

## Article

# Technology Integration and System Synergy: Key Elements, Implementation Pathways, and Necessary Conditions for Value Creation in Organic Agriculture

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## Abstract

When digital technologies are disconnected from organizational routines, they fail to create and capture real value in organic agriculture. Anchored in socio-technical systems theory, a five-dimensional analytical framework covering technology, structure, people, tasks, and rules is proposed in this study. Using survey data from 753 organic farms in China, this study combines PLS-SEM, fsQCA, NCA, and NConfA to uncover the core factors and the configurational and necessary mechanisms that drive value creation in organic agriculture through digitalization. The findings reveal that task and structure are the most central drivers of value creation. High value creation results from three equifinal configurations, namely a dual-core people–task path, a deep socio-technical coupling path, and an institution–structure–task support path, whereas low value creation is directly associated with the absence of task or structure. Task, people, and structure are also identified as necessary conditions for high value creation. In contrast, the value creation process exhibits stage-dependent threshold effects, with the dominant logic shifting from individual capability-driven mechanisms to system collaborative mechanisms across development stages and organizational contexts. These results indicate that value creation in organic agriculture driven by digitalization is not a simple linear extension of technology into production, but a process of socio-technical reconfiguration embedded in specific task settings.

**Keywords:** value creation in organic agriculture; socio-technical systems theory; configuration pathways; necessary condition analysis; digitalization



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## 1. Introduction

The relationship between digital technologies and sustainable agricultural transformation is a topic at the frontier of management and agricultural economics research [1,2]. Technologies such as the internet of things, big data, blockchain, and artificial intelligence are widely expected to reduce information asymmetries, reshape value distribution, and transform agri-food value chains [3–5]. Organic agriculture is an alternative farming system that delivers ecological, health-related, and market value [6]. Its economic viability largely depends on price premiums, consumer trust, and stable market linkages [7]. Digital technologies are increasingly viewed as key enablers for converting ecological value into economic value. Nevertheless, the diffusion of digitalization in sustainable agriculture has

not followed the linear progress expected by early technological optimism [8]. The overall adoption level of digital technologies remains limited [9]. Cost pressure, technological complexity, poor equipment suitability, and limited user awareness still constrain the adoption and effective use of digital technologies [6]. More importantly, existing studies do not support the simple assumption that digital technologies automatically lead to performance improvement. Some studies have observed cost savings, reduced inputs, and increases in yield or profit [10]. Yet many studies have also found that the economic benefits are not significant [11]. In some cases, the returns are limited, and environmental benefits also vary strongly across contexts [12]. Thus, technologies do not automatically generate value gains. This raises a core question: under what conditions can digital technologies be effectively translated into value creation?

Existing studies have approached this issue from three main perspectives. One stream of research focuses on the direct enabling effects of digital technologies. It emphasizes the positive role of digital technologies in precision production, input management, quality traceability, and supply chain optimization [5,13,14]. Another stream of research emphasizes the context-dependent nature of technological outcomes. It suggests that factors such as farmers' education, infrastructure conditions, technology compatibility, and digital skills shape the effectiveness of digital technologies [6,9]. The third stream of research extends the analytical focus from technological effects to value distribution. It argues that the benefits of digitalization do not necessarily accrue to producers. Value creation and capture are often shaped by platform governance, organizational relationships, and institutional rules [14,15]. Collectively, these studies show that digital technologies do not automatically create agricultural value. Their effects depend on the social, organizational, and institutional environments in which the technologies are embedded. However, existing research has not yet provided a systematic analytical framework to explain how these multidimensional conditions interact, combine, and eventually lead to different value-creation outcomes.

This analytical gap is particularly evident in the context of organic agriculture. Digital technologies can generate value only when they are embedded in specific practices, such as production management, quality traceability, certification governance, market linkages, and stakeholder coordination. It is therefore necessary to move beyond the simplified logic of technological determinism and examine the complex interactions between technology and society through the lens of the Socio-Technical Systems (STS) framework [4]. STS theory argues that technological effectiveness depends on the alignment among technology, structure, people, and tasks [16]. Some studies have introduced STS into digital and sustainable agriculture research. They emphasized that the key challenge has shifted from improving technological performance to embedding digital technologies responsibly within specific organizational and institutional contexts [5]. However, existing studies remain largely at the macro level of explanation or case-based discussion. They have not yet developed a testable analytical framework. Moreover, they pay limited attention to institutional rules. In organic agriculture, however, policy environments, certification standards, and consumer culture are central constraints and incentives for technology use [17].

To address this limitation, this study introduces the rules dimension into the classical four-element STS framework. We develop a five-dimensional analytical framework consisting of technology, structure, people, tasks, and rules. This framework transforms STS from a broad interpretive perspective into an operational and measurable model for analyzing value-creation mechanisms. Moreover, we use a mixed-method approach to reveal the necessity and sufficiency relationships among these dimensions. Thus, this study responds to several deeper questions: How do socio-technical elements affect value creation

in organic agriculture? Which combinations of conditions can lead to high value creation? Which elements, or combinations of elements, are necessary for high value creation? How do these relationships differ across development stages and organizational contexts?

Examining these issues has implications that extend beyond economic efficiency. Organic agriculture is widely regarded as an important pathway toward climate-neutral agriculture because it reduces the use of synthetic inputs, enhances soil organic carbon sequestration, and lowers greenhouse gas emissions [18,19]. This recognition has been incorporated into national and regional sustainability strategies. The European Union's Farm to Fork Strategy sets a target of increasing organic farming to 25% of agricultural land by 2030. More recently, the Vision for Agriculture and Food identified digital transformation and green development as two central pillars of agricultural reform. The strategy promotes the use of satellite remote sensing, geographic information systems, and digital records to support more precise environmental management in organic agriculture. In China, multiple government agencies jointly issued the Guidelines for the Coordinated Transformation of Digitalization and Green Development in 2024. The guidelines similarly emphasize the coordinated advancement of agricultural digital and green transformation. Through precision monitoring and data traceability, digital technologies have the potential to transform the environmental benefits of organic agriculture into verifiable and tradable low-carbon assets. Understanding how digital technologies drive value creation in organic agriculture is therefore not only an economic question but also a matter of designing institutional tools to support the transition toward climate-neutral agricultural systems. This study uses China as the research context because it is representative of the development of organic agriculture and digitalization. This provides a rich setting for examining how digital technologies are embedded in organic production, certification, circulation, and market connection.

This study makes two main contributions. First, it moves beyond a technology-deterministic perspective by developing and testing a five-dimensional socio-technical synergy framework for value creation in organic agriculture. This provides a new pathway for the empirical operationalization of STS theory. Second, this study goes beyond prior research that mainly uses linear models to estimate the net effects of single factors. This study identifies multiple configurations and threshold mechanisms associated with high value creation in organic agriculture. The findings offer empirical evidence for designing differentiated digitalization strategies in the organic agriculture sector of developing economies.

## 2. Theoretical Framework and Hypothesis Development

### 2.1. A Five-Dimensional Analytical Framework Based on Socio-Technical Systems Theory

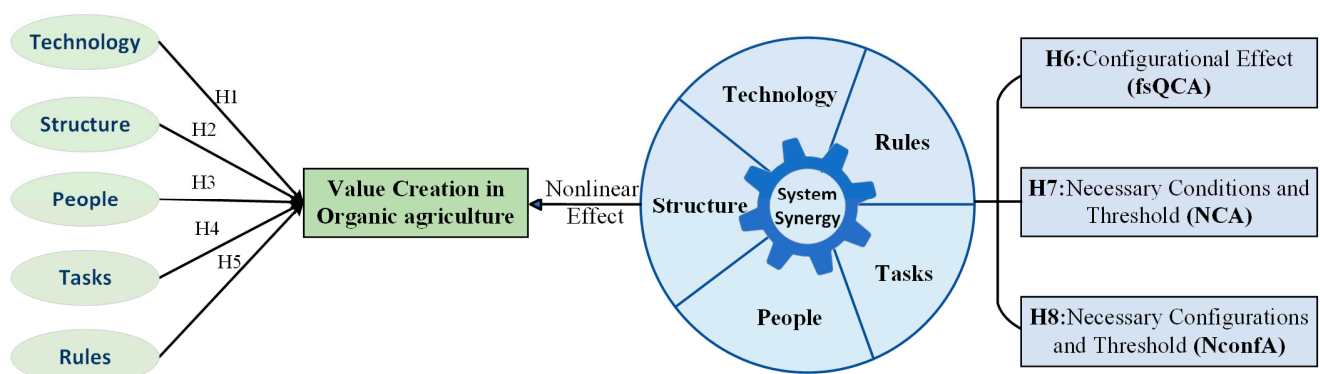
STS theory argues that organizational performance depends on the joint optimization and interaction of social and technical elements [16]. In this study, STS is suitable for understanding how digital technologies enable value creation in organic agriculture. Organic agriculture is a typical socio-ecological–technical system. Its value creation and realization depend not only on digital tools, but are also deeply linked to production organization, farmers' capabilities, ecological circular tasks, and institutional rules [20]. Digitalization is not a neutral technological intervention. It can systematically reshape production processes, organizational structures, role divisions, and even institutional rules [20–22].

