based on related research by Hair et al. [137].

Table 3. Reflective indicator loadings and internal consistency reliability.

Code	Outer Loadings	VIF	Cronbach's Alpha	CR	AVE
LAB1	0.909	2.354	0.789	0.877	0.706
LAB2	0.707	1.350			
LAB3	0.889	2.184			
TEC1	0.675	1.242	0.613	0.811	0.689
TEC2	0.960	1.242			
ECO1	0.854	2.180	0.823	0.881	0.650
ECO2	0.752	1.832			
ECO3	0.833	1.952			
ECO4	0.783	2.005			
TM1	0.834	1.771	0.679	0.823	0.608
TM2	0.737	1.187			
TM3	0.766	1.580			
IM1	0.931	1.885	0.813	0.914	0.842
IM2	0.904	1.885			
SUS1	0.876	2.500	0.818	0.873	0.582
SUS2	0.702	1.865			
SUS3	0.864	2.535			
SUS4	0.710	2.277			
SUS5	0.631	1.445			

When there is a high correlation between independent variables in the measurement model, multicollinearity issues arise, leading to unstable regression coefficient estimates, increased standard errors, and affecting the model's explanatory power and the accuracy of significance tests [138]. This study uses the Variance Inflation Factor (VIF) as a measurement indicator; the larger the VIF value, the more severe the collinearity problem. As shown in Table 3, the VIF values of all observed variables in this study are less than or equal to 2.535, which is lower than the critical threshold of 5.0 [139], indicating that the collinearity issues among the variables used in this study are relatively minor, thereby maintaining the stability and reliability of the regression analysis.

Due to the presence of measurement errors, reliability and validity tests of the data are required. Reliability tests are used to assess the consistency and stability of the measurement tool in repeated measurements, i.e., whether the measurement results are reliable. This includes internal consistency reliability tests (usually measured by Cronbach's Alpha) and Composite Reliability (CR) tests. The closer Cronbach's Alpha is to 1, the higher the reliability, the lower the measurement error, and the better the stability. When Cronbach's Alpha is $\geq$0.7, it is considered high reliability; when 0.35 $\leq$ Cronbach's Alpha < 0.7, it is considered moderate reliability; and when Cronbach's Alpha is <0.35, it is considered low reliability. According to Table 3, all Alpha coefficients range between 0.613 and 0.823, indicating medium to high reliability and good measurement reliability. According to the research by Fornell [138] and Bagozzi [140], a composite reliability greater than 0.6 ensures internal consistency when all observed variables measure a unified latent variable. As shown in Table 3, the CR values are all greater than or equal to 0.803, far exceeding 0.6 and meeting the standard. This indicates that all variables have passed the reliability test, exhibiting good consistency and stability. Validity testing aims to ensure that the measurement tool effectively captures and reflects the concepts or constructs it is designed to measure, thereby verifying the accuracy and relevance of the measurement results. Validity

testing primarily includes the assessment of discriminant validity and convergent validity. The former is used to detect exclusivity issues, while the latter focuses on comprehensiveness issues. Convergent validity is usually judged through the Average Variance Extracted (AVE) value, which measures the shared variance among the measurement variables within a latent variable. Typically, an AVE value greater than 0.5 is considered the standard for good convergent validity. As shown in Table 3, the AVE values for all latent variables exceed 0.5, indicating a significant internal correlation between the measurement variables and the latent variables.

5.1.2. Validity Indicators Testing Analysis

This study adopts the method proposed by Henseler et al. [109], which calculates the heterotrait–monotrait ratio (HTMT) by comparing the correlations between different latent variables with the correlations among indicators within the same latent variable. When the HTMT value is below 0.90, it indicates good discriminant validity among latent variables [70,141]. Compared to the traditional Fornell–Larcker criterion, HTMT provides a more sensitive test for discriminant validity 139]. As shown in Table 4, all HTMT values between latent variables are below 0.9, indicating that the latent variables maintain a certain degree of distinctiveness.

Table 4. Discriminant validity, heterotrait–monotrait ratio (HTMT) matrix.

	AgrO	ECO	IM	LAB	SUS	TEC
AgrO						
ECO	0.163					
IM	0.109	0.319				
LAB	0.357	0.851	0.516			
SUS	0.207	0.680	0.872	0.895		
TEC	0.421	0.341	0.518	0.305	0.498	
TM	0.624	0.527	0.428	0.526	0.740	0.494

Note: HTMT ratio for discriminant validity (HTMT < 0.900) and model fit.

Reliability and validity testing of the data ensures high cohesion and low coupling of the structural equation model, enhancing the model's robustness and reliability. Meanwhile, the R^2 (coefficient of determination) of the observed model is one of the key indicators for measuring the goodness of fit of the model. The R^2 value reflects the explanatory power of the latent variables on the observed variables in the model, ranging from 0 to 1. The closer the R^2 value is to 1, the higher the degree to which the model explains the data and the better the fit. Specifically, a larger R^2 value indicates a stronger explanatory power of the independent variables on the dependent variables in the model, enabling a more effective revelation of latent relationships. In the field of social sciences, it is generally considered that an R^2 value greater than 0.2 indicates a relatively ideal fit of the model, while an R^2 value close to or greater than 0.5 signifies that the model has strong explanatory ability [142]. Here, only IM's R^2 is slightly below 0.2, but is still in the acceptable range. The details are shown in Table 5.

Table 5. R-squared overview.

Latent Variables	R-Squared	R-Squared Adjusted
Agricultural Ecology (ECO)	0.489	0.488
Agricultural Output Value Standards (AgrO)	0.462	0.456
Intangible Materials (IM)	0.192	0.189
Sustainable Agricultural Development (SUS)	0.779	0.777

Note: $R^2 \geq 0.2$ represents a relatively ideal fit.

5.2. Structural Mechanisms of NQP in Sustainable Agricultural Development

5.2.1. Direct Effect Results Analysis

In the significance testing of path coefficients, the Bootstrapping method can provide *p*-values for each path, thereby determining whether each path is statistically significant. Generally, when the *p*-value of a path is less than the preset significance level (such as 0.05 or 0.01), it indicates that the path is statistically significant. In this way, this study can effectively identify which relationships between latent variables are significantly supported by the data and which paths do not show sufficient statistical evidence.

The experimental results are shown in Table 6.When the significance level is set at 0.01, all hypotheses passed the significance test and were supported. Among them, Hypothesis H2b (tangible materials → Agricultural High-Quality Development) and H3b (New Quality Agricultural Laborers → Economic Efficiency) have standardized path coefficients of 0.727 and 0.700, respectively, with T-values exceeding 15 (H2b: 15.952) and 35 (H3b: 35.015), indicating that the causal relationships between these two sets of variables have strong explanatory power and statistical robustness, highlighting the core driving role of tangible resource input and labor quality in the process of agricultural modernization. It is worth noting that the path coefficient of agricultural ecology to sustainable development (H1a) is 0.082, which is statistically significant (T = 2.488, $p = 0.013$); however, the effect strength is notably weaker compared to other paths. This may reflect that the direct impact of agricultural ecological construction on sustainable development needs to be achieved more through intermediary mechanisms, such as technological penetration or institutional innovation, with its direct effect being gradual and systemic in nature. Furthermore, the multidimensional significant impacts of New Quality Agricultural Laborers on Economic Efficiency (H3b), intangible materials (H3c), and sustainable development (H3a) (path coefficients ranging from 0.438 to 0.700) confirm the pivotal role of human capital enhancement in agricultural transformation and upgrading, particularly in forming synergistic effects in knowledge spillover, technology application, and organizational optimization. From the overall structure, hypotheses with path coefficients exceeding 0.4 (H2a, H2b, H3a, H3b, H3c, H4a) all show high significance ($p < 0.001$), validating the strong correlation between the synergy of tangible or intangible resources, labor quality improvement, and sustainable development goals. This indicates that high-quality agricultural development is a complex system process involving the dynamic interaction of multiple dimensions, such as technological factors, ecological constraints, human capital, and the institutional environment.

Table 6. Path coefficients, mean, STDEV, T-values, and *p*-values.

Hypothesis	Path	Path Coefficients	T-Value	*p*-Value	Confidence Level	Hypothetical Results
H1a	Agricultural Ecology → SUS	0.082 *	2.488	0.013	98.70%	Supported
H1b	Agricultural Technology → AgrO	0.113 **	2.818	0.005	99.50%	Supported
H2a	Intangible Materials → SUS	0.523 ***	14.268	0.000	99.99%	Supported
H2b	Tangible Materials → AgrO	0.727 ***	15.952	0.000	99.99%	Supported
H3a	New Quality Agricultural Laborers → SUS	0.459 ***	11.205	0.000	99.99%	Supported
H3b	New Quality Agricultural Laborers → ECO	0.700 ***	35.015	0.000	99.99%	Supported
H3c	New Quality Agricultural Laborers → IM	0.438 ***	10.306	0.000	99.99%	Supported
H4a	Sustainable Agricultural Development → AgrO	0.438 ***	9.650	0.000	99.99%	Supported

Note: Significance level = 0.01, Subsamples = 5000, *** ($p < 0.001$), ** ($p < 0.01$), * ($p < 0.05$).

Based on the significance analysis of the direct paths in Table 6 and the indications in Figure 3, mediation effects between path structures can be further revealed, as shown as follows in Table 7.

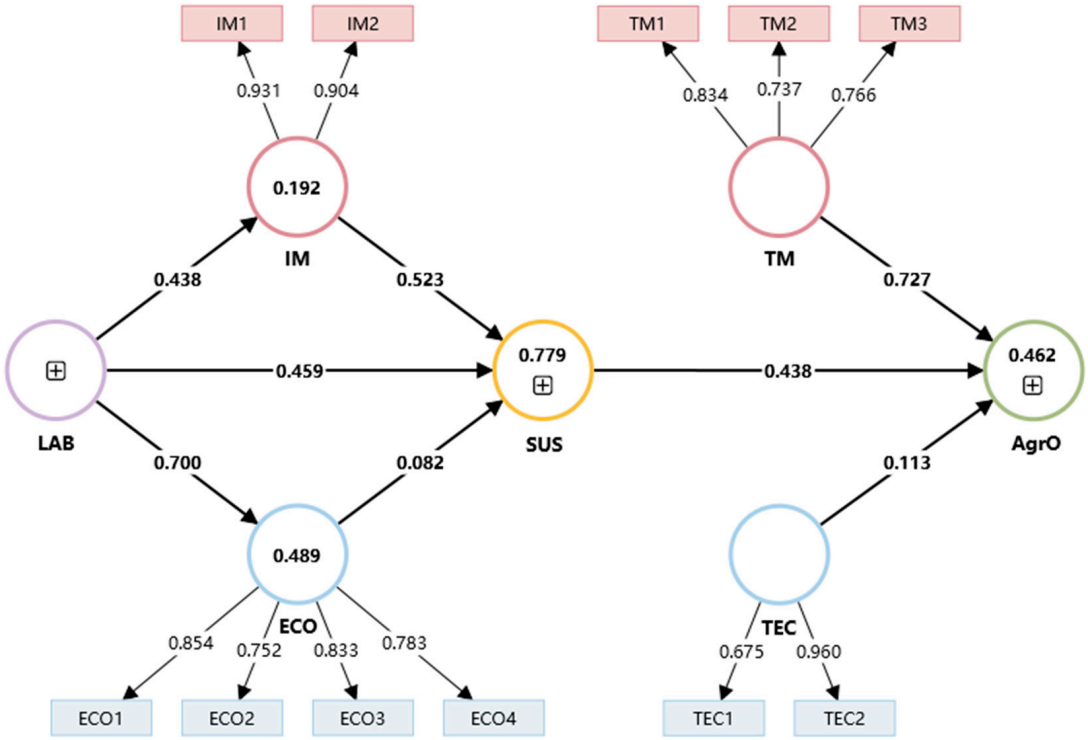


Figure 3. PLS-SEM experimental structure diagram.

