

Article

Spatial Differentiation and Influencing Factors of Innovative Perception Among New-Type Agricultural Business Entities: A Case Study of Anhua National Modern Agricultural Industrial Park

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Abstract

The United Nations 2030 Agenda for Sustainable Development (UN SDGs) frames sustainable agriculture as a core pathway to advance zero hunger (SDG 2) and protect life on land (SDG 15). As critical platforms for the green transition of agriculture, innovative perception among new-type agricultural business entities inside national modern agricultural industrial parks constitutes a prerequisite cognitive factor shaping sustainable farming practices. Taking Anhua National Modern Agricultural Industrial Park—China’s sole industrial park specialized in dark tea—as the research case, this study develops a four-dimensional measurement framework for innovative perception covering innovation cognition, motivation, demand, and intention, grounded in 363 field micro-survey questionnaires. Factor analysis is adopted to quantify township-level composite innovative perception scores, and the Geodetector model is integrated to detect driving factors as well as their interactive coupling effects behind spatial disparities. The results indicate the following: (1) Marked spatial heterogeneity characterizes innovative perception levels of new-type agricultural business entities across the park, which maintain an overall high standard. The core zone registers an average score of 4.209 versus 3.726 for the demonstration zone; innovative perception in the core zone is statistically higher, presenting a typical core–periphery gradient pattern across townships. (2) Individual endogenous attributes, including age, educational attainment, and farming experience, show strong explanatory capacity. The interaction between age and innovation applicability yields a q-statistic of 0.961, the strongest pairwise spatial association observed within the present sample; nevertheless, q-statistics from the Geographical Detector are sample-specific descriptive metrics for spatially stratified explained variance and do not represent causal effect sizes. This research uncovers the core–periphery polarization rule and multi-factor spatial coupling patterns underlying innovative perception of operators within specialized agricultural industrial zones. The empirical micro-evidence generated in this work informs the design of tiered, differentiated governance policies aimed at mitigating intra-park spatial disparities, delivering empirical insights into the cognitive foundations of the park’s green transition. This analysis targets innovative perception



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as the cognitive prerequisite for sustainable farming practices instead of direct sustainability outcomes; empirical tracing of the perception-to-behavior-to-outcome causal chain would require longitudinal outcome-focused datasets, which constitutes a key avenue for future inquiry.

Keywords: innovative perception; new-type agricultural business entities; spatial differentiation; influencing factors; Anhua National Modern Agricultural Industrial Park

1. Introduction

The United Nations 2030 Agenda for Sustainable Development (UN SDGs) frames the transition toward sustainable agriculture as a core pathway to reconcile Zero Hunger (SDG 2) and Life on Land (SDG 15). As one of the world's major agricultural nations, China takes national modern agricultural industrial parks as pivotal platforms to stimulate agricultural innovation potential through cultivating new-type agricultural business entities—namely, specialized large growers, family farms, and farmer cooperatives. Such policy design aims to resolve dual bottlenecks: the limited scale of conventional farming and ecological pressures, including agricultural non-point source pollution, soil erosion, and water resource degradation. Nevertheless, heterogeneous innovative perception among operators inside industrial parks is expected to shape their green-production decisions, underscoring the practical relevance of understanding how this cognitive dimension is spatially distributed and driven. Against this backdrop, unpacking the spatial differentiation patterns and the multi-factor spatial associations underlying operators' innovative perception constitutes both a core theoretical topic in agricultural innovation geography and a critical practical priority for advancing agricultural sustainable transformation.

1.1. Literature Review

From the Multilevel Perspective on Sociotechnical Transitions (MLP), specialized agricultural industrial parks can be defined as “niche spaces” within the sociotechnical regime—that is, arenas that provide protected institutional environments for the experimentation and diffusion of novel ideas and practices. The MLP theory stresses that the strategies, expectations, and learning processes of niche actors act as core drivers of shifts in sociotechnical regimes [1]. Accordingly, disparities in the innovative