Previous studies have provided evidence that the STS perspective is moving from macro-level explanation to mechanism analysis [17]. Yet a testable empirical framework is still lacking. Moreover, existing STS research has a key limitation when applied to organic agriculture. In this context, rules cannot be ignored. Rules include policy environments and social-cultural recognition [17]. Rules determine whether digital technologies can create value through resource support [9,14,23,24], trust building [25–27], and value transmission

mechanisms [28,29]. From both an economic logic and a policy perspective, institutional frameworks are key mediating conditions. They shape whether digitalization can promote the sustainable transformation of agriculture [30]. It is therefore necessary to incorporate rules into the analytical framework.

Building on this argument, this study extends the classical four-element STS model and develops an integrated five-dimensional framework of technology, structure, people, tasks, and rules. Each dimension represents a distinct but interconnected aspect of value creation in organic agriculture. Technology represents an enabling dimension that supports data-driven production processes, intelligent decision-making, and digital coordination across agricultural value chains. It provides the technological foundation for integrating information flows, optimizing resource utilization, and enhancing transparency in production and market activities [3,5,13]. Structure functions as a coordination dimension that facilitates the organization and alignment of fragmented agricultural actors. It shapes patterns of interaction, enabling resource allocation, multi-actor collaboration, and knowledge exchange among farmers, cooperatives, enterprises, and institutional stakeholders [6,17]. People constitute a capability dimension reflecting the human and cognitive capacities required for digital transformation. This includes farmers' digital literacy, learning adaptability, and collaborative competencies, which jointly determine their ability to effectively adopt, interpret, and utilize digital technologies in agricultural practices [9,31,32]. Tasks represent a value-realization dimension through which digital technologies are embedded into concrete production and management activities. This includes their application in production optimization, ecological farming practices, quality control, and market expansion, thereby translating technological inputs into observable economic and environmental outcomes [3,20,33]. Rules operate as an institutional dimension that shapes behavioral incentives and coordination norms within the agricultural system. This includes formal policy frameworks and informal socio-cultural norms that jointly influence trust formation, market recognition, and legitimacy of digital and green agricultural practices [14,25,28,29].

The five dimensions constitute a dynamically coupled socio-technical system in which value creation in organic agriculture emerges from both direct interactions and higher-order inter-dependencies. Accordingly, this study develops an integrated analytical framework that combines a linear perspective (H1–H5) to examine the net effects of each dimension, and a nonlinear perspective (H6–H8) to capture multiple synergistic pathways, necessary conditions, and threshold effects through which system elements jointly drive value creation. The analytical framework is shown in Figure 1.



**Figure 1.** The analytical framework. Source: Authors' own elaboration, extending Leavitt's (1965) [16] four-element STS model by integrating the rules dimension specific to the organic agriculture value-creation context.

## 2.2. Research Hypotheses

### 2.2.1. Direct Net Effects of Each Dimension on Value Creation in Organic Agriculture

Based on the five-dimensional framework, the direct effects of each dimension on value creation in organic agriculture are first examined.

The technology dimension affects value creation through three pathways. First, it enables precision operations. The use of digital and intelligent technologies enables precise weather services, soil moisture monitoring, seeding, fertilization, and irrigation. Technologies can significantly reduce labor input and agricultural material consumption [12,34]. They can also enhance farms' capacity to respond to climate risks [35,36]. Second, technologies strengthen trust. Agricultural cloud platforms and blockchain traceability systems can create tamper-proof product records, reducing information asymmetry between producers and consumers and providing a technological basis for premium capture [28,29,37]. Third, it improves decision-making. The accumulation and analysis of multi-source data can support production decisions and improve the efficiency of resource allocation [38]. Digital tools are also widely seen to facilitate communication, knowledge exchange, and experience sharing among stakeholders, thereby strengthening trust across the supply chain [6]. Accordingly, the following hypothesis is proposed:

**H1.** *The technology dimension positively affects value creation in organic agriculture.*

The structure dimension promotes value creation through resource allocation and collaborative governance. At the level of industrial organization, cooperatives reduce the costs and risks faced by dispersed operators through resource sharing, information flows, collective bargaining, financial support, and technology integration [39]. At the level of collaboration networks, vertical linkages among governments, research institutions, firms, and farms can support technology localization. In contrast, horizontal linkages, such as alliances with logistics providers and sales terminals, can integrate complementary resources and improve logistics efficiency and product quality [40]. At the level of process optimization, digital upgrading across the entire chain, from production to certification, can reduce transaction costs and improve efficiency [17]. Accordingly, the following hypothesis is proposed:

**H2.** *The structure dimension positively affects value creation in organic agriculture.*

The people dimension functions as the converter through which technological potential is transformed into actual returns [41]. In terms of digital literacy, farmers with stronger digital capabilities are better able to operate smart devices, interpret environmental sensor data, and analyze market dynamics. This enables a shift from experience-based farming to dual decision-making based on data and ecological knowledge [3,31]. In terms of cross-departmental collaboration, information sharing and coordinated responses with agricultural technical experts, certification bodies, e-commerce platforms, and other actors can help overcome sectoral barriers. They can also connect value across the full chain of production, certification, circulation, and consumption [42]. In addition, differences in actor cognition across agricultural contexts should be considered. Studies show that farmers in conventional and organic agriculture differ systematically in their perceptions of technology and value judgments. Organic farmers are more concerned with whether technologies are consistent with ecological principles, rather than simply pursuing efficiency [43]. This means that the people dimension is more complex in the context of organic agriculture. Accordingly, the following hypothesis is proposed:

**H3.** *The people dimension positively affects value creation in organic agriculture.*

The tasks dimension is the direct interface through which technological effectiveness is translated into value. Smart crop and livestock production enables data-driven precision ecological management. This not only reduces costs but also improves product quality and resource-use efficiency through standardized production, thereby laying the material foundation for higher value creation [3,44]. Ecological circular chains are developed through digitalization to drive cycles of resources, data, and regeneration. This creates cost advantages while reinforcing brand ESG value through verifiable low-carbon footprints [45]. The integration of agriculture, culture, tourism, and commerce breaks traditional sectoral boundaries and creates multidimensional value scenarios, transforming production units into system-level projects that jointly generate economic, ecological, and social benefits [35]. Schnebelin [20] showed that the actual effects of digital technologies depend on the agricultural model in which they are embedded. Conventional and organic farmers differ systematically in how they perceive and use technology, which suggests that task settings are a key variable shaping the variation in technological effects. Accordingly, the following hypothesis is proposed:

**H4.** *The tasks dimension positively affects value creation in organic agriculture.*

The rules dimension affects value creation through legitimacy endorsement and market space creation. At the policy level, national strategies and targeted financial support can lower the threshold for transformation and provide both institutional guarantees and resource leverage for technology application. Giagnocavo et al. [6] identified government financial support as a key driver of digitalization in organic agriculture. At the socio-cultural level, the rise in green consumption creates room for premiums [46]. Middle-income and high-income consumers' pursuit of healthy diets and low-carbon lifestyles has stimulated a model of trust-based consumption supported by data visualization [47]. On the production side, overcoming cultural inertia requires training, promotion, and cognitive reframing to reduce farmers' psychological resistance to technology use [48]. Manzoor et al. [9] further showed that the institutional environment is a core moderator of digital agricultural technology adoption, and that its effects vary across socioeconomic and technological conditions. Accordingly, the following hypothesis is proposed:

**H5.** *The rules dimension positively affects value creation in organic agriculture.*

#### 2.2.2. Configurational Effects and Equifinal Pathways

One of the core insights of STS theory is that different elements can generate similar levels of organizational effectiveness through different combinations. This implies that in organic agriculture, high value creation may be achieved through multiple equifinal pathways rather than through a single optimal model. This view is consistent with configuration theory [49].