Table 7. Mediation effect test.

Independent Variable	Mediating Variable	Dependent Variable	Direct Effect	Indirect Effect	Total Effect	VAF
LAB	ECO	SUS	0.459 **	0.057	0.516 **	11.12%
LAB	IM	SUS	0.459 **	0.229 **	0.688 **	33.28%

Note: ** ($p < 0.01$).

5.2.2. Indirect Effect Results Analysis

Variance Accounted For (VAF) > 0.8: The mediating effect is dominant, indicating that the mediating variable plays a very strong role between the independent and dependent variables. For 0.2 < VAF $\leq$ 0.8: The mediating effect and direct effect work together, indicating that the mediating variable plays a certain role in the path model. For VAF $\leq$ 0.2: The mediating effect is weak, and the direct effect is dominant, meaning that the mediating variable has a relatively small role, mainly influencing the dependent variable through direct paths [70]. Based on the definition of VAF, the VAF for the path LAB $\rightarrow$ ECO $\rightarrow$ SUS is 11.12%, indicating that the mediating effect of agricultural ecology in the relationship between New Quality Agricultural Laborers and sustainable agricultural development is relatively weak, with the direct effect being dominant. This suggests that the impact of New Quality Agricultural Laborers on agricultural sustainable development mainly occurs through direct paths, while the role of agricultural ecology is relatively small, exhibiting weak indirect effects. On the other hand, the VAF for the path LAB $\rightarrow$ IM $\rightarrow$ SUS is 33.28%, suggesting that intangible materials play a certain mediating role in the relationship between New Quality Agricultural Laborers and Agricultural Sustainable Development. Although the direct effect still accounts for a larger portion, intangible materials have a

non-negligible mediating effect in promoting agricultural sustainable development. This indicates that New Quality Agricultural Laborers, by improving intangible materials, have contributed to the sustainable development of agriculture, with both working together to enhance agricultural sustainability.

5.3. Analysis of NQP in Agricultural Functional Zones

5.3.1. OL-TOPSIS Based on the Classification of Agricultural Functional Zones

In this study, the evaluation work serves solely as an auxiliary analytical tool to support the understanding and comparison of New Quality Agricultural Productivity. We did not consider the evaluation to be the main objective of the research. Instead, we used a simplified evaluation process to assist in exploring the relationships among relevant indicators and the differences between regions. This evaluation not only provides a theoretical basis for our analytical framework but also offers preliminary references for subsequent, more in-depth empirical research and policy recommendations. Leveraging the advantages of TOPSIS, we integrated the indicators of New Quality Agricultural Labor Inputs (NQLI) and New Quality Agricultural Production Inputs (NQPI) to conduct a three-dimensional analysis of new quality productivity. Additionally, we chose agricultural functional zoning as the basis for classification, which differs from the more commonly used geographical division methods [143–145]. In the OL-TOPSIS model, we calculate and sum the NQL, NQLI, and NQPI for each province in each partition, and the calculation results are shown in Table 8.

Table 8. OL-TOPSIS results.

Indicators	Regions	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
NQL	Production Regions	4.1806	4.3655	4.5664	5.1263	5.0789	5.3743	5.3845	5.1828	4.9689	5.0885
	Balanced Regions	1.7963	1.8842	1.8474	2.2149	2.4304	2.6068	2.7123	2.6112	2.5719	2.5777
	Consumption Regions	4.0543	4.1584	4.5211	4.9415	5.0530	5.1726	5.1677	4.8460	4.4801	4.5821
NQLI	Production Regions	4.3326	4.4456	4.0664	3.9715	3.7710	3.6087	3.2181	3.0285	3.1512	3.3388
	Balanced Regions	2.3490	2.5018	2.1976	2.1574	2.2223	2.1304	1.8105	1.6387	1.6970	1.8118
	Consumption Regions	2.8284	2.7262	2.6199	2.5442	2.6028	2.5014	2.3463	2.3447	2.4126	2.4492
NQPI	Production Regions	4.0199	3.9462	3.5825	3.4975	3.3805	3.4542	3.6299	3.6038	3.7436	3.7508
	Balanced Regions	2.1530	2.0789	1.8400	1.8797	1.8765	1.9180	1.9395	1.9424	1.9912	1.9791
	Consumption Regions	1.8011	1.7637	1.8719	1.7594	1.7264	1.7717	1.8103	1.7990	1.8593	1.8637

As shown in Table 8, the classification of agricultural functional zones includes consumption zones, balanced zones, and production zones, each with its unique characteristics and functions. Consumption zones are primarily concentrated in economically developed and densely populated areas, such as Beijing, Shanghai, and Guangdong. Although these regions have limited land resources and smaller agricultural land areas, leading to limited agricultural production capacity, they also exhibit certain scales of agricultural development, and agricultural productivity is often high. These zones mainly focus on green agriculture, high-end agricultural product processing, and agricultural technological innovation. Balanced zones are areas where agricultural production and consumption are relatively balanced, such as Gansu and Shaanxi. These regions not only possess strong

agricultural production capabilities but also can meet the agricultural needs of local and surrounding areas, with favorable natural conditions and resource bases. Production zones are concentrated in areas rich in agricultural resources, such as Hebei, Henan, and Shandong, and serve as the main force in China's agricultural production, undertaking the production of bulk grains and economic crops. Production zones have relatively well-developed agricultural production conditions and strong production capacities, but they also face issues, such as lagging overall agricultural labor quality and over-exploitation of resources.

This functional zoning-based analysis method better meets the balance requirements of environmental protection, resource conservation, and economic growth in modern agricultural development, thereby more effectively promoting the sustainable transformation of agriculture. The differences among production zones, balanced zones, and consumption zones across these three dimensions enable policymakers to adopt targeted policy measures. We visualized the results from Tables 8 and 9 to analyze the regions within the agricultural functional zoning, and the visualization results are shown in Figure 4.

Table 9. Agricultural functional zoning.

Regions	Provinces
Consumption regions	Beijing, Tianjin, Shanghai, Zhejiang, Fujian, Guangdong, and Hainan
Balanced regions	Shanxi, Guangxi, Chongqing, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang
Production regions	Hebei, Inner Mongolia, Liaoning, Jilin, Heilongjiang, Jiangsu, Anhui, Jiangxi, Shandong, Henan, Hunan, Hubei, and Sichuan

Note: The data for Hong Kong, Macao, and Taiwan are incomplete. Refer to [16] for classification.



Figure 4. Three dimensions of agricultural functional zoning. Note: The map was created based on the standard map service from the Ministry of Natural Resources with the review number GS(2024)0650, and no alterations have been made to the base map boundaries.

5.3.2. OL-TOPSIS Result Analysis

In the consumption zone, the value of New Quality Agricultural Laborers (NQL) (4.0543 in 2012 and 4.5821 in 2021) shows a steady growth trend, indicating continuous improvement in the quality of agricultural laborers. This change can be attributed to the relatively superior infrastructure and higher labor quality in the consumption zone. Economically developed areas typically have strong agricultural technological innovation capabilities and more advanced agricultural infrastructure (such as irrigation systems, agricultural machinery, etc.), which effectively drive the enhancement of agricultural laborer quality, further supporting high-end agricultural production and technological applications. However, despite the good performance of NQL, the values of New Quality Agricultural Labor Inputs (NQLI) and New Quality Agricultural Production Inputs (NQPI) are lower, indicating that these regions face certain deficiencies in local agricultural inputs and rely heavily on external supplies. This also suggests that the insufficient agricultural resource input in the consumption zone may be due to lower dependence on agriculture in the region, as well as policy direction and land resource constraints that affect the further development of local agriculture. The lack of policy support and infrastructure limitations may lead to insufficient agricultural input in this region, especially regarding the introduction of new agricultural production materials.

In the balanced zone, the value of NQL increased from 1.7963 in 2012 to 2.5777 in 2021, reflecting a gradual improvement in the quality of agricultural laborers. However, fluctuations in NQLI (2.3490 in 2012 and 1.8118 in 2021) and NQPI (2.1530 in 2012 and 1.9791 in 2021) indicate some instability in the input of agricultural labor objects and the configuration of production materials. These fluctuations may result from insufficient infrastructure construction and the current state of the labor market in the balanced zone. The balanced zone is often located in economically underdeveloped areas, where education and agricultural technology levels are relatively low, leading to slower improvements in agricultural laborer quality and affecting the introduction and configuration of modern agricultural production materials. Regarding policy support, although the balanced zone may benefit from some local supportive policies, these policies still fall short of enhancing agricultural productivity. To improve agricultural productivity in this region, it is necessary to further strengthen infrastructure, education and training, optimize labor force allocation, and increase agricultural input.

In the production zone, the NQL value (4.3326 in 2012 and 5.0885 in 2021) shows a year-on-year growth trend, indicating that these regions have relatively sufficient and highly skilled agricultural laborers capable of effectively supporting large-scale agricultural production. However, the lower values of NQLI (2.3490 in 2012 and 1.8118 in 2021) and NQPI (2.1530 in 2012 and 1.9791 in 2021) reflect deficiencies in the management of agricultural labor objects and the investment in production materials in the production zone. This phenomenon may be closely related to the current state of the labor market, infrastructure, and agricultural policy support in the production zone. The agricultural labor force in the production zone mainly comes from rural populations, which, while large in number, have relatively low comprehensive quality. The application of agricultural technology and the introduction of modern production equipment are relatively underdeveloped. Furthermore, agricultural production in the production zone still relies on traditional farming methods, with limited investment in modern agricultural technologies and equipment, leading to lower efficiency in the use of agricultural production materials. Although the state provides some subsidies and support for agricultural production zones, efforts to optimize resources and develop modern agriculture still need to be strengthened. Therefore, to improve agricultural productivity in the production zone, more investment in

agricultural technology, labor quality enhancement, and the modernization of agricultural production materials are needed.