In organic agriculture, digital technologies do not create value merely by automating production. They reconfigure value-chain activities, information flows, actors, and governance relationships. In doing so, they create conditions for efficiency gains, quality assurance, traceability premiums, and new forms of value capture [17]. Under different resource endowments, institutional environments, and organizational foundations, organic farms may therefore achieve similar levels of value creation through different combinations of socio-technical elements. Accordingly, the following hypothesis is proposed:

**H6.** *There are multiple configuration pathways to high value creation in organic agriculture, and these pathways are equifinal.*

### 2.2.3. Necessary Conditions and Bottleneck Thresholds

Some elements may have threshold effects. If they do not reach a certain minimum level, the expected outcome cannot be achieved even when other conditions are favorable [50]. This logic aligns closely with the STS view of systemic balance. The absence of key elements may disrupt the system and prevent technological potential from being realized. For example, if farmers lack basic digital literacy, even advanced equipment and supportive institutions may fail to generate effective outcomes [23,51]. Likewise, if core tasks such as smart crop and livestock production are not implemented, investment in other elements may remain ineffective [3,52]. This implies that some individual dimensions may constitute the necessary conditions for achieving high value creation. Accordingly, the following hypotheses are proposed:

**H7.** *Some of the five dimensions constitute necessary conditions for achieving high value creation in organic agriculture. Different levels of value creation impose different threshold requirements on each dimension.*

### 2.2.4. Necessary Configurations and Configuration Thresholds

In organic agriculture, technologies need task settings to become useful, tasks require organizational coordination, and people need structural support to convert digital tools into value [5,17]. Therefore, necessity may exist not only at the level of single dimensions, but also at the level of specific combinations of dimensions. Necessary configuration analysis provides a way to identify such indispensable combinations. Accordingly, the following hypotheses are proposed:

**H8.** *Some configurations of the five dimensions constitute necessary conditions for achieving high value creation in organic agriculture. Moreover, different levels of value creation impose different threshold requirements on such necessary configurations.*

### 2.2.5. Heterogeneity in Value Creation Mechanisms

Finally, the logic of value creation in organic agriculture may vary across development stages and organizational contexts. Years of organic certification reflect the degree of institutionalization of an organic farm [53]. Newly established and mature organic farms differ systematically regarding capability accumulation, resource networks, and institutional embeddedness [54,55]. Existing research shows that digitalization does not automatically translate into value creation. Its effects on agricultural value creation and value capture depend on the organizational arrangements and governance structures surrounding producers [15]. Cooperative members can access technology extension, collective marketing, and other shared services. These services may reshape their dependence on specific factors and create different pathways of value realization [3,39,56]. To explore such heterogeneity, this study proposes the following research question:

RQ: Does the logic of value creation differ significantly across organic farms with different years of organic certification and different patterns of participation in cooperative organizations?

## 3. Materials and Methods

### 3.1. Sampling and Data Collection

The data for this study were collected through field surveys conducted between June and August 2025 in seven Chinese provinces: Jiangxi, Guizhou, Yunnan, Sichuan, Hunan, Shanxi, and Shaanxi. These provinces differ in their patterns of organic agricultural development and in the application of digital technologies. This diversity provides a solid

empirical basis for identifying multiple pathways of value creation in organic agriculture. For example, Jiangxi, Yunnan, Shanxi, and Shaanxi have developed distinctive practices in green agriculture, organic product certification, organic industry development, and organic dryland farming. Sichuan, Guizhou, and Hunan have also explored smart agriculture, digital platforms, intelligent agricultural machinery, and the digitalization of characteristic agricultural industries. Second, the seven provinces span central, western, and southwestern China. They cover diverse geographical settings, including plains, hills, mountains, and plateaus. They also differ in ecological resource endowments, industrial foundations, market access, cooperative development, digital infrastructure, and policy support. This regional diversity enables a more nuanced understanding of how digital technologies drive value creation in organic agriculture across different contexts.

The target respondents were the principal persons in charge of organic farms. The survey team consisted of graduate students and senior undergraduate students from relevant university programs. All investigators received systematic training before the formal survey. The questionnaire was administered through face-to-face interviews. Any questions raised by respondents were addressed on site. Each completed questionnaire was checked and collected immediately after the interview.

A total of 840 questionnaires were distributed. Of these, 753 were valid, yielding an effective response rate of 89.64%. The respondents of these valid questionnaires were distributed across the seven provinces as follows: 106 from Jiangxi, 108 from Guizhou, 103 from Yunnan, 110 from Sichuan, 113 from Hunan, 104 from Shaanxi, and 109 from Shanxi.

In terms of sample characteristics, 79.0% of the respondents were male, and the largest age group was 35–45 years, accounting for 51.93% of the sample, followed by the 46–60 age group, which accounted for 20.45%. Among the sampled organic farms, 61.29% had held organic certification for more than three years, and 56.22% participated in cooperative organizations. Overall, the sample was dominated by organic farms with relatively long certification histories and comparatively high levels of organizational participation, thereby providing a robust empirical basis for examining heterogeneity in digital technology-enabled value creation in organic agriculture.

### 3.2. Questionnaires and Measurements

The measurement instrument included six constructs: technology, structure, people, tasks, rules, and value creation in organic agriculture. The five explanatory constructs were grounded in STS theory. Technology, structure, people, and tasks were derived from the classical STS framework, while rules were added to capture the institutional and socio-cultural context of organic agriculture. Value creation in organic agriculture served as the outcome construct. The dependent variable was measured directly with three items capturing economic premiums, ecological positive externalities, and social welfare improvement [8,33]. The independent variables were specified as reflective hierarchical component models, in which measurement items reflect their respective first-order constructs and the first-order constructs reflect the corresponding second-order constructs. The technology construct was reflected in three first-order dimensions: hardware infrastructure, platform tools, and data resources [57]. The structure construct was reflected in industrial organization, collaboration networks, and process optimization [17]. The people construct was reflected in digital literacy and cross-functional collaboration [30]. The task construct was reflected in smart crop and livestock production, ecological circular-chain development, and the integration of agriculture with culture, tourism, and commerce [18]. The rules construct was reflected in the institutional environment and the socio-cultural environment [9].

Each first-order dimension was measured using two or three items. The specific items and their sources are reported in Appendix A Table A1. All items were measured using a five-point Likert scale. The measurement items were adapted from established studies and further refined to fit the context of organic agriculture through expert interviews. A pilot survey was conducted before the formal investigation, and the wording of the items was further improved based on the feedback received.

### 3.3. Mixed-Method Analytical Strategy

Value creation in organic agriculture is a complex process shaped by the alignment of technology, structure, people, tasks, and rules [56]. In addition, high value creation may be constrained by necessary conditions or bottleneck levels [58]. Therefore, to provide a more complete explanation of value creation by linking net effects, sufficient pathways, individual necessary conditions, and necessary configurations, this study integrates partial least squares structural equation modeling (PLS-SEM), fuzzy-set qualitative comparative analysis (fsQCA), necessary condition analysis (NCA), and necessary configuration analysis (NConfA) [59,60]. This integrated design provides a more complete explanation of the complex mechanisms of value creation in organic agriculture.

First, PLS-SEM is used to test the net effects of the five dimensions on value creation in organic agriculture. It also assesses the reliability and validity of the measurement model and provides reliable construct scores for subsequent analyses [60]. Second, NCA follows a necessity logic. It tests whether any single dimension is a necessary but not sufficient condition for high value creation. Its bottleneck analysis further identifies the minimum levels required for different levels of value creation [61,62]. Third, fsQCA examines the sufficiency of multiple condition combinations. It identifies equifinal pathways that lead to high value creation [59,63]. Finally, NConfA tests whether key combinations constitute necessary configurations for high value creation [64]. This step complements NCA, which focuses on single conditions. It also goes beyond fsQCA, which identifies sufficient configurations [62].

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

In this study, PLS-SEM is used to test the direct effects of the five dimensions on value creation in organic agriculture. PLS-SEM was selected for three reasons. First, the aim of the study is to predict key constructs rather than to test a well-established theory, and PLS-SEM is more suitable for prediction-oriented research objectives [63]. Second, the model includes second-order constructs, and PLS-SEM is more robust for estimating complex models. Lastly, PLS-SEM imposes fewer assumptions on data distribution and is therefore more appropriate for field survey data.

The analysis was conducted using SmartPLS 4.0. Path coefficients were estimated using the partial least squares algorithm, and their significance levels were assessed through bootstrapping with 5000 resamples.

To further explore contextual heterogeneity, the sample was divided according to two grouping variables: years of organic certification ( $\leq 3$  years, 3–6 years, and  $> 6$  years) and participation in cooperative organizations. Partial least squares multi-group analysis (PLS-MGA) was then used to test whether path coefficients differed significantly across groups, and measurement invariance was assessed using the three-step MICOM procedure [65].

#### 3.3.2. Necessary Condition Analysis (NCA)

NCA is a specialized method for identifying necessary conditions. If X is a necessary condition for Y, then the presence of Y requires X to reach a certain minimum level. When X falls below that threshold, Y cannot be achieved, regardless of how favorable the other

conditions may be [48,56]. This study follows the NCA framework proposed by Dul [50,59]. The analysis was conducted in R version 4.3.1. The ceiling technique was implemented using the ceiling regression-free disposal hull (CR-FDH) method. Statistical significance was assessed through permutation tests with 10,000 resamples [58].