From 2012 to 2021, the NQL, NQLI, and NQPI indicators of the agricultural functional zones showed overall fluctuations; however, in general, the agricultural productivity in the consumption zone, balanced zone, and production zone all showed relatively stable development trends. This suggests that although there are differences in the performance of New Quality Agricultural Laborers, Agricultural Labor Inputs, and Agricultural Production Inputs across regions, these differences are not entirely determined by the region's natural conditions. More importantly, they are influenced by factors such as infrastructure construction, labor market conditions, policy support, and education levels. The high NQL value in the consumption zone reflects its superior economic conditions and high agricultural technology application capabilities, while the balanced zone and production zone face more challenges in the allocation of agricultural production resources and technological inputs. To address the agricultural productivity disparities across regions, future policies should focus on improving regional agricultural infrastructure, strengthening agricultural education and training, enhancing labor quality, optimizing agricultural resource allocation, and promoting the introduction and application of modern agricultural production materials.

5.4. Necessary Conditions for NQP to Promote Sustainable Agricultural Development

5.4.1. NCA Result Presentation

The Conditional Efficiency Free Disposable Hull model (CE-FDH), by introducing conditional variables, enables more refined and conditional efficiency assessments while taking external environmental factors into account. It is suitable for situations that require controlling the influence of these environmental or contextual factors. In contrast, the Conditional Robust Free Disposable Hull (CR-FDH) model further enhances resistance to data noise and uncertainty based on the CE-FDH model [122]. Through robust optimization techniques, it ensures stable and reliable efficiency assessment results, even when there are fluctuations in data quality or uncertainties. This study adopts CE-FDH as the model demonstration, aligning with the proponents of cIPMA. Necessary Condition Analysis (NCA) was conducted in SmartPLS 4.0, resulting in Table 10.

The bottleneck table reveals the "bottleneck" effect among different indicators. During the phase with lower sustainable agricultural development (SUS) values (such as between 5% and 50%), the growth of New Quality Agricultural Labor Inputs (NQLI) and New Quality Agricultural Production Inputs (NQPI) is relatively slow, particularly for NQPI, which remains at a low level during most phases. This indicates that in the early stages of sustainable agricultural development, investment in production materials and the management of New Quality Agricultural Labor Inputs are the main bottlenecks in agricultural development. As the SUS value surpasses 50%, these bottlenecks begin to break through, with NQPI and NQLI values showing significant growth. This suggests that the improvement of production materials and labor inputs is a key factor in driving sustainable agricultural development. The change in New Quality Agricultural Laborers (NQL) in the table shows a relatively steady trend, especially after the SUS value exceeds 50%, where the growth of NQL remains stable and high. This indicates that once agricultural development reaches a certain level, the impact of improving labor quality on agriculture weakens, and the improvement of production materials and technology becomes a more significant bottleneck. Therefore, it can be concluded that the promotion of sustainable agricultural development relies not only on the enhancement of laborer quality but also on strengthening investment in production materials and the management of labor inputs. The coordinated development of these factors will have a decisive impact on the sustainability of agriculture.

Table 10. Bottleneck table Sustainable Agriculture Development (SUS), actual values.

	SUS	NQL	NQLI	NQPI
0%	0.000	NN	NN	NN
5%	5.000	NN	2.1980	NN
10%	10.000	NN	2.1980	NN
15%	15.000	NN	15.409	NN
20%	20.000	12.819	15.409	NN
25%	25.000	12.819	15.409	NN
30%	30.000	12.819	15.409	NN
35%	35.000	26.307	16.101	17.446
40%	40.000	26.307	17.764	17.446
45%	45.000	26.307	17.764	17.446
50%	50.000	43.666	38.104	23.460
55%	55.000	43.666	38.104	23.460
60%	60.000	60.441	38.104	34.043
65%	65.000	60.441	38.104	34.043
70%	70.000	60.441	38.104	34.043
75%	75.000	60.441	38.104	34.043
80%	80.000	69.782	69.395	34.043
85%	85.000	69.782	69.395	34.043
90%	90.000	69.782	69.395	34.043
95%	95.000	69.782	69.395	34.043
100%	100.000	69.782	69.395	34.043

5.4.2. cIPMA Result Analysis

Subsequently, cIPMA is required; set the number of permutations to 5000 and the significance level to 0.10, using Sustainable Agriculture Development (SUS) as the target, and run the NCA permutation. The NCA permutation algorithm allows us to determine the statistical significance of the necessity effect size d from the necessary condition analysis (NCA). The authors of [84] suggested that $0 < d < 0.1$ can be characterized as a small effect, $0.1 \leq d < 0.3$ can be characterized as a medium effect, $0.3 \leq d < 0.5$ can be characterized as a large effect, and $d \geq 0.5$ can be characterized as a very large effect. The results are shown in Table 11.

Table 11. Summary of the results from both the IPMA and the NCA.

Antecedent Construct	Importance	Performance	Percentage of Cases That Do Not Meet the Necessity Condition [1]	Necessity Effect Size d (p Value)
NQL	0.523	19.502	76.667	0.378(0.016 **)
NQLI	0.746	44.153	83.333	0.329(0.014 **)
NQPI	0.082	34.56	56.667	0.191(0.143)

Note: [1] Based a desired Sustainable Agriculture Development (SUS) outcome level of 85. ** ($p < 0.05$).

Using Table 11, the cIPMA of Sustainable Agriculture Development (SUS) can be visualized, as shown in Figure 5.

Unlike traditional IPMA, cIPMA still divides the IPMA chart into four quadrants. However, by incorporating necessary conditions, if a factor in any of the four quadrants does not meet the necessary condition, a prioritized action should be taken [85]. In Figure 5, we can see that NQPI does not meet the necessary condition; therefore, a prioritized action should be taken for it. Hauff et al. [85] mentioned that antecedent structures showing weak and non-significant PLS-SEM effects might be necessary conditions; that is, without these antecedents, specific outcomes cannot be achieved.

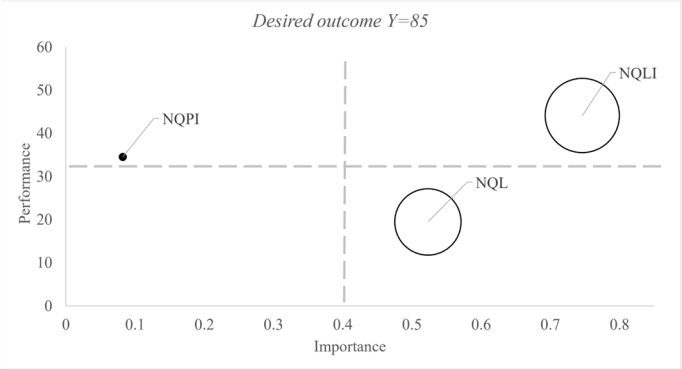


Figure 5. Combined Importance–Performance Map of sustainable Agricultural development (SUS). **Note**: For the desired level of the outcome: ● = construct is not necessary; ○ = construct is necessary. The bubble sizes represent the percentage of cases that have not achieved the required desired level outcome [85].

The cIPMA results show that the necessity level of New Quality Agricultural Production Inputs (NQPI) (0.191) is lower than the critical value (0.3), indicating that it does not constitute a necessary condition for sustainable agricultural development (SUS). Combining the OL-TOPSIS results, it is found that the NQPI score in production areas fluctuates upwards but relies on traditional tangible materials (TM) like fertilizer machinery, leading to high ecological costs (ECO path is 0.082, weak). In consumer areas, the input of intangible materials (IM) is lagging (NQPI score is only 1.86), limiting the potential for achieving SUS (IM→SUS path unsaturated). Based on this, it is recommended to implement a "tangible-intangible resource rebalancing" plan, setting an upper limit for TM usage in production areas and reallocating about one-quarter of the agricultural machinery subsidy to smart agricultural machinery (technology → AgrO, 0.113). For consumer areas, an agricultural digital innovation voucher system should be established to specifically increase the proportion of IM investment to 50% (based on the elasticity of IM→SUS, 0.523).

For New Quality Agricultural Laborers (NQL) and New Quality Agricultural Labor Inputs (NQLI), both meet the necessary condition (NQL: 0.378 > 0.35; NQLI: 0.329 > 0.35). PLS-SEM shows that NQL has a strong transmission effect on both ECO (0.700) and IM (0.438), forming the human capital threshold for SUS. However, the NQL score in the balanced area is the lowest (2021: 2.58), and it is strongly correlated with educational investment. Therefore, it is recommended to launch a "New Farmer Revitalization Project", implementing a "Farmer-Technician Dual-Certification System" in production areas, linking digital skills certification with subsidies (NQL→IM, 0.438). In the balanced area, a digital agricultural technology pairing mechanism between the eastern and western regions should be established, with compulsory support from agricultural universities in the eastern region (e.g., Shaanxi-Shanghai Alliance).

For NQLI, the synergy between technology (TEC) and ecology (ECO) is significant (TEC → AgrO, 0.113; ECO → SUS, 0.082), but the NQLI score in production areas continues to decline (2012: 4.33 → 2021: 3.34), reflecting an imbalance in the investment in technology and ecology. It is recommended to implement the "TEC-ECO Synergy Index" assessment, linking agricultural project approval with the TEC/ECO coupling degree, such as requiring smart water-saving irrigation projects to commit to a carbon sink increase of about 5%. Additionally, an agricultural green technology bank should be piloted in consumer areas, allowing ecological contributions (ECO) to be converted into technology introduction quotas.

Based on the OL-TOPSIS score dynamics and the cIPMA necessity diagnosis, this study further constructs a "three-dimensional-three-zone" policy recommendation matrix,

integrating the three dimensions of NQL, NQLI, and NQPI into the production, balanced, and consumer zones, respectively proposing differentiated policy toolboxes. (1) In production areas, NQPI scores are low, particularly regarding the use of traditional agricultural production materials. Therefore, policies should prioritize the application of smart agricultural technologies and reduce the use of traditional fertilizers, aiming to decrease fertilizer usage by 20% within the next five years. Furthermore, improving NQL is crucial, especially by enhancing farmers' skill levels, aiming to achieve 80% dual-certification coverage in the next five years to drive agricultural modernization. In terms of NQLI, policies should continue to strengthen the coupling of agricultural technology and ecology, promoting a 3% annual increase in the TEC-ECO coupling index, while ensuring that more than 50% of ecological compensation funds are used for technological innovation and upgrading, thereby enhancing the greenness and sustainability of agricultural production. (2) In balanced areas, while NQL and NQLI meet the necessary conditions, NQPI still requires further optimization. Here, policies should increase fiscal allocation to intangible resources (e.g., agricultural digitalization and technological innovation) to improve overall agricultural production efficiency. To further promote agricultural technology, it is recommended that each province implement at least five agricultural technology pairing projects, strengthen the agricultural technology support system, and ensure that more than 50% of ecological compensation funds are used for green technology innovation and application. (3) In consumer areas, NQPI scores are low; therefore, an agricultural digital innovation fund should be established, ensuring an annual investment of at least 0.5% of GDP to drive the digital transformation and innovation of agriculture. At the same time, considering the importance of high-end talent for sustainable agricultural development, a green channel for high-end agricultural talents should be established to attract more professionals to contribute to agricultural development. In terms of NQLI, policies should promote a 15% annual increase in the transaction volume of the green technology bank to encourage the widespread application of green technology and innovation.

Additionally, through PLS-SEM-driven policy design, OL-TOPSIS monitoring of policy effects, and cIPMA dynamic calibration, a "model diagnosis-policy implementation-effect monitoring" closed loop is formed to ensure the policy conversion of academic results. For example, based on NQL→ECO (0.700), the new farmer training course should include at least one-quarter of ecological modules. The target for NQPI in production areas should be a 2% annual growth, corresponding to a penetration rate of smart agricultural machinery greater than a set threshold. Every three years, the necessity threshold should be re-evaluated, and if NQPI remains below 0.35, a TM-IM mandatory replacement mechanism should be triggered (e.g., replacing 1 ton of fertilizer quota with 100,000 RMB worth of digital service vouchers). This not only reveals the impact mechanism of NQP on sustainable agriculture but also provides policymakers with actionable and quantifiable optimization strategies to promote the realization of high-quality agricultural development.

6. Conclusions and Policy Recommendations

6.1. Conclusions

This study uses panel data from 30 provincial-level administrative regions in China between 2012 and 2021 as the research object. Based on a comprehensive evaluation of the development status of new quality productivity (NQP), focusing on the three core dimensions of New Quality Agricultural Laborers (NQL), New Quality Agricultural Production Inputs (NQPI), and New Quality Agricultural Labor Inputs (NQLI), an empirical analysis using the PLS-SEM model is conducted to explore the pathways and impact structures of how NQP empowers agricultural sustainable development. Additionally, based on agricultural functional zoning, the OL-TOPSIS model is applied to quantify the regional

level of comprehensive agricultural NQP. Furthermore, the cIPMA model is used to assess the actual contributions and optimization potential of various indicators for sustainable agricultural development. The aim is to provide targeted optimization strategies and practical guidance for policy formulation. Taking China as a case study, this paper hopes to provide a useful reference for other countries to explore agricultural transformation and upgrading, as well as the optimal allocation of resources, by revealing effective paths for new agricultural productivity to promote sustainable agricultural practices and the coordinated development of regional agriculture, thus contributing to the promotion of global agricultural sustainable development in the real world. Experience and theoretical support. Based on this research, the following conclusions are drawn:

(1) Empirical analysis shows that agricultural NQP significantly promotes sustainable agricultural development and output growth through multidimensional synergistic effects. Specifically, in terms of New Quality Agricultural Labor Inputs, agricultural technology has a significant positive impact on agricultural output, further confirming that technological innovation is one of the key drivers of agricultural economic growth. Agricultural ecology, due to its gradual and systematic mechanism, mainly influences agricultural sustainability through indirect paths like technological upgrades, resource optimization, and institutional innovations, thus having a relatively weaker positive impact on sustainable agricultural development. In terms of New Quality Agricultural Production Inputs, tangible production inputs serve as the foundational guarantee for agricultural development and have a direct positive effect on agricultural output. Intangible production inputs, through the innovation and application of elements such as knowledge, technology, and data, optimize resource allocation, enhance production efficiency, and reduce environmental burdens, thereby significantly promoting agricultural sustainability. New Quality Agricultural Laborers (NQL) not only directly contribute to sustainable agricultural development and output growth but also enhance their indirect impact through the mediating effects of intangible materials and agricultural ecology, fully demonstrating that high-quality laborers are the core driving force behind agricultural transformation and upgrading. The above conclusions reveal the logical relationship and synergy between various factors within new quality productivity and provide a theoretical basis and practical inspiration for policy optimization and sustainable agricultural development in developing countries such as China, as well as in developed countries.

(2) Based on agricultural functional zoning, the OL-TOPSIS model is used to quantify the regional comprehensive NQP level, visualizing the differences in New Quality Agricultural Productivity among regions. Through systematic analysis, this study proves that each functional zone has a relatively stable and continuous development trend, reflecting the coordinated development of different regions across various dimensions. In the consumption areas, the high quality of agricultural laborers has driven high-end agricultural production and technology application. However, their strong dependence on external supplies of production materials and labor inputs has restricted the improvement of local agricultural inputs. In the balanced zones, the quality of agricultural laborers has gradually improved, but the investment in labor inputs and the configuration of production materials remain unstable. Infrastructure construction and education and training need to be further strengthened to optimize the allocation and investment of production factors. As the main agricultural production area, the production zone supports large-scale production with a sufficient number of agricultural laborers but still faces significant room for improvement in modernization development and resource optimization efficiency due to weak management of agricultural labor inputs and insufficient investment in production

materials. The results of this study can assist policymakers in implementing differentiated strategies according to the characteristics of each agricultural functional zone, thereby effectively promoting the transformation and upgrading of Chinese agriculture and regional coordinated development. At the same time, the idea of coordinated development of functional zoning proposed in this study provides a new theoretical perspective and practical reference for other countries facing limited agricultural resources and uneven regional development.

(3) This study innovatively utilizes cIPMA to combine importance, performance, and necessity, based on desired sustainable agricultural development (SUS), to accurately identify and assess the key roles and areas for improvement of various factors in sustainable agricultural development. The results show that New Quality Agricultural Laborers (NQL) are an important driver of agricultural system transformation, significantly enhancing the synergy between ecological effectiveness (ECO) and intangible resources (IM). However, their development in balanced zones is limited by insufficient educational investment, indicating the need to intensify comprehensive human capital training and support. New Quality Agricultural Labor Inputs (NQLI) play an important role in the synergy between technology (TEC) and ecology (ECO), but uneven investment in the production zone further emphasizes the necessity of coupling technology and ecological governance. Meanwhile, New Quality Agricultural Production Inputs, which do not meet the necessary conditions, need to be prioritized for action. This confirms that relying solely on the input of production factors is insufficient to directly promote sustainability, and comprehensive optimization of resource allocation and governance structures must be achieved on the basis of balancing ecological, social, and economic factors.

6.2. Policy Recommendations

For New Quality Agricultural Laborers (NQL), it is suggested to reshape the structural advantages of agricultural laborers' quality through a regionalized skill certification system; that is, to adapt measures to local conditions and build a targeted skills certification framework, which will help countries around the world accurately cultivate high-quality workers who align with regional characteristics. (1) In China, within agricultural production zones, the focus should be on mechanization ability certification, especially addressing the shortcomings in smart agricultural machinery operation in staple grain production areas. Farmers with advanced certifications can be given priority when applying for subsidies for the purchase of high-performance agricultural machinery and, at the same time, obtain policy preferences in agricultural machinery sharing services, land transfer, and cooperative resource allocation, thereby encouraging the transformation and improvement of the traditional labor force. (2) In consumer areas, the focus should be on attracting high-value agricultural talent, and pilot programs for "Agricultural Technology Innovation Talent Visas" should be implemented in urban areas to provide long-term residence convenience for overseas experts engaged in high value-added agricultural science and technology fields, such as precision irrigation algorithm development and biological seed research and development. A municipal-level open-source agricultural digital tools community should be established to encourage settled enterprises to establish technical cooperation and share digital resources with local agricultural business entities in exchange for R&D tax credits. (3) In balanced areas, a cross-regional skill offset network should be established by selecting agricultural universities in the eastern regions and vocational training institutions in the central and western regions to form joint research and teaching bodies. Digital training packages covering specialized courses on soil carbon sink monitoring, drought-resistant variety breeding, etc., should be developed, and credit transfer between regions should be

linked to the distribution of ecological compensation funds, compensating for differences in regional resource endowments through knowledge flow. For developing countries facing insufficient mechanization levels and shortcomings in agricultural labor skills, it is also possible to pilot a regionalized skills certification mechanism to optimize the labor structure by strengthening intelligent agricultural machinery operations and agricultural digital technology training.

For New Quality Agricultural Labor Inputs (NQLI), a technology penetration-driven framework for labor input intensification should be established to optimize resource allocation through technology application and improve the efficiency and sustainability of international agricultural production. (1) In China, production areas should implement a rigid linkage mechanism between resource consumption intensity and financial subsidies, promote intelligent monitoring equipment in water-tight areas such as North China, and incorporate green indicators, such as irrigation water efficiency and the organic fertilizer substitution ratio, into the policy support and project approval reference conditions. This approach will provide policy-based green credit support to entities that achieve resource conservation goals. (2) In consumer areas, technological advantages as a source of innovation should be leveraged, and pilot programs for Agricultural SaaS platforms (Software as a Service) should be implemented, encouraging enterprises located in the digital industrial park to export core algorithm services to surrounding counties for free or at a preferential rate. The total platform service output should be dynamically linked to the local government's special bond application limits. (3) In balanced areas, a cross-domain compensation pool for production factor turnover should be established, and the turnover of intangible resources, such as shared agricultural machinery services and soil formula data, should be tracked at the county level. A differentiated points system should be established based on categories like "East technology to West" or "North intelligence to South support", allowing points to be exchanged for land fallow subsidies or technology priority procurement rights, thereby breaking down administrative barriers to resource flow. For countries with low agricultural resource utilization efficiency, we can also promote policies linking resource consumption intensity to fiscal incentives, popularize intelligent irrigation monitoring equipment, and explore cross-regional agricultural machinery sharing and data transfer compensation mechanisms to optimize resource allocation and improve agricultural sustainability development capabilities.

For New Quality Agricultural Production Inputs (NQPI), a structural adaptation project for the supply side of production materials should be implemented; by optimizing resource allocation and technology supply, production materials can more efficiently match actual demand and improve the overall operating efficiency of the international agricultural system. To address the bottleneck in upgrading key equipment in production areas, a negative list system for intelligent agricultural machinery upgrades should be established. (1) In light of the bottleneck in upgrading key equipment in production areas, we should explore the establishment of a management and control system for the renewal and iteration of intelligent agricultural machinery, implement agricultural machinery emission standard restriction policies in key areas, gradually phase out diesel engine models below the National III level, and, at the same time, establish a special fund for clean energy agricultural machinery transformation to achieve clean energy. Agricultural entities with alternative targets will be given policy incentives, such as warehousing land indicator rewards. (2) Consumption areas need to build a comprehensive supervision system for urban agricultural technology, open agricultural demonstration parks to promote intelligent crop monitoring and quality testing technologies, incorporate indicators such as equipment networking rate and the standardization degree of data open interfaces into the park's star rating, and explore incentive mechanisms to link these with digital agriculture project funding. (3) In

balanced areas, a chain reaction plan for technology incubators should be launched, creating hybrid research and development platforms in areas with severely fragmented arable land. This initiative should be funded by government investments, with technical contributions from research institutes and management by new business entities. Priorities should be given to developing modular small agricultural machinery, biodegradable film substitution technologies, and other innovations that suit small farm scenarios. Patent-derived income should be proportionally injected into county-level agricultural green development risk compensation funds, forming a closed-loop mechanism in which technological dividends feed back into ecological protection. In areas with outdated agricultural equipment and low resource utilization, we can also promote intelligent agricultural machinery renewal and clean energy transformation plans, promote the standardized application of crop monitoring and quality testing technologies, and, at the same time, build a technology incubation platform suitable for the small-scale farmer economy to improve the modernization level of agricultural equipment and support the development of green agriculture.