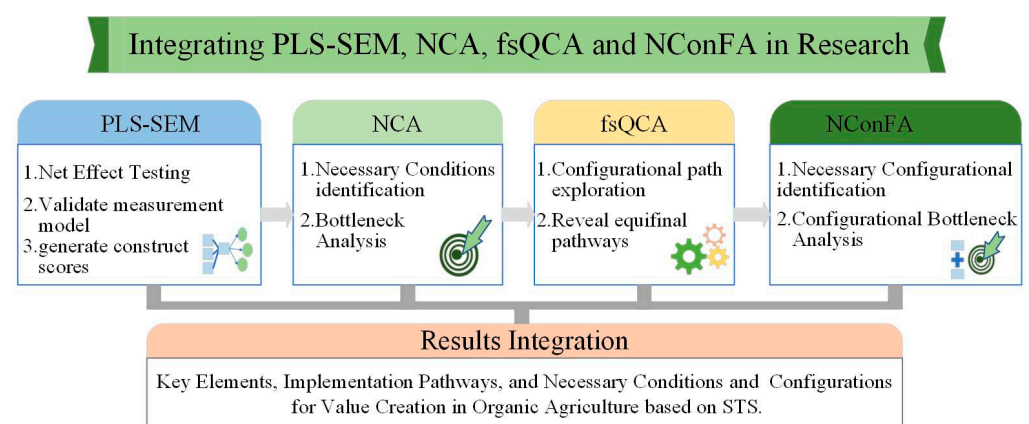
### 3.3.3. Fuzzy-Set Qualitative Comparative Analysis (fsQCA)

fsQCA adopts a configuration perspective. The method is grounded in set theory and Boolean algebra. Its core assumption is that outcomes are usually generated by combinations of conditions rather than by single conditions in isolation, and that different combinations may be equifinal [49,58].

fsQCA was performed following the standard procedure proposed by Ragin [58]. The analysis was conducted in fsQCA 4.0. First, the data were calibrated using the direct calibration method, and three qualitative anchors were specified: full membership (0.95), the crossover point (0.50), and full non-membership (0.05). Second, necessity analysis was conducted to examine whether any single condition was necessary for the outcome, including both high value creation and non-high value creation, using a consistency threshold of 0.90. Third, a truth table was constructed using a frequency threshold of 3 and a raw consistency threshold of 0.80, thereby transforming fuzzy-set membership scores into Boolean values [58–60]. Fourth, sufficiency analysis was performed through Boolean minimization. Fifth, robustness was assessed by increasing the consistency threshold to 0.85 and the PRI threshold to 0.75 [66].

### 3.3.4. Necessary Configuration Analysis (NConFA)

NConFA extends necessity logic to combinations of conditions. High-level outcomes may depend on specific configurations of multiple conditions [67]. The analysis was conducted in R version 4.3.1. In this study, a three-step procedure was adopted [60,62]. First, based on the sufficient configurations obtained from fsQCA, combinations of conditions that appeared repeatedly in at least two pathways were selected as candidate necessary configurations for further analysis. Second, the effect sizes of the candidate necessary configurations were further examined. The effect size of 0.10 or above was taken as evidence of necessity. Third, bottleneck analysis was conducted. Bottleneck tables were produced to show the threshold levels required by necessary configurations at different levels of value creation. Figure 2 presents the overall research logic and analytical procedure of this study.



**Figure 2.** Analysis process. Note: The arrows indicate the sequence of the analytical workflow.

## 4. Results

### 4.1. PLS-SEM Results

#### 4.1.1. Measurement Model Assessment

Before testing the structural model, the reliability and validity of the measurement model were first assessed. As shown in Tables 1 and A2, Cronbach's alpha values for all first-order and second-order constructs exceeded 0.70, composite reliability (CR) values were all above 0.80, and average variance extracted (AVE) values were all above 0.50. These results indicate satisfactory internal consistency and convergent validity.

**Table 1.** Internal consistency and convergent validity of the measurement model.

|    | TE           | ST           | PE           | TA           | RU           | VA           | CR    | AVE   |
|----|--------------|--------------|--------------|--------------|--------------|--------------|-------|-------|
| TE | <b>0.728</b> |              |              |              |              |              | 0.878 | 0.530 |
| ST | 0.483        | <b>0.767</b> |              |              |              |              | 0.851 | 0.588 |
| PE | 0.412        | 0.394        | <b>0.723</b> |              |              |              | 0.871 | 0.523 |
| TA | 0.456        | 0.521        | 0.447        | <b>0.759</b> |              |              | 0.916 | 0.576 |
| RU | 0.378        | 0.415        | 0.362        | 0.398        | <b>0.748</b> |              | 0.836 | 0.560 |
| VA | 0.512        | 0.578        | 0.496        | 0.603        | 0.435        | <b>0.839</b> | 0.877 | 0.704 |

Note: TE = technology, ST = structure, PE = person, TA = task, RU = rules, VA = value creation in organic agriculture. Bold diagonal values are the square roots of AVE; the lower triangle presents inter-construct correlations. Composite reliability (CR), and average variance extracted (AVE) were used to assess internal consistency reliability and convergent validity. CR values above 0.70 and AVE values above 0.50 indicate acceptable reliability and convergent validity.

As reported in Table 1, the square root of the AVE for each construct was greater than its correlations with all other constructs, thus meeting the Fornell–Larcker criterion [67]. The results reported in Appendix A Table A3 show that all HTMT values were below 0.85, which further supports satisfactory discriminant validity (see Appendix A Table A3).

#### 4.1.2. Structural Model Assessment and Tests of Direct Effects

The direct effects of the five dimensions on value creation in organic agriculture, estimated by PLS-SEM, are reported in Table 2. The TE ( $\beta = 0.182$ ,  $p < 0.001$ ), structure ( $\beta = 0.254$ ,  $p < 0.001$ ), PE ( $\beta = 0.153$ ,  $p < 0.01$ ), TA ( $\beta = 0.276$ ,  $p < 0.001$ ), and RU ( $\beta = 0.119$ ,  $p < 0.05$ ) dimensions all exert significant positive effects on value creation in organic agriculture. Therefore, H1 to H5 are all supported.

**Table 2.** Results of the structural model analysis (bootstraps = 5000).

| Relationship | $\beta$ | T-Statistics | p-Values | 95% CI         |
|--------------|---------|--------------|----------|----------------|
| TE → VA      | 0.182   | 4.439        | <0.001   | [0.102, 0.262] |
| ST → VA      | 0.254   | 6.684        | <0.001   | [0.179, 0.329] |
| PE → VA      | 0.153   | 3.255        | <0.01    | [0.061, 0.245] |
| TA → VA      | 0.276   | 6.571        | <0.001   | [0.194, 0.358] |
| RU → VA      | 0.119   | 2.288        | <0.05    | [0.017, 0.221] |

Note:  $\beta$  = Path Coefficient.  $R^2 = 0.588$  and  $Q^2 > 0$ . In addition, both RMSE and MAE are lower than those of the linear model (LM).

The model explains 58.8% of the variance in value creation in organic agriculture ( $R^2 = 0.588$ ), indicating a moderate level of explanatory power [63]. Predictive relevance was further assessed using Stone–Geisser's  $Q^2$ , obtained through the blindfolding procedure. All  $Q^2$  values were greater than zero, indicating that the model has satisfactory predictive capability [65].

#### 4.1.3. Multi-Group Analysis

To explore the heterogeneity of the value creation logic across different development stages and organizational contexts, the sample was divided according to years of organic certification and participation in cooperative organizations. Then PLS-MGA was used to test the significance of between-group differences in path coefficients (Table 3). The MICOM results indicate that the measurement models satisfy the requirement of partial measurement invariance across groups (Appendix A Table A4), which supports meaningful group comparisons [65,68].

**Table 3.** Multi-group analysis based on years of organic certification.

| Paths   | Grouping by Years of Organic Certification |                         |                       | Grouping by Cooperative Membership           |
|---------|--------------------------------------------|-------------------------|-----------------------|----------------------------------------------|
|         | Diff.<br>Short vs. Mid                     | Diff.<br>Short vs. Long | Diff.<br>Mid vs. Long | Diff.<br>Participation vs. Non-Participation |
| PE → VA | 0.133 **                                   |                         | 0.102 **              |                                              |
| TA → VA |                                            | 0.204 **                |                       | −0.098 **                                    |
| TE → VA | 0.123 **                                   | 0.169 **                |                       | −0.094 **                                    |
| ST → VA |                                            | −0.103 ***              |                       |                                              |
| RU → VA | −0.166 **                                  |                         | −0.146 **             | −0.098 ***                                   |

Note: \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ ; only paths showing significant between-group differences are reported.

The group comparison results show that the effect coefficient of PE on organic agriculture value creation is larger among farms with shorter certification periods. The effect coefficient of TA is also larger among farms with shorter certification periods. For TA, the effect is significantly stronger in the short-certification group than in the long-certification group. Similarly, the effect of TE is significantly stronger in the short-certification group than in both the mid-certification group (Diff. = 0.123,  $p < 0.01$ ) and the long-certification group (Diff. = 0.169,  $p < 0.01$ ). These results suggest that PE, TA and TE play a more prominent role in the early stage of organic certification.

By contrast, the effect of RU is significantly weaker in the short-certification group than in the mid-certification and long-certification groups. This indicates that organic farms with longer certification histories are better able to use rule-based advantages to support certification management, market credibility, and value creation. A significant between-group difference was found for the effect of ST on VA. Specifically, the path coefficient was 0.103 lower for farms with shorter certification histories than for those with longer certification histories ( $\Delta\beta = -0.103$ ,  $p < 0.001$ ). These findings suggest ST and RU become more influential as certification experience accumulates.

The path coefficient of RU is significantly higher among organic farms that participate in cooperative organizations than those that do not. This suggests that cooperative organizations help transform external rules into organizational and capital advantages by establishing unified standards. In contrast, the path coefficients of TE and TA are significantly stronger in the non-participation group. This indicates that, under an individual operating model without organizational support, producers must rely more heavily on their own refined task management and technology use to cope with market risks.