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Abbreviations

The following abbreviations are used in this manuscript:

NQL	New Quality Agricultural Laborers
NQLI	New Quality Agricultural Labor Inputs
TEC	Agricultural technology
ECO	Agricultural ecology
NQPI	New Quality Agricultural Production Inputs
TM	Tangible materials
IM	Intangible materials
SUS	Sustainable agricultural development
AgrO	Agricultural Output Value Standards
NQP	New Quality Productivity
PLS-SEM	Partial Least Squares Structural Equation Modeling
OL-TOPSIS	Outer Loadings TOPSIS
cIPMA	Combined Importance–Performance Map Analysis

Appendix A

Mathematical explanation that the Outer Loadings of PLS-SEM are effective as TOPSIS indicator weights.

(Step 1) Mathematical Calculations for Outer Loadings: We focus on quantifying the relationship between observed variables and latent variables through outer loadings [70]. The outer loading, λ_j, represents the standardized regression coefficient between the observed variable, x_j, and the latent variable, ξ_j, and is calculated as follows:

$$\lambda_j = \frac{\mathrm{Cov}(x_j, \xi)}{\mathrm{Var}(\xi)} \tag{A1}$$

Covariance $\mathrm{Cov}(x_j, \xi)$: This measures the linear relationship between the observed variable, x_j, and the latent variable, ξ. If x_j and ξ move in the same direction (i.e., when ξ increases, x_j also increases, or vice versa), the covariance will be positive. If they move in opposite directions, the covariance will be negative. Variance $\mathrm{Var}(\xi)$: This describes the dispersion or spread of the latent variable, ξ, that is, how much the latent variable varies across observations. Standardized Regression Coefficient: The outer loading, λ_j, is standardized by dividing the covariance by the variance of the latent variable. This standardization ensures that the outer loading is dimensionless and allows for comparisons between different observed variables. Larger values of λ_j indicate stronger relationships between an observed variable and the latent variable.

Thus, the outer loading, λ_j, reflects the strength of the relationship between each observed variable and the latent variable, and it is expressed as a standardized coefficient.

(Step 2) Embedding Theoretical Information into Weights: Transform the outer loadings into weights, which better describe each observed variable's relative contribution to the latent variable. The formula is as follows:

$$w_j^{OL} = \frac{|\lambda_j|}{\sum_{k=1}^{m} |\lambda_k|} \tag{A2}$$

We take the absolute value of the outer loadings, λ_j, as we are concerned with the strength of the relationship rather than the direction (positive or negative). By using absolute values, we focus on how strongly the observed variables contribute to the latent variable, without considering whether the relationship is positive or negative. Each outer loading's absolute value is divided by the total sum of the absolute values of all outer loadings. This ensures that the sum of all weights equals 1. This step is performed to eliminate the influence of the scale of the data and to enable comparison between the relative contributions of different observed variables.

Through this process, we obtain the weight for each observed variable, which is proportional to its outer loading. The weight has two important properties: Non-negativity, $w_j^{OL} \geq 0$: Since the absolute value of the outer loadings is always non-negative, the weights are also non-negative. Normalization, $\sum w_j^{OL} = 1$: This means that the total of all weights is 1. This ensures that the weights represent relative contributions, rather than absolute quantities.

(Step 3) Statistical Significance Constraint: To improve the model's accuracy and interpretability, we often want to **filter out** insignificant variables. Statistical significance is

typically determined through hypothesis testing, often using a p-value to decide whether an outer loading is significant. The significance indicator function, I_j, is defined as follows:

$$I_j = \begin{cases} 1 & \text{if } \lambda_j \text{ is significant} \\ 0 & \text{otherwise} \end{cases} \tag{A3}$$

$I_j = 1$ indicates that the outer loading, λ_j, is significant (often with a p-value less than 0.05). $I_j = 0$ indicates that λ_j is not significant, and the observed variable, x_j, is excluded from contributing to the latent variable.

When we introduce statistical significance, the effective weight w_j^{OL} is as follows:

$$w_j^{OL} = \frac{|\lambda_j| \cdot I_j}{\sum_{k=1}^{m} |\lambda_k| \cdot I_k} \tag{A4}$$

This means that only the significant outer loadings (i.e., those for which $I_j = 1$) will contribute to the weight calculation. In other words, insignificant variables are excluded from the calculation.

(Step 4) Maximizing the Latent Variable's Explained Variance: To ensure the effectiveness of the model and its explanatory power, PLS-SEM aims to optimize the outer loadings matrix, Λ, to **maximize the latent variable's explained variance** in the observed variables. This optimization goal is expressed as follows:

$$\max_{\Lambda} \mathrm{Tr}(\Lambda' \Sigma_X \Lambda) \text{ s.t. } \Lambda' \Lambda = I \tag{A5}$$

Tr represents the trace of a matrix, which is the sum of its diagonal elements. In this case, the trace represents the total variance explained by the latent variable, ξ, in the observed variables, X. $\Lambda' \Sigma_X \Lambda$: This part expresses the explained variance of the observed variables, X, by the latent variable, ξ. By optimizing the outer loadings matrix, Λ, we aim to maximize the latent variable's explanatory power over the observed variables. Constraint $\Lambda' \Lambda = I$: This constraint ensures that the columns of the outer loadings matrix are orthogonal, meaning that each latent variable explains a unique component of the observed variables, without redundancy due to multicollinearity.

By iteratively optimizing this problem, PLS-SEM adjusts the outer loadings matrix, Λ, to maximize the explanatory power of the latent variables on the observed variables, thereby achieving the best possible model fit.

Based on the relationship of the entire outer loadings calculation structure mentioned above, in the methodological framework, the λ weights optimized by Partial Least Squares Structural Equation Modeling (PLS-SEM) are essentially adaptive adjustment parameters on the latent variable dimensions. These weights converge to the steady state with maximum explanatory power through the iterative calculation of the external model and are then fixed as external inputs embedded into the normalized decision matrix of TOPSIS. The key point is that the λ coefficient, as the weight generation mechanism, originates from an external optimization process independent of the ranking algorithm. Using λ as the weight essentially means that an optimized coefficient with theoretical explanatory power is used as the indicator weight in TOPSIS. However, the essence of the TOPSIS calculation paradigm still strictly follows the original axioms proposed by Hwang and Yoon [115]. λ merely assigns explanatory power to each indicator and does not affect the fundamental framework of the TOPSIS algorithm.

Appendix B

Table A1. Gaussian copula analysis.

	B	(M)	(STDEV)	T Statistics	*p* Values
GC(LAB) → CO	−1.439	−0.482	1.202	1.198	0.231
GC(ECO) → SUS	0.019	0.019	0.022	0.860	0.390
GC(TEC) → AgrO	0.014	0.026	0.083	0.164	0.870
GC(TM) → AgrO	−0.197	−0.162	0.201	0.982	0.326
GC(LAB) → IM	−0.642	−0.346	0.976	0.658	0.511

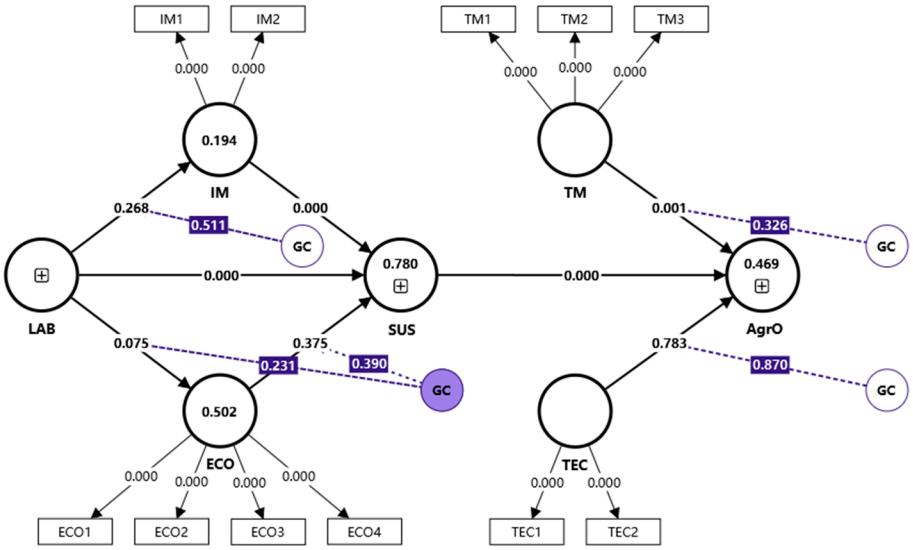


Figure A1. Gaussian copula in PLS-SEM.