Taking these results together, the multi-group analysis shows that the logic of value creation evolves dynamically with the development stage and organizational embeddedness of organic farms, shifting from an individual capability-driven logic to a system collaboration-driven logic.

## 4.2. fsQCA Results

### 4.2.1. Data Calibration

Before conducting the fsQCA, the latent variable scores obtained from the PLS-SEM analysis were converted into normalized scores ranging from 0 to 1 using the formula:

$$x_{norm} = \frac{x_i - x_{min}}{x_{max} - x_{min}}$$

After rescaling the data to a common range, the scores were calibrated into fuzzy sets using fsQCA 4.1. Following Sukhov et al. [60], the thresholds for each variable were set at 0.05, 0.50, and 0.95. In the final step, all cases with a membership score of exactly 0.50 were reassigned a value of 0.501 [49]. The calibration thresholds are reported in Appendix A, Table A5.

### 4.2.2. Configurations for High Value Creation

After the necessity analysis, a truth table was constructed, and sufficiency analysis was performed. In line with prior studies, and considering the sample size of 753 cases, the frequency threshold was set to 3 and the consistency threshold to 0.80 [49]. Table 4 reports the configuration pathways leading to high value creation in organic agriculture. The overall solution coverage is 0.549. The overall solution consistency is 0.754. These findings indicate that the four configurations explain approximately 54.9% of the cases with high value creation. The four configurations can be grouped into three typical mechanisms, which together support H6.

**Table 4.** Configurations of conditions for high and non-high value creation in organic agriculture.

| Condition                    | High Value Creation |       |       |       | Non-High Value Creation |       |       |       |
|------------------------------|---------------------|-------|-------|-------|-------------------------|-------|-------|-------|
|                              | HC1a                | HC1b  | HC2   | HC3   | NH1                     | NH2   | NH3   | NH4   |
| PE                           | ●                   | ●     | ●     |       |                         |       | ⊗     | ○     |
| RU                           | ●                   | ⊙     | ●     | ●     |                         |       |       | ⊙     |
| ST                           | ⊙                   | ●     | ●     | ●     |                         | ⊗     |       |       |
| TA                           | ●                   | ●     | ○     | ●     | ⊗                       |       |       |       |
| TE                           | ○                   | ○     | ●     | ○     |                         |       | ○     | ⊗     |
| Raw coverage                 | 0.321               | 0.317 | 0.284 | 0.305 | 0.861                   | 0.874 | 0.261 | 0.184 |
| Unique coverage              | 0.105               | 0.104 | 0.025 | 0.046 | 0.072                   | 0.074 | 0.016 | 0.031 |
| Consistency                  | 0.801               | 0.817 | 0.84  | 0.863 | 0.941                   | 0.906 | 0.907 | 0.951 |
| Overall solution coverage    |                     |       | 0.549 |       |                         |       | 0.972 |       |
| Overall solution consistency |                     |       | 0.754 |       |                         |       | 0.886 |       |

Note: ● and ⊗ indicate the presence and absence of a core condition, respectively; ○ and ⊙ indicate the presence and absence of a peripheral condition, respectively, and blank indicates “don’t care”.

The first mechanism is a dual-core PE–TA mechanism (HC1a and HC1b). Under the joint core role of PE and TA, high value creation can still be achieved even when the structure or rules dimensions are only peripheral. This suggests that immediate value creation in organic agriculture is linked to who uses the technology, how coordination is organized, and in what kind of task setting the technology is embedded [20].

The second mechanism is a deep socio-technical coupling mechanism (HC2). In this configuration, PE, RU, ST, and TE are all core conditions. Value creation is achieved through the systemic alignment of infrastructure improvement, platform-tool embedding, data resource integration, and the coordinated functioning of institutions, organizational arrangements, and human capabilities [4,17]. Even when task innovation, such as multi-industry integration, is not yet a core condition, value creation can still be realized through efficiency gains, quality control, and brand premiums.

The third mechanism is an RU–ST–TA system support mechanism (HC3). In this configuration, RU, ST, and TA constitute the core support, while TE is only peripheral. High value creation can still be achieved even when the people dimension is not a core condition. This suggests that when rules, structure, and task integration form a strong systemic support base, shortcomings in individual capabilities can be partially absorbed through organizational and institutional arrangements [6].

#### 4.2.3. Configurations for Non-High Value Creation

As shown in Table 4, the configurations leading to non-high value creation are more parsimonious. The absence of the TA or ST is sufficient to produce non-high value creation. In addition, the configuration combining the absence of PE with the presence of TE reveals the mismatch between TE and PE. This suggests that digital tools alone cannot generate value without adequate human competence. In addition, the pathway characterized by the absence of technology and weak rule support shows that human effort is insufficient when digital infrastructure and institutional safeguards are lacking. These findings reveal the causal asymmetry between high and low value creation [43]. The robustness test, conducted by raising the consistency threshold to 0.85, confirms the stability of the configuration results.

#### 4.3. NCA Results

The analysis was based on the latent variable scores derived from the preceding PLS-SEM analysis, which were imported into R for further NCA after being extracted from the PLS-SEM model [60,68]. The results of this study are based on the CR-FDH ceiling technique. As shown in Table 5, TA, PE, and ST exhibit characteristics indicative of necessary conditions for value creation in organic agriculture. Their effect sizes all exceed the empirical threshold of 0.10. TA shows the largest effect size, followed by PE and ST. All three fall within the range of medium effect size. By contrast, the effect sizes of TE and RU fall within the small-effect range, indicating that they do not reach the threshold for necessity and are more likely to operate in combination with other dimensions.

**Table 5.** Effect size (d) and its significance for NCA using CR-FDH.

| Condition | Method | Effect Size | <i>p</i> -Value | Necessary Condition | Constraint Degree |
|-----------|--------|-------------|-----------------|---------------------|-------------------|
| PE        | CR-FDH | 0.130       | <0.01           | Yes                 | Medium            |
| RU        | CR-FDH | 0.045       | <0.01           | No                  | Small             |
| ST        | CR-FDH | 0.118       | <0.01           | Yes                 | Medium            |
| TA        | CR-FDH | 0.156       | <0.01           | Yes                 | Medium            |
| TE        | CR-FDH | 0.069       | <0.01           | No                  | Small             |

Note: an effect size of  $\geq 0.10$  was used as the threshold for necessity.

Then, a bottleneck table was constructed. Table 6 reports the results. It shows the minimum threshold levels of each socio-technical element required to achieve different levels of value creation in organic agriculture. All threshold values are presented in percentage terms. The results show that higher levels of value creation require higher threshold levels, especially for tasks, people, and structure. Although technology and rules show lower bottleneck values at high outcome levels, their effect sizes do not reach the threshold for a single necessary condition. They should therefore be interpreted as enabling conditions rather than strict standalone bottlenecks. These results support H7.

**Table 6.** Bottleneck table for NCA using CR-FDH.

| VA (%) | PE (%) | RU (%) | ST (%) | TA (%) | TE (%) |
|--------|--------|--------|--------|--------|--------|
| 0      | NN     | NN     | NN     | NN     | NN     |
| 10     | NN     | NN     | NN     | NN     | NN     |
| 20     | NN     | NN     | NN     | NN     | NN     |
| 30     | NN     | NN     | NN     | 2.2    | NN     |
| 40     | NN     | NN     | NN     | 7.9    | NN     |
| 50     | 0.9    | NN     | 6.3    | 13.7   | NN     |
| 60     | 10.9   | NN     | 12.9   | 19.4   | 0.5    |
| 70     | 20.9   | 1.7    | 19.6   | 25.1   | 8.9    |
| 80     | 31     | 10.5   | 26.3   | 30.9   | 17.3   |
| 90     | 41     | 19.3   | 32.9   | 36.6   | 25.7   |
| 100    | 51     | 28.1   | 39.6   | 42.3   | 34.1   |

Note: NN indicates that no significant bottleneck is present; numerical values indicate the minimum configurational level required to achieve the corresponding level of value creation.

#### 4.4. NConfA Results

Following Rasoolimanesh and Olya [60], this study applies NConfA to identify configurations that are necessary for achieving high value creation in organic agriculture. Based on the results of fsQCA, four configurations (e.g., TA×ST, ST×TE, ST×PE and RU×ST) appeared in 50% of sufficient configurations and were thus selected as candidate necessary configurations for NConfA [64]. The effect size using CR-FDH for four necessary configurations is reported in Table 7. The effect sizes of TA×ST, ST×TE, and ST×PE are 0.131, 0.112, and 0.122, respectively. They are all above the 0.10 threshold. As a result, TA×ST, ST×TE, and ST×PE met the necessity threshold [60]. Moreover, their c-accuracy values are all close to 99%, indicating stable configuration necessity [61,64].

**Table 7.** Effect size (d) and its significance for NConfA using CR-FDH.

| Configuration | Effect Size | Accuracy (%) | p-Value | Necessary Condition | Constraint Degree |
|---------------|-------------|--------------|---------|---------------------|-------------------|
| TA×ST         | 0.131       | 99.20        | <0.001  | Yes                 | Medium            |
| ST×PE         | 0.112       | 99.30        | <0.001  | Yes                 | Medium            |
| ST×TE         | 0.122       | 98.90        | <0.001  | Yes                 | Medium            |
| RU×ST         | 0.048       | 99.70        | <0.05   | No                  | Small             |

The bottleneck table (Table 8) was produced to further show clear stage-specific threshold characteristics for the necessary configurations. It shows the minimum threshold levels of each configuration required to achieve different levels of value creation in organic agriculture. All threshold values are presented in percentage terms. Table 8 shows that it is necessary to have the combined value of TA×ST greater than 29.9%, the combined value of ST×PE greater than 26.1%, and the combined value of ST×TE greater than 29.1% to generate a high value creation (greater than 80%). This suggests that high value creation depends on the simultaneous presence of key combinations of conditions. Overall, the results support H8.

**Table 8.** Bottleneck table for NConfA using CR-FDH.

| VA (%) | TA×ST (%) | ST×PE (%) | ST×TE (%) |
|--------|-----------|-----------|-----------|
| 0      | NN        | NN        | NN        |
| 10     | NN        | NN        | NN        |
| 20     | NN        | NN        | NN        |
| 30     | NN        | NN        | NN        |
| 40     | NN        | 5.8       | NN        |

**Table 8.** *Cont.*

| VA (%) | TA×ST (%) | ST×PE (%) | ST×TE (%) |
|--------|-----------|-----------|-----------|
| 50     | 11.3      | 10.9      | 10.6      |
| 60     | 17.5      | 16        | 16.8      |
| 70     | 23.7      | 21.1      | 23        |
| 80     | 29.9      | 26.1      | 29.2      |
| 90     | 36.1      | 31.2      | 35.4      |
| 100    | 42.2      | 36.3      | 41.6      |

## 5. Discussion

### 5.1. Integration and Discussion of the Overall Research Findings

This study has examined how digitalization contributes to value creation in organic agriculture through a socio-technical systems lens. By integrating the analytical results (see Table 9), this study reveals that digital technologies do not create value through a simple technology-to-performance logic. Rather, value creation depends on how technologies are embedded in tasks, organizational structures, actor capabilities, and institutional rules. This finding qualifies the optimistic view that digital tools can automatically improve agricultural efficiency and market performance [3,13]. It is more consistent with recent work that views agricultural digitalization as a socio-technical process rather than a purely technical transition [5,14].

**Table 9.** Combined results of the expanded analytical process.

| Factors | PLS-SEM Results                     | NCA Results                                                                | fsQCA Results                               | NConfA Results                                 | Combined Results                                           |
|---------|-------------------------------------|----------------------------------------------------------------------------|---------------------------------------------|------------------------------------------------|------------------------------------------------------------|
| TA      | has strongest direct effect on VA   | necessary condition (>30.9% for high VA)                                   | core condition in multiple high-VA pathways | element of one necessary configuration         | is most robust carrier of value conversion                 |
| ST      | has strong direct effect on VA      | necessary condition (>26.3% for high VA)                                   | core condition in multiple high-VA pathways | element of three necessary configurations      | is organizational basis for system synergy                 |
| PE      | has Significant direct effect on VA | necessary condition (>31% for high VA)                                     | core condition in multiple high-VA pathways | element of one necessary configuration         | is capability condition for technology conversion          |
| TE      | has Significant direct effect on VA | not necessary condition singly (shows a lower bottleneck value at high VA) | core condition in multiple high-VA pathways | element of one necessary configuration         | is embedded enabling condition                             |
| RU      | has Significant direct effect on VA | not necessary condition singly (shows a lower bottleneck value at high VA) | core condition in multiple high-VA pathways | not an element of the necessary configurations | is institutional support and contextual enabling condition |

TA and ST play the strongest roles in value creation. This extends prior studies that emphasize the technical benefits of precision farming, traceability, and platform-based coordination [13,14]. Our results suggest that these benefits are realized only when digital technologies are linked to concrete tasks. Thus, tasks are the practical interface through which digital technologies become economic value. The importance of ST also supports studies that highlight cooperation, knowledge sharing, and collective organization in organic and agroecological systems [6,39].

The role of PE further explains why digitalization outcomes vary across farms. Previous research has shown that education, digital skills, income, and user capabilities shape agricultural technology adoption [9,30]. Our findings go beyond adoption. They show that people also determine whether technologies can be understood, coordinated, and converted into value. This is especially important in organic agriculture. Organic farmers must not only use digital technologies. They must also understand ecological production, certification rules, quality traceability, and consumer trust. This supports the findings by Leduc et al. [43]. In this sense, PE is a conversion capability that links digital technologies, ecological practices, and market value.

TE and RU are the embedded roles of value creation in organic agriculture. TE has a significant positive effect, but it is not a single necessary condition. This challenges a technology-deterministic interpretation of digital agriculture. Digital technologies matter, but the effects depend on their alignment with structure, tasks, and people. This finding echoes Daniel et al. [4] and Wu and Zhong [5]. RU shows a similar pattern. Certification standards, policy support, data governance, and consumer trust do not create value alone. Yet they shape the conditions under which ecological value can be converted into market value. This is consistent with studies showing that digital value creation and value capture are shaped by governance structures and institutional arrangements [14,39].

The configurational results further show that there is no single best pathway to high value creation. This finding supports the configuration view that complex outcomes may arise from different combinations of conditions [49,58]. It also provides quantitative support for Schnebelin's qualitative observation that digital technologies are used differently across farming models and actor groups [20]. The NCA and NConfA results support Dul's [50,59] argument that high-level outcomes may be constrained by bottlenecks. In organic agriculture, value creation is therefore both flexible and constrained. Different paths are possible, but key socio-technical thresholds must be met.

Overall, the findings suggest that digital technologies create value in organic agriculture only when they are embedded in task settings, supported by organizational structures, enacted by capable actors, and enabled by institutional rules. This helps explain why digitalization sometimes produces efficiency gains and market premiums, but sometimes remains limited or fragmented. The difference lies not in technology alone, but in the quality of socio-technical alignment.

## 5.2. Theoretical Implications

This study shows that digitalization enables value creation in organic agriculture only when key socio-technical elements are aligned. Organic agriculture is an appropriate context to examine this process due to its dependence on certification systems, trust, and institutional coordination. Although prior studies have examined digitalization in sustainable agriculture, they have not fully explained how digital technologies create value in organic agricultural systems. This study provides a starting point for understanding this issue.

First, this study extends STS to the organic agriculture value creation context. We develop a five-dimensional framework consisting of technology, structure, people, tasks, and rules based on the classical STS model [16]. This extension is theoretically important. In organic agriculture, rules are institutional mechanisms that shape whether digital technologies can be transformed into value gains. This treatment responds to discussions on institutions, governance, and social embeddedness in agricultural digitalization research [5,14,17].

Second, this study shifts the analytical focus from technology adoption to technology embedding. Existing studies have mainly explained adoption behavior and its determi-

nants [9,13], but have paid limited attention to how digital technologies are integrated into production tasks, organizational coordination, and institutional settings. Therefore, this study conceptualizes digitalization as an embedded socio-technical process. And argue that value creation depends on the depth of integration between technologies and contextual elements rather than mere adoption.

Third, this study provides a configuration and necessity-based explanation of value creation using a multi-method approach. Prior studies explained less about how different conditions combine to produce different value creation outcomes [14,15]. By combining PLS-SEM, fsQCA, NCA, and NConfA in a sequential and complementary design, this study develops a richer and more fine-grained causal account. It identifies both necessary single conditions and core necessary configurations [49,58,64]. It also reveals multiple sufficient pathways leading to the desired outcome. This study responds to the view that complex management issues and sustainability outcomes should be explained through multiple causal logics [50,60].

Overall, digital technologies function as embedded enabling elements rather than independent drivers. Value creation depends on the alignment of technology, structure, people, tasks and rules in specific contexts.

### 5.3. Practical Implications

The findings of this study provide several practical implications for policymakers, cooperative organizations, and organic farm managers. It should be noted that these implications are derived from empirical evidence collected from 753 organic farms across seven provinces in China. Therefore, they are most applicable to contexts characterized by fragmented farm structures, uneven levels of digital capability, developing cooperative organizations, and continuously evolving certification and market systems. Within these boundaries, the analytical framework and diagnostic logic developed in this study may also offer useful insights for other developing economies that share similar structural characteristics. Nevertheless, policy design and implementation should be adapted to specific institutional arrangements and market conditions in each national context.

First, policymakers may consider shifting from general equipment subsidies to task-oriented digital upgrading, especially in the context of fragmented organic farms and uneven digital capabilities in China. The results of H1–H5 and the NCA results show that tasks play a central role in value creation. These findings suggest that policy efforts may benefit from moving beyond a sole focus on expanding technology supply. Greater attention could be given to facilitating the integration of digital technologies into specific value-creating activities. Policymakers may consider supporting digital transformation in key task areas, such as smart farming, ecological circular production chains, quality traceability, certification data management, and the integration of agriculture, culture, tourism, and commerce. Such measures can help promote a shift from simple technology investment toward task-based digital application. In practice, governments can support scenario-based demonstration projects. They can also build shared digital service platforms and provide task-based training programs. These measures can help embed digital technologies into production, certification, circulation, and market connection. They can also improve the actual conversion efficiency of digital investment.