References

1. Food and Agriculture Organization of the United Nations (FAO). *The State of Food and Agriculture 2021: Making Agrifood Systems More Resilient to Shocks and Stresses*; FAO: Rome, Italy, 2021. Available online: https://openknowledge.fao.org/server/api/core/bitstreams/1e61f82a-618c-467a-a37f-545580094a1d/content (accessed on 10 January 2025).
2. United Nations (UN). *Transforming Our World: The 2030 Agenda for Sustainable Development*; UN: New York, NY, USA, 2015. Available online: https://docs.un.org/en/A/RES/70/1 (accessed on 10 January 2025).
3. Chartzoulakis, K.; Bertaki, M. Sustainable water management in agriculture under climate change. *Agric. Agric. Sci. Procedia* **2015**, *4*, 88–98. [CrossRef]
4. Singh, A.; Mehrotra, R.; Rajput, V.D.; Dmitriev, P.; Singh, A.K.; Kumar, P.; Tomar, R.S.; Singh, O.; Singh, A.K. Geoinformatics, artificial intelligence, sensor technology, big data: Emerging modern tools for sustainable agriculture. In *Sustainable Agriculture Systems and Technologies*; Wiley: Hoboken, NJ, USA, 2022; pp. 295–313.
5. Pham, L.V.; Smith, C. Drivers of agricultural sustainability in developing countries: A review. *Environ. Syst. Decis.* **2014**, *34*, 326–341. [CrossRef]
6. Bathaei, A.; Štreimikienė, D. Renewable energy and sustainable agriculture: Review of indicators. *Sustainability* **2023**, *15*, 14307. [CrossRef]
7. Fuglie, K. R&D capital, R&D spillovers, and productivity growth in world agriculture. *Appl. Econ. Perspect. Policy* **2018**, *40*, 421–444.
8. Chen, M.; Zhou, Y.; Huang, X.; Ye, C. The integration of new-type urbanization and rural revitalization strategies in China: Origin, reality and future trends. *Land* **2021**, *10*, 207. [CrossRef]
9. Yu, F.; Huang, X. Thinking on the path of high-quality agricultural development in the new era. *J. China Exec. Leadersh. Acad. Jinggangshan* **2019**, *12*, 128–135. (In Chinese)
10. Luo, B.; Geng, P. New quality agricultural productivity: Theoretical context, basic core and improvement path. *Agric. Econ. Issues* **2024**, *4*, 13–26. (In Chinese)
11. Gao, F. The logic, multi-dimensional connotation and contemporary significance of "new quality productivity". *Political Econ. Rev.* **2023**, *14*, 127–145. (In Chinese)

12. Zhou, W.; Xu, L. On the new quality of productivity: Connotation, characteristics and key points. *Reform* **2023**, *10*, 1–13. (In Chinese)
13. Niu, Z. Digital economy empowers agricultural modernization: Mechanism of action, practical challenges and promotion path. *Smart Agric. Guide* **2025**, *5*, 103–106. (In Chinese) [CrossRef]
14. Raman, S. *Agricultural Sustainability: Principles, Processes, and Prospects*; CRC Press: Boca Raton, FL, USA, 2024.
15. Pu, Q.; Xiang, W. The connotation, characteristics, internal logic and realization methods of new quality productivity—A new driving force for promoting Chinese modernization. *J. Xinjiang Norm. Univ. Philos. Soc. Sci. Ed.* **2024**, *45*, 77–85. (In Chinese) [CrossRef]
16. Zhu, D.; Ye, L. China's new agricultural productivity: Level measurement and dynamic evolution. *Stat. Decis. -Mak.* **2024**, *40*, 24–30. (In Chinese) [CrossRef]
17. Li, Z.; Wang, J.; Wang, W. New quality productivity empowers high-quality agricultural development: An empirical analysis based on spatial spillover effect and threshold effect. *Jiangsu Agric. Sci.* **2024**, *52*, 1–12. (In Chinese). Available online: http://www.jsnykx.cn/oa/DArticle.aspx?type=view&id=202424036 (accessed on 10 January 2025).
18. Li, Z.; Wang, H. Digital new quality productivity and high-quality development of the real economy: Theoretical analysis and empirical test. *Stat. Decis. -Mak.* **2024**, *40*, 12–16. (In Chinese) [CrossRef]
19. Hu, X.; Yang, Y.; Li, Y. Can VAT Reform Drive the Upgrading of the Service Industry? Test from the Realization Path of New Quality Productivity. *Financ. Forum*. 2025, pp. 1–13. (In Chinese). Available online: https://www.chndoi.org/Resolution/Handler?doi=10.13762/j.cnki.cjlc.20241226.001 (accessed on 10 January 2025).
20. Malthus, T. *An Essay on the Principle of Population//British Politics and the Environment in the Long Nineteenth Century*; Routledge: London, UK, 2023; pp. 77–84.
21. Harwood, R.R. *A History of Sustainable Agriculture//Sustainable Agricultural Systems*; CRC Press: Boca Raton, FL, USA, 2020; pp. 3–19.
22. Gumbau-Albert, M.; Maudos, J. The importance of intangible assets in regional economic growth: A growth accounting approach. *Ann. Reg. Sci.* **2022**, *69*, 361–390. [CrossRef]
23. Khan, N.; Ray, R.L.; Sargani, G.R.; Ihtisham, M.; Khayyam, M.; Ismail, S. Current progress and future prospects of agriculture technology: Gateway to sustainable agriculture. *Sustainability* **2021**, *13*, 4883. [CrossRef]
24. Waleed, M.; Um, T.-W.; Kamal, T.; Khan, A.; Iqbal, A. Determining the precise work area of agriculture machinery using internet of things and artificial intelligence. *Appl. Sci.* **2020**, *10*, 3365. [CrossRef]
25. Wan, S.; Zhao, K.; Lu, Z.; Li, J.; Lu, T.; Wang, H. A modularized ioT monitoring system with edge-computing for aquaponics. *Sensors* **2022**, *22*, 9260. [CrossRef]
26. Froiz-Míguez, I.; Lopez-Iturri, P.; Fraga-Lamas, P.; Celaya-Echarri, M.; Blanco-Novoa, Ó.; Azpilicueta, L.; Falcone, F.; Fernández-Caramés, T.M. Design, implementation, and empirical validation of an IoT smart irrigation system for fog computing applications based on Lora and Lorawan sensor nodes. *Sensors* **2020**, *20*, 6865. [CrossRef]
27. Inoue, Y. Satellite-and drone-based remote sensing of crops and soils for smart farming–a review. *Soil Sci. Plant Nutr.* **2020**, *66*, 798–810. [CrossRef]
28. Merz, M.; Pedro, D.; Skliros, V.; Bergenhem, C.; Himanka, M.; Houge, T.; Matos-Carvalho, J.P.; Lundkvist, H.; Cürüklü, B.; Hamrén, R.; et al. Autonomous UAS-based agriculture applications: General overview and relevant European case studies. *Drones* **2022**, *6*, 128. [CrossRef]
29. Wang, R.F.; Su, W.H. The application of deep learning in the whole potato production Chain: A Comprehensive review. *Agriculture* **2024**, *14*, 1225. [CrossRef]
30. Khaki, S.; Wang, L.; Archontoulis, S.V. A CNN-RNN framework for crop yield prediction. *Front. Plant Sci.* **2020**, *10*, 1750. [CrossRef]
31. Mazzia, V.; Khaliq, A.; Chiaberge, M. Improvement in land cover and crop classification based on temporal features learning from Sentinel-2 data using recurrent-convolutional neural network (R-CNN). *Appl. Sci.* **2019**, *10*, 238. [CrossRef]
32. Nejad, S.M.M.; Abbasi-Moghadam, D.; Sharifi, A.; Farmonov, N.; Amankulova, K.; Laszlz, M. Multispectral crop yield prediction using 3D-convolutional neural networks and attention convolutional LSTM approaches. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2022**, *1*, 254–266. [CrossRef]
33. Yang, F.; Zhang, D.; Zhang, Y.; Zhang, Y.; Han, Y.; Zhang, Q.; Zhang, Q.; Zhang, C.; Liu, Z.; Wang, K. Prediction of corn variety yield with attribute-missing data via graph neural network. *Comput. Electron. Agric.* **2023**, *211*, 108046. [CrossRef]
34. Shukla, J.S.; Pandya, R.J. Deep learning-oriented c-GAN models for vegetative drought prediction on peninsular India. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2023**, *17*, 282–297. [CrossRef]
35. Kulkarni, P.; Wyawahare, M.; Karwande, A.; Kolhe, T.; Kamble, S.; Joshi, A. *Agricultural Field Analysis Using Satellite Hyperspectral Data and Autoencoder//International Conference on Recent Trends in Image Processing and Pattern Recognition*; Springer International Publishing: Cham, Switzerland, 2021; pp. 363–375.

36. Bedi, P.; Gole, P. Plant disease detection using hybrid model based on convolutional autoencoder and convolutional neural network. *Artif. Intell. Agric.* **2021**, *5*, 90–101. [CrossRef]
37. Das, S.; Ray, M.K.; Panday, D.; Mishra, P.K. Role of biotechnology in creating sustainable agriculture. *PLOS Sustain. Transform.* **2023**, *2*, e0000069. [CrossRef]
38. Kim, H.S.; Kwak, S.S. Crop biotechnology for sustainable agriculture in the face of climate crisis. *Plant Biotechnol. Rep.* **2020**, *14*, 139–141. [CrossRef]
39. Pe'Er, G.; Bonn, A.; Bruelheide, H.; Dieker, P.; Eisenhauer, N.; Feindt, P.H.; Hagedorn, G.; Hansjürgens, B.; Herzon, I.; Lomba, Â.; et al. Action needed for the EU Common Agricultural Policy to address sustainability challenges. *People Nat.* **2020**, *2*, 305–316. [CrossRef]
40. Mazzucato, M. Mission-oriented innovation policies: Challenges and opportunities. *Ind. Corp. Change* **2018**, *27*, 803–815. [CrossRef]
41. Czyżewski, B.; Matuszczak, A.; Grzelak, A.; Guth, M.; Majchrzak, A. Environmental sustainable value in agriculture revisited: How does Common Agricultural Policy contribute to eco-efficiency? *Sustain. Sci.* **2021**, *16*, 137–152. [CrossRef]
42. Shreck, A.; Getz, C.; Feenstra, G. Social sustainability, farm labor, and organic agriculture: Findings from an exploratory analysis. *Agric. Hum. Values* **2006**, *23*, 439–449. [CrossRef]
43. Prause, L. Digital agriculture and labor: A few challenges for social sustainability. *Sustainability* **2021**, *13*, 5980. [CrossRef]
44. Raji, E.; Ijomah, T.I.; Eyieyien, O.G. Improving agricultural practices and productivity through extension services and innovative training programs. *Int. J. Appl. Res. Soc. Sci.* **2024**, *6*, 1297–1309. [CrossRef]
45. Sánchez-Bravo, P.; Chambers, E.V.; Noguera-Artiaga, L.; Sendra, E.; Chambers, E., IV; Carbonell-Barrachina, Á.A. Consumer understanding of sustainability concept in agricultural products. *Food Qual. Prefer.* **2021**, *89*, 104136. [CrossRef]
46. Wojciechowska-Solis, J.; Barska, A. Exploring the preferences of consumers' organic products in aspects of sustainable consumption: The case of the Polish consumer. *Agriculture* **2021**, *11*, 138. [CrossRef]
47. Smith, A. An Inquiry into the Nature and Causes of the Wealth of Nations. In *Readings in Economic Sociology*; Wiley: Hoboken, NJ, USA, 2002; pp. 6–17.
48. Ricardo, D. *From the Principles of Political Economy and Taxation//Readings in the Economics of the Division of Labor: The Classical Tradition*; World Scientific: Singapore, 2005; pp. 127–130. [CrossRef]
49. Solow, R.M. A contribution to the theory of economic growth. *Q. J. Econ.* **1956**, *70*, 65–94. [CrossRef]
50. Arrow, K.J. The economic implications of learning by doing. *Rev. Econ. Stud.* **1962**, *29*, 155–173. [CrossRef]
51. Romer, P.M. Endogenous technological change. *J. Political Econ.* **1990**, *98 Pt 2*, S71–S102. [CrossRef]
52. Lucas, R.E., Jr. On the mechanics of economic development. *J. Monet. Econ.* **1988**, *22*, 3–42. [CrossRef]
53. Brynjolfsson, E.; Rock, D.; Syverson, C. The productivity J-curve: How intangibles complement general purpose technologies. *Am. Econ. J. Macroecon.* **2021**, *13*, 333–372. [CrossRef]
54. Haskel, J.; Westlake, S. Capitalism without capital: The rise of the intangible economy. *Economics* **2020**, *44*, 147–152.
55. Mondejar, M.E.; Avtar, R.; Diaz, H.L.B.; Dubey, R.K.; Esteban, J.; Gómez-Morales, A.; Hallam, B.; Mbungu, N.T.; Okolo, C.C.; Prasad, K.A.; et al. Digitalization to achieve sustainable development goals: Steps towards a Smart Green Plane. *Sci. Total Environ.* **2021**, *794*, 148539. [CrossRef]
56. Stern, N. The economics of climate change. *Am. Econ. Rev.* **2008**, *98*, 1–37. [CrossRef]
57. Steffen, W.; Richardson, K.; Rockström, J.; Cornell, S.E.; Fetzer, I.; Bennett, E.M.; Biggs, R.; Carpenter, S.R.; De Vries, W.; De Wit, C.A.; et al. Planetary boundaries: Guiding human development on a changing planet. *Science* **2015**, *347*, 1259855. [CrossRef]
58. Carlsson, B.; Acs, Z.J.; Audretsch, D.B.; Braunerhjelm, P. Knowledge creation, entrepreneurship, and economic growth: A historical review. *Ind. Corp. Change* **2009**, *18*, 1193–1229. [CrossRef]
59. Švarc, J.; Dabić, M. Evolution of the knowledge economy: A historical perspective with an application to the case of Europe. *J. Knowl. Econ.* **2017**, *8*, 159–176. [CrossRef]
60. Xu, Z.; Zheng, L.; Cheng, M. The inherent logic and practical concept of new quality productivity to empower high-quality development. *Contemp. Econ. Res.* **2023**, *339*, 51–58. (In Chinese)
61. Tang, J. New Quality Productivity and China's Strategic Shift Towards Sustainable and Innovation-Driven Economic Development. *J. Interdiscip. Insights* **2024**, *2*, 36–45.
62. Xie, F.; Jiang, N.; Kuang, X. Towards an accurate understanding of 'new quality productive forces'. *Econ. Political Stud.* **2024**, 1–15. [CrossRef]
63. Yue, S.; Bajuri, N.H.; Khatib, S.F.; Lee, Y. New quality productivity and environmental innovation: The hostile moderating roles of managerial empowerment and board centralization. *J. Environ. Manag.* **2024**, *370*, 122423. [CrossRef]
64. Shao, C.; Dong, H.; Gao, Y. New Quality Productivity and Industrial Structure in China: The Moderating Effect of Environmental Regulation. *Sustainability* **2024**, *16*, 6796. [CrossRef]
65. Xu, T.; Yang, G.; Chen, T. The role of green finance and digital inclusive finance in promoting economic sustainable development: A perspective from new quality productivity. *J. Environ. Manag.* **2024**, *370*, 122892. [CrossRef]

66. Wang, J.; Qiao, L.; Zhu, G.; Di, K.; Zhang, X. Research on the driving factors and impact mechanisms of green new quality productive forces in high-tech retail enterprises under China's Dual Carbon Goals. *J. Retail. Consum. Serv.* **2025**, *82*, 104092. [CrossRef]
67. Lin, L.; Gu, T.; Shi, Y. The influence of new quality productive forces on high-quality agricultural development in China: Mechanisms and empirical testing. *Agriculture* **2024**, *14*, 1022. [CrossRef]
68. Huang, Q.; Guo, W.; Wang, Y. A Study of the Impact of New Quality Productive Forces on Agricultural Modernization: Empirical Evidence from China. *Agriculture* **2024**, *14*, 1935. [CrossRef]
69. Li, Y.; Wei, C.; Liu, D. Research on the impact of new agricultural productivity on the high-quality development of my country's agriculture—Based on the analysis of the mediating effect of agricultural production technology efficiency and the regulatory effect of agricultural insurance. *Southwest Financ.* **2024**, *517*, 1–13. (In Chinese)
70. Hair, J.F., Jr.; Hult, G.T.M.; Ringle, C.M.; Sarstedt, M.; Danks, N.P.; Ray, S. *Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R: A Workbook*; Springer Nature: Berlin/Heidelberg, Germany, 2021.
71. Lan, Y.; Hu, M.; Xie, X. Diverse professional experiences and high-quality development of family farms: Based on the mediating effect of dynamic capabilities. *Agric. Mod. Res.* **2024**, *45*, 649–660. (In Chinese) [CrossRef]
72. Xu, X.; Yang, W.; Wu, B. Multiple paths for rural digital economy to enhance agricultural total factor productivity: A configuration analysis based on county-level data in Zhejiang Province. *Chin. Rural Econ.* **2024**, 84–103. (In Chinese) [CrossRef]
73. Gao, X.; Yang, Z.; Sun, Z. An empirical study on inclusive innovation performance based on PLS-SEM model. *Sci. Technol. Prog. Countermeas.* **2019**, *36*, 26–32. (In Chinese)
74. Zhang, H.; Hou, X.; Jin, Y. The impact of fallow policy on farmers' behavior in protecting cultivated land quality. *Resour. Sci.* **2023**, *45*, 2196–2209. (In Chinese)
75. Guo, S.; Xu, Y.; Huang, J. Evaluation of agricultural green development level based on entropy weight TOPSIS model: A case study of Henan Province. *J. Zhejiang Univ. (Agric. Life Sci.)* **2024**, *50*, 221–230. (In Chinese)
76. Xu, X.; Hou, L.; Lin, H. Regionalization of China's agricultural sustainable development based on comparative advantage. *Acta Geogr. Sin.* **2002**, *4*, 451–458. (In Chinese)
77. Leite de Almeida, A.C.; Dale, A.; Hay, R.; Everingham, Y.; Lockie, S. Environmental, social and governance (ESG) in agriculture: Trends and gaps on research. *Australas. J. Environ. Manag.* **2024**, 1–30. [CrossRef]
78. Huang, H.; Zhang, Z. Statistical measurement of new quality productivity and regional difference analysis. *Stat. Decis. Mak.* **2025**, *41*, 28–33. (In Chinese)
79. Ma, X.; Zhang, S.; Guo, L.; Yang, J. The Influence of Traditional Ethnic Villages on Forest Structure Based on PLS-SEM: A Case Study of Miao Inhabited Area. *Forests* **2023**, *14*, 2011. [CrossRef]
80. Nas, T.F. *Cost-Benefit Analysis: Theory and Application*; Lexington Books: Lanham, MD, USA, 2016. Available online: https://rowman.com/ISBN/9781498522526/Cost-Benefit-Analysis-Theory-and-Application-2nd-Edition (accessed on 10 January 2025).
81. Wang, S.; Yu, S.; Hu, J. Research on the influencing factors of financial support policies for small and micro enterprises in Hunan Province from the perspective of policy process: A comprehensive exploration based on grounded theory, AHP and DEMATEL methods. *Enterp. Reform Manag.* **2009**, *24*, 123–125. (In Chinese) [CrossRef]
82. Zhang, W.; Xi, Z. Application of Delphi method in screening of indexes for measuring soil pollution value evaluation. *Environ. Sci. Pollut. Res.* **2021**, *28*, 6561–6571. [CrossRef]
83. Huang, M.; Chen, J. Analysis of key influencing factors of public health emergency risk perception in urban-rural fringe areas based on ISM and AHP. *Saf. Environ. Eng.* **2024**, *31*, 47–53+64. (In Chinese) [CrossRef]
84. Teeluckdharry, N.B.; Teeroovengadum, V.; Seebaluck, A.K. A roadmap for the application of PLS-SEM and IPMA for effective service quality improvements. *TQM J.* **2024**, *36*, 1300–1345. [CrossRef]
85. Hauff, S.; Richter, N.F.; Sarstedt, M.; Ringle, C.M. Importance and performance in PLS-SEM and NCA: Introducing the combined importance-performance map analysis (cIPMA). *J. Retail. Consum. Serv.* **2024**, *78*, 103723. [CrossRef]
86. Huang, Q.; Sheng, F. New Quality Productivity System: Element Characteristics, Structural Load and Functional Orientation. *Reform*. 2024, pp. 15–24. (In Chinese). Available online: https://www.scirp.org/reference/referencespapers?referenceid=3835990 (accessed on 14 January 2025).
87. Ab Hamid, M.R.; Sami, W.; Sidek, M.H.M. *Discriminant Validity Assessment: Use of Fornell & Larcker Criterion Versus HTMT Criterion//Journal of Physics: Conference Series*; IOP Publishing: Beijing, China, 2017; Volume 890, p. 012163.
88. Hair, J.F., Jr.; Hult, G.T.M.; Ringle, C.; Sarstedt, M. *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*; Sage Publishing: Thousand Oaks, CA, USA, 2016.
89. Hair, J.F.; Risher, J.J.; Sarstedt, M.; Ringle, C.M. When to use and how to report the results of PLS-SEM. *Eur. Bus. Rev.* **2019**, *31*, 2–24. [CrossRef]
90. Marx, K. *Capital: Critique of Political Economy*; Princeton University Press: Princeton, NJ, USA, 2024; Volume 1.
91. O'brien, R.; Williams, M. *Global Political Economy: Evolution and Dynamics*; Bloomsbury Publishing: London, UK, 2024.