In addition, based on the NCA results, policy instruments should be configured around the three necessary conditions (e.g., tasks, people, and structure) rather than being distributed evenly across different areas. The NCA findings show that all three dimensions are necessary for high value creation and are subject to bottleneck constraints. This implies that advanced technologies alone cannot generate high levels of value if farms lack digital literacy, task management capabilities, or organizational coordination. Based on these

findings, policymakers may consider combining digitalization programs with task-oriented training, shared digital service platforms, and organizational capacity building. Training programs could focus on specific tasks, such as smart equipment operation, ecological monitoring, traceability recording, certification documentation, e-commerce management, and consumer communication. In addition, public service platforms or regional digital agriculture service centers could provide affordable support for small and medium-sized organic farms. Such services may include data collection, quality traceability, brand promotion, and market linkage. These measures can help strengthen digital capabilities and facilitate the effective application of digital technologies in organic agriculture.

Second, cooperative organizations can play an important role as organizational carriers of digital value creation. The PLS-SEM results show that ST has a strong direct effect on value creation. The NConfA results further reveal that ST is a core component of three necessary configurations (e.g.,  $TA \times ST$ ,  $ST \times TE$ , and  $ST \times PE$ ). These findings suggest that structure is not merely a supporting condition. Rather, it serves as a critical organizational channel linking tasks, technology, and people. It is an organizational channel that connects technologies, actors, and tasks. Cooperatives, industry associations, and socialized service organizations may consider providing shared equipment, unified production standards, joint certification, traceability management, brand building, technical extension, and market linkage services. Such services may be particularly valuable for small and fragmented organic farms. They can help reduce the costs of digital transformation and facilitate the conversion of individual technology use into regional branding capacity and collective competitive advantage.

Third, organic farm managers may consider treating digital technologies as embedded tools rather than isolated investment projects. Digital technologies can support value creation more effectively when they are integrated into daily farm routines and management processes. Farm managers may embed internet of things sensors, blockchain-based traceability systems, agricultural cloud platforms, and smart irrigation systems into production management, ecological record-keeping, certification documentation, quality control, and market communication. At the same time, farms may further strengthen the capability conditions required for effective technology utilization. Training should not remain at the level of general digital awareness. Instead, it may focus on practical task-oriented skills, including data interpretation, smart equipment operation, traceability recording, certification management, and online market communication.

The effectiveness of these recommendations depends on specific institutional and market conditions. They should be adapted to local levels of organizational development, digital infrastructure, and certification systems when applied to other developing economies with similar characteristics.

## 6. Conclusions

Based on STS theory, this study develops an analytical framework consisting of five dimensions: technology, structure, people, tasks, and rules. The framework is used to explain the mechanisms through which digital technologies drive value creation in organic agriculture. Using survey data from 753 organic farms in seven provinces of China, this study integrates PLS-SEM, fsQCA, NCA, and NConfA. These methods are used to examine the net effects, sufficient configurations, necessary conditions, and necessary configurations. The results show that the five dimensions have significant positive effects on value creation in organic agriculture. Among them, tasks and structure have stronger direct effects. The results also identify three equifinal pathways to high value creation: the PE-TA dual-core pathways, the deep socio-technical coupling pathways, and the RU-ST-TA system support pathways. In addition, tasks, people, and structure constitute necessary conditions

for high value creation. The configurations of TA×ST, ST×TE, and ST×PE constitute necessary configurations.

These findings suggest a fundamental pattern through which digital technologies enable value creation in organic agriculture. The key to releasing the effects of technologies does not lie in technological advancement alone. It lies in the systemic alignment of technologies with tasks, structure, people, and rules. Only by moving beyond the myth of technological determinism and toward a paradigm of system reconfiguration can the problem of technology practice decoupling be addressed. This is also necessary for achieving a higher level of value creation in organic agriculture.

Moreover, these findings provide direct implications for both global and Chinese efforts toward climate-neutral agricultural transformation. Digital technologies can simultaneously generate economic value and climate benefits only when they are embedded in organic agricultural systems through the coordinated interaction of tasks, structure, people, and rules. Such integration is essential for advancing sustainable development goals and achieving net-zero emission strategies.

This study has several limitations. First, the data were collected from organic farms in seven provinces of China. Although the sample covers different regions and operational contexts, the findings mainly reflect the contextual experience of digital transformation in China's organic agriculture. The conclusions still need further examination in developed economies, where agricultural organization, certification systems, digital infrastructure, and consumer markets are more mature. They also need to be tested in other developing countries with different institutional environments and market conditions. Future studies could conduct cross-country comparisons. Such research could examine how socio-technical system synergy differs across institutional and market contexts. Second, this study uses cross-sectional survey data. This design can reveal relationships among variables and configuration pathways. However, it cannot fully capture the dynamic evolution of digital transformation and value creation in organic agriculture. Future studies could adopt longitudinal research designs or panel data methods. They could examine how technology, structure, people, tasks, and rules co-evolve over time. They could also explore how different threshold conditions change across different stages of development. Third, this study did not directly measure climate performance indicators. Future studies could employ Life Cycle Assessment (LCA) or carbon footprint analysis to provide a more comprehensive evaluation of the environmental outcomes associated with digitalization in organic agriculture.

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## Appendix A

**Table A1.** Questionnaire.

| Construct                                  |     | Items                                                                                                                                                                                                                   |
|--------------------------------------------|-----|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Value creation in organic agriculture (VA) | va1 | Our digital management, such as smart irrigation and precision fertilization, has improved the efficiency of water and fertilizer use and enhanced the ecological environment of farmland.                              |
|                                            | va2 | Digital transformation has enabled our organic products to achieve higher market premiums and more stable profit growth through greater quality credibility and brand value.                                            |
|                                            | va3 | Our digital business model has created more local employment opportunities and strengthened consumer trust and community recognition, thereby improving the sustainability and overall competitiveness of our business. |
| Hardware infrastructure (HI)               | hi1 | Our farm is equipped with advanced smart agricultural machinery, such as smart tractors and drones.                                                                                                                     |
|                                            | hi2 | We use IoT sensors to monitor soil, climate, and other environmental conditions in real time to support precision organic farming operations.                                                                           |
|                                            | hi3 | We use blockchain technology to record organic fertilizer application and testing data in a tamper-proof manner.                                                                                                        |
| Platform tools (PL)                        | pl1 | We use agricultural cloud platforms to manage the entire process of production, processing, and circulation, which strengthens consumer trust in our organic products.                                                  |
|                                            | pl2 | We use big data analytics tools to support production decisions and optimize compliance with organic standards.                                                                                                         |
|                                            | pl3 | Our digital platform enables intelligent control of key processes, such as irrigation and fertilization.                                                                                                                |
| Data resources (DR)                        | dr1 | We regularly collect and update environmental monitoring data, such as soil quality and water quality data.                                                                                                             |
|                                            | dr2 | We use market consumption data to guide our organic production planning and sales strategies.                                                                                                                           |
|                                            | dr3 | Our data resources are shared through digital platforms to support decision-making in organic agricultural operations.                                                                                                  |
| Digital literacy (DL)                      | dl1 | Our employees can proficiently operate sensors, smart machinery, and other intelligent farming equipment.                                                                                                               |
|                                            | dl2 | Our employees can interpret environmental sensor data and make decisions related to organic production.                                                                                                                 |
|                                            | dl3 | Our employees can analyze market data and optimize the product mix and sales strategies of our organic products.                                                                                                        |
| Cross functional collaboration (CC)        | cc1 | We maintain close collaboration with actors such as organic farming experts, certification agencies, and logistics firms.                                                                                               |
|                                            | cc2 | We work collaboratively with supply chain partners through shared data platforms, thereby breaking information silos.                                                                                                   |
|                                            | cc3 | Cross-functional collaboration helps us respond quickly to changes in market demand and reduce circulation losses.                                                                                                      |

Table A1. Cont.