92. Zhang, L.; Pu, Q. The connotation characteristics, theoretical innovation and value connotation of new quality productivity. *J. Chongqing Univ. Soc. Sci. Ed.* **2023**, *29*, 137–148. (In Chinese)
93. Zhang, H.; Wang, Z. New agricultural productivity: Theoretical connotation, practical foundation and improvement paths. *J. Nanjing Agric. Univ. Soc. Sci. Ed.* **2024**, *24*, 28–38. (In Chinese)
94. Chengjun, S.; Renhua, S.; Zuliang, S.; Yinghao, X.; Jiuchen, W.; Zhiyu, X.; Shangbin, G. Construction process and development trend of ecological agriculture in China. *Acta Ecol. Sin.* **2022**, *42*, 624–632. [CrossRef]
95. Alston, J.M.; Pardey, P.G. Agriculture in the global economy. *J. Econ. Perspect.* **2014**, *28*, 121–146. [CrossRef]
96. Emerick, K.; De Janvry, A.; Sadoulet, E.; Dar, M.H. Technological innovations, downside risk, and the modernization of agriculture. *Am. Econ. Rev.* **2016**, *106*, 1537–1561. [CrossRef]
97. Sethi, L.; Behera, B.; Sethi, N. Do green finance, green technology innovation, and institutional quality help achieve environmental sustainability? Evidence from the developing economies. *Sustain. Dev.* **2024**, *32*, 2709–2723. [CrossRef]
98. Radcliffe, C.; Raman, A.; Parissi, C. Entwining Indigenous Knowledge and Science Knowledge for Sustainable Agricultural Extension: Exploring the Strengths and Challenges. *J. Agric. Educ. Ext.* **2021**, *27*, 133–151. [CrossRef]
99. Yao, Y.; Chen, W.; Li, X. Research on the relationship between environmentally friendly agricultural technology innovation and agricultural economic growth. *China Popul. Resour. Environ.* **2014**, *24*, 122–130. (In Chinese)
100. Salam, A. *Internet of Things in Agricultural Innovation and Security//Internet of Things for Sustainable Community Development: Wireless Communications, Sensing, and Systems*; Springer International Publishing: Cham, Switzerland, 2024; pp. 71–112.
101. Zou, B.; Mishra, A.K. Modernizing smallholder agriculture and achieving food security: An exploration in machinery services and labor reallocation in China. *Appl. Econ. Perspect. Policy* **2024**, *46*, 1662–1691. [CrossRef]
102. Chen, W.; Wang, Q.; Li, Q.; Wang, Y.; Zheng, W. Exploring the impact of rural labor transfer on the production and ecological sustainability of crop planting structure in China. *Environ. Sci. Pollut. Res.* **2023**, *30*, 22668–22685. [CrossRef]
103. Padhiary, M.; Kumar, R. *Assessing the Environmental Impacts of Agriculture, Industrial Operations, and Mining on Agro-Ecosystems//Smart Internet of Things for Environment and Healthcare*; Springer Nature: Cham, Switzerland, 2024; pp. 107–126.
104. Pachiappan, K.; Anitha, K.; Pitchai, R.; Sangeetha, S.; Satyanarayana, T.V.V.; Boopathi, S. *Intelligent Machines, IoT, and AI in Revolutionizing Agriculture for Water Processing//Handbook of Research on AI and ML for Intelligent Machines and Systems*; IGI Global: Hershey, PA, USA, 2024; pp. 374–399.
105. Henseler, J.; Ringle, C.M.; Sinkovics, R.R. *The Use of Partial Least Squares Path Modeling in International Marketing//New Challenges to International Marketing*; Emerald Group Publishing Limited: Bradford, UK, 2009; pp. 277–319.
106. Nerlove, M. *Essays in Panel Data Econometrics*; Cambridge University Press: Cambridge, UK, 2005.
107. Kline, R.B. *Principles and Practice of Structural Equation Modeling*; Guilford Publications: New York, NY, USA, 2023.
108. Angrist, J.D.; Pischke, J.S. *Mostly Harmless Econometrics: An Empiricist's Companion*; Princeton University Press: Princeton, NJ, USA, 2009.
109. Henseler, J.; Ringle, C.M.; Sarstedt, M. A new criterion for assessing discriminant validity in variance-based structural equation modeling. *J. Acad. Mark. Sci.* **2015**, *43*, 115–135. [CrossRef]
110. Hair, J.F.; Sarstedt, M.; Ringle, C.M.; Mena, J.A. An assessment of the use of partial least squares structural equation modeling in marketing research. *J. Acad. Mark. Sci.* **2012**, *40*, 414–433. [CrossRef]
111. Leguina, A. A primer on partial least squares structural equation modeling (PLS-SEM). *Int. J. Res. Method Educ.* **2015**, *38*, 220–221. [CrossRef]
112. Hair, J.F.; Sarstedt, M.; Ringle, C.M. Ringle. Rethinking some of the rethinking of partial least squares. *Eur. J. Mark.* **2019**, *53*, 566–584. [CrossRef]
113. Huete-Alcocer, N.; López-Ruiz, V.-R.; Alfaro-Navarro, J.L.; Nevado-Peña, D. European citizens' happiness: Key factors and the mediating effect of quality of life, a PLS approach. *Mathematics* **2022**, *10*, 367. [CrossRef]
114. Simon, H.A. *Administrative Behavior*; Simon and Schuster: New York, NY, USA, 2013.
115. Hwang, C.L.; Yoon, K.; Hwang, C.L.; Yoon, K. Methods for multiple attribute decision making. Multiple attribute decision making: Methods and applications a state-of-the-art survey. In *Multiple Attribute Decision Making*; Springer: Berlin/Heidelberg, Germany, 1981; pp. 58–191.
116. Tzeng, G.H.; Huang, J.J. *Multiple Attribute Decision Making: Methods and Applications*; CRC Press: Boca Raton, FL, USA, 2011.
117. Behzadian, M.; Otaghsara, S.K.; Yazdani, M.; Ignatius, J. A state-of the-art survey of TOPSIS applications. *Expert Syst. Appl.* **2012**, *39*, 13051–13069. [CrossRef]
118. Ren, G.P.; Liu, L.M.; Sun, J.; Yuan, C.; Zhuo, D. Multifunction orientation of rural landscape in metropolitan suburbs based on GRA and TOPSIS models. *Geogr. Res.* **2018**, *37*, 263–280. (In Chinese)
119. Zhang, Y. Cultivated Land Safety Evaluation and Obstacle Factor Diagnosis Based on DPSIR-TOPSIS Model. *J. Yunnan Agric. Univ. Soc. Sci.* **2022**, *16*, 117–125. (In Chinese)
120. Song, H.; Lu, B.; Ye, C.; Li, J.; Zhu, Z.; Zheng, L. Fraud vulnerability quantitative assessment of Wuchang rice industrial chain in China based on AHP-EWM and ANN methods. *Food Res. Int.* **2021**, *140*, 109805. [CrossRef]

121. de FSM Russo, R.; Camanho, R. Criteria in AHP: A systematic review of literature. *Procedia Comput. Sci.* **2015**, *55*, 1123–1132. [CrossRef]
122. Alinezhad, A.; Khalili, J. CRITIC Method. In *New Methods and Applications in Multiple Attribute Decision Making (MADM)*; Springer: Cham, Switzerland, 2019; pp. 199–203.
123. Yan, M.; Zhao, J.; Yan, M. Patterns, Processes, and Differentiation Mechanisms of China's Transition from Old to New Economic Drivers. *J. Geogr. Sci.* **2024**, *34*, 1697–1718. [CrossRef]
124. Bai, J.; Liu, J.; Chen, W. Analysis of influencing factors of forest ecological security based on structural equation model. *Acta Ecol. Sin.* **2019**, *39*, 2842–2850. (In Chinese)
125. Zhu, Y.; Tian, D.; Yan, F. Effectiveness of entropy weight method in decision-making. *Math. Probl. Eng.* **2020**, *2020*, 3564835. [CrossRef]
126. Harker, P.T.; Vargas, L.G. The theory of ratio scale estimation: Saaty's analytic hierarchy process. *Manag. Sci.* **1987**, *33*, 1383–1403. [CrossRef]
127. Bellman, R.E.; Zadeh, L.A. Decision-Making in a Fuzzy Environment. *Manag. Sci.* **1970**, *17*, B-141–B-164. [CrossRef]
128. Triantaphyllou, E.; Triantaphyllou, E. *Multi-Criteria Decision Making Methods*; Springer: New York, NY, USA, 2000.
129. Dul, J. Necessary Condition Analysis (NCA) Logic and Methodology of "Necessary But Not Sufficient" Causality. *Organ. Res. Methods* **2016**, *19*, 10–52. [CrossRef]
130. Martilla, J.A.; James, J.C. Importance-performance analysis. *J. Mark.* **1977**, *41*, 77–79. [CrossRef]
131. Slack, N. The Importance-Performance Matrix as a Determinant of Improvement Priority. *Int. J. Oper. Prod. Manag.* **1994**, *14*, 59–75. [CrossRef]
132. Kristensen, K.; Martensen, A.; Gronholdt, L. Customer satisfaction measurement at post Denmark: Results of application of the European customer satisfaction index Methodology. *Total Qual. Manag.* **2000**, *11*, 1007–1015. [CrossRef]
133. Wold, R.J.; Hinze, W.J. (Eds.) *Geology and Tectonics of the Lake Superior Basin*; Geological Society of America: Boulder, CO, USA, 1982. [CrossRef]
134. Lohmöller, J.B. *Latent Variable Path Modeling with Partial Least Squares*; Springer Science & Business Media: Berlin/Heidelberg, Germany, 2013.
135. Dul, J.; Hauff, S.; Bouncken, R.B. Necessary condition analysis (NCA): Review of research topics and guidelines for good practice. *Rev. Manag. Sci.* **2023**, *17*, 683–714. [CrossRef]
136. Dul, J. Conducting Necessary Condition Analysis for Business and Management Students; Sage, London, England. 2019. Available online: https://www.torrossa.com/en/resources/an/5017872# (accessed on 10 January 2025).
137. Hair, L.S.; Symmans, F.; Powers, J.M.; Carmel, P. Immunohistochemistry and proliferative activity in Lhermitte-Duclos disease. *Acta Neuropathol.* **1992**, *84*, 570–573. [CrossRef]
138. Fornell, C.; Larcker, D.F. Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *J. Mark. Res.* **1981**, *18*, 39–50. [CrossRef]
139. O'brien, R.M. A Caution Regarding Rules of Thumb for Variance Inflation Factors. *Qual Quant* **2007**, *41*, 673–690. [CrossRef]
140. Bagozzi, R.; Yi, Y. On the Evaluation of Structural Equation Models. *J. Acad. Mark. Sci.* **1988**, *16*, 74–94. [CrossRef]
141. Benitez, J.; Henseler, J.; Castillo, A.; Schuberth, F. How to perform and report an impactful analysis using partial least squares: Guidelines for confirmatory and explanatory IS research. *Inf. Manag.* **2020**, *57*, 103168. [CrossRef]
142. Sofwan, M.; Habibi, A.; Attar, R.W.; Alqahtani, T.M.; Alahmari, S.A.; Alhazmi, A.H. Factors Affecting Teachers' Behavior of Innovative Teaching with Technology: Structural Equation Modelling. *Sustainability* **2024**, *16*, 8496. [CrossRef]
143. Liu, Y.; Zhang, Z.; Wang, J. Regional differentiation of agriculture in China and modern agricultural zoning scheme. *Acta Geogr. Sin.* **2018**, *73*, 203–218. (In Chinese)
144. Zhou, Y.; Guo, Y.; Liu, Y. Regional types and regional development paths of rural areas in China. *Geogr. Res.* **2019**, *38*, 467–481. (In Chinese)
145. Fang, Y.; Liu, B.; Liu, J. Regional types and optimization strategies of agricultural multifunctionality: A case study of Jilin Province. *Prog. Geogr.* **2019**, *38*, 1349–1360. (In Chinese) [CrossRef]

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