| Construct                                                        |      | Items                                                                                                                                                                    |
|------------------------------------------------------------------|------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Policy environment (PO)                                          | po1  | Government policies, such as the digital village strategy and financial support programs, support our digital transformation.                                            |
|                                                                  | po2  | The certification system for organic products encourages us to adopt digital technologies such as blockchain.                                                            |
|                                                                  | po3  | Local policies, such as carbon trading pilot programs, drive us to optimize our organic production processes.                                                            |
| Socio-cultural environment (SC)                                  | sc1  | We actively respond to market demand for product transparency and verifiable ecological value.                                                                           |
|                                                                  | sc2  | We strive to overcome traditional production habits and adapt to a culture of data-driven decision-making in order to meet consumer demand for healthy organic products. |
|                                                                  | sc3  | We operate in a socio-cultural environment that increasingly recognizes and supports transparent, trustworthy, and sustainably produced organic products.                |
| Integration of agriculture, culture, tourism, and commerce (ACT) | act1 | We develop activities such as agritourism and cultural experiences to expand value-creation opportunities in organic agriculture.                                        |
|                                                                  | act2 | We integrate agriculture, culture, tourism, and commerce to create multiple forms of value.                                                                              |
|                                                                  | act3 | This integration enhances the market competitiveness and social influence of our organic business.                                                                       |
| Smart crop and livestock production (SP)                         | sp1  | We use data to support precision fertilization, irrigation, and other production activities, thereby reducing organic production costs.                                  |
|                                                                  | sp2  | Smart crop and livestock production helps us improve product quality and resource-use efficiency.                                                                        |
|                                                                  | sp3  | Standardized production provides a stronger foundation for higher-value organic products.                                                                                |
| Ecological circular chain development (EC)                       | ec1  | We have established an ecological circular system that reduces dependence on external inputs.                                                                            |
|                                                                  | ec2  | Our organic production methods allow low-carbon footprints to be verified, thereby strengthening our brand's ESG value.                                                  |
|                                                                  | ec3  | The ecological circular chain strengthens the sustainability and ecological integrity of our organic business.                                                           |
| Industrial organization (IO)                                     | io1  | We participate in cooperatives or agricultural service organizations to share equipment and technical resources.                                                         |
|                                                                  | io2  | We share experience in organic production through informal organizations such as family farm alliances.                                                                  |
|                                                                  | io3  | Organizational innovation helps us integrate fragmented production units and improve efficiency.                                                                         |
| Collaboration networks (CN)                                      | cn1  | We maintain vertical collaboration with governments, research institutions, and firms to promote the localization of organic agricultural technologies.                  |
|                                                                  | cn2  | We build horizontal alliances with logistics providers and sales terminals to improve logistics efficiency and product quality.                                          |
|                                                                  | cn3  | Collaboration networks help us access complementary resources and improve premium realization.                                                                           |
| Process optimization (PR)                                        | pr1  | We use big data-based smart production to optimize our production processes.                                                                                             |
|                                                                  | pr2  | We use data platforms to share smart machinery, data resources, and operational experience more efficiently.                                                             |
|                                                                  | pr3  | We use blockchain technology to optimize certification and traceability processes and improve transparency.                                                              |

**Table A2.** Indicator means, loadings, reliability, and validity of the latent constructs.

| Construct | Item | CA    | CR    | AVE   | Mean  | SD    | Factor Loading |
|-----------|------|-------|-------|-------|-------|-------|----------------|
| VA        | va1  | 0.790 | 0.877 | 0.704 | 4.200 | 0.980 | 0.858          |
|           | va2  |       |       |       | 4.032 | 1.044 | 0.818          |
|           | va3  |       |       |       | 3.864 | 1.073 | 0.841          |
| HI        | hi1  | 0.797 | 0.881 | 0.711 | 3.768 | 1.071 | 0.842          |
|           | hi2  |       |       |       | 3.674 | 1.097 | 0.855          |
|           | hi3  |       |       |       | 3.802 | 1.111 | 0.832          |
| PL        | pl1  | 0.763 | 0.864 | 0.679 | 3.789 | 1.064 | 0.832          |
|           | pl2  |       |       |       | 3.647 | 1.062 | 0.827          |
|           | pl3  |       |       |       | 3.451 | 1.104 | 0.812          |
| DR        | dr1  | 0.812 | 0.888 | 0.726 | 3.942 | 1.084 | 0.869          |
|           | dr2  |       |       |       | 3.836 | 1.083 | 0.850          |
|           | dr3  |       |       |       | 3.733 | 1.083 | 0.837          |
| DL        | dl1  | 0.836 | 0.901 | 0.753 | 4.141 | 1.016 | 0.876          |
|           | dl2  |       |       |       | 3.982 | 1.060 | 0.870          |
|           | dl3  |       |       |       | 3.825 | 1.091 | 0.857          |
| CC        | cc1  | 0.702 | 0.870 | 0.770 | 3.886 | 1.034 | 0.845          |
|           | cc2  |       |       |       | 3.701 | 1.059 | 0.838          |
|           | cc3  |       |       |       | 3.506 | 1.112 | 0.832          |
| PO        | po1  | 0.836 | 0.901 | 0.753 | 4.023 | 1.080 | 0.887          |
|           | po2  |       |       |       | 3.926 | 1.098 | 0.884          |
|           | po3  |       |       |       | 3.827 | 1.098 | 0.832          |
| SC        | sc1  | 0.788 | 0.876 | 0.702 | 3.740 | 1.091 | 0.873          |
|           | sc2  |       |       |       | 3.736 | 1.089 | 0.882          |
|           | sc3  |       |       |       | 3.736 | 1.089 | 0.882          |
| ACT       | act1 | 0.799 | 0.882 | 0.713 | 3.900 | 1.018 | 0.859          |
|           | act2 |       |       |       | 3.729 | 1.040 | 0.856          |
|           | act3 |       |       |       | 3.604 | 1.045 | 0.811          |
| SP        | sp1  | 0.796 | 0.880 | 0.709 | 3.658 | 1.129 | 0.868          |
|           | sp2  |       |       |       | 3.541 | 1.138 | 0.870          |
|           | sp3  |       |       |       | 3.389 | 1.161 | 0.859          |
| EC        | ec1  | 0.833 | 0.900 | 0.749 | 3.717 | 1.060 | 0.863          |
|           | ec2  |       |       |       | 3.645 | 1.085 | 0.855          |
|           | ec3  |       |       |       | 3.588 | 1.090 | 0.814          |
| IO        | io1  | 0.783 | 0.873 | 0.696 | 3.899 | 1.008 | 0.854          |
|           | io2  |       |       |       | 3.737 | 1.041 | 0.852          |
|           | io3  |       |       |       | 3.560 | 1.069 | 0.796          |
| CN        | cn1  | 0.742 | 0.886 | 0.795 | 3.430 | 1.093 | 0.884          |
|           | cn2  |       |       |       | 3.435 | 1.115 | 0.899          |
| PR        | pr1  | 0.784 | 0.874 | 0.698 | 3.842 | 1.016 | 0.856          |
|           | pr2  |       |       |       | 3.704 | 1.052 | 0.851          |
|           | pr3  |       |       |       | 3.524 | 1.086 | 0.798          |

**Table A3.** Discriminant validity of the measurement model (HTMT).

|    | PE    | RU    | ST    | TA    | TE    | VA |
|----|-------|-------|-------|-------|-------|----|
| PE |       |       |       |       |       |    |
| RU | 0.288 |       |       |       |       |    |
| ST | 0.350 | 0.310 |       |       |       |    |
| TA | 0.482 | 0.376 | 0.351 |       |       |    |
| TE | 0.404 | 0.286 | 0.321 | 0.669 |       |    |
| VA | 0.688 | 0.451 | 0.581 | 0.74  | 0.696 |    |

**Table A4.** Measurement invariance assessment (MICOM results).

| Construct | Configural Invariance | Original Correlation (c) | 5% Quantile | p-Value | Mean Difference | p-Value | Variance Difference | p-Value |
|-----------|-----------------------|--------------------------|-------------|---------|-----------------|---------|---------------------|---------|
| TE        | Yes                   | 0.998                    | 0.995       | 0.312   | 0.143           | <0.001  | −0.228              | 0.171   |
| PE        | Yes                   | 1                        | 0.998       | 0.616   | 0.621           | <0.001  | −0.427              | 0.008   |
| ST        | Yes                   | 0.999                    | 0.997       | 0.329   | 0.54            | <0.001  | −0.462              | 0.007   |
| TA        | Yes                   | 1                        | 0.999       | 0.704   | 0.496           | <0.001  | −0.421              | 0.047   |
| RU        | Yes                   | 0.976                    | 0.947       | 0.129   | 0.474           | <0.001  | −0.228              | 0.171   |
| VA        | Yes                   | 0.988                    | 0.52        | 0.125   | 0.506           | <0.001  | −0.387              | 0.015   |

**Table A5.** Calibration thresholds.

| Construct | Full Non-Membership (0.05) | Crossover Point (0.50) | Full Membership (0.95) |
|-----------|----------------------------|------------------------|------------------------|
| TE        | 0.191                      | 0.675                  | 0.904                  |
| PE        | 0.223                      | 0.706                  | 0.927                  |
| ST        | 0.331                      | 0.747                  | 0.936                  |
| TA        | 0.356                      | 0.701                  | 0.950                  |
| RU        | 0.287                      | 0.751                  | 0.955                  |
| VA        | 0.341                      | 0.761                  | 0.965                  |

**Table A6.** Summary of hypothesis testing results.

| Hypothesis | Analytical Method | Main Empirical Evidence                                                                              | Support Status |
|------------|-------------------|------------------------------------------------------------------------------------------------------|----------------|
| H1–H5      | PLS-SEM           | TE, ST, PE, TA, and RU have positive effects on value creation in organic agriculture                | Supported      |
| H6         | fsQCA             | Four configurations leading to high value creation are identified                                    | Supported      |
| H7         | NCA               | TA, PE, and ST meet the threshold for single necessary conditions                                    | Supported      |
| H8         | NConfA            | The configurations of TA × ST, ST × PE, and ST × TE meet the threshold for necessary configurations. | Supported      |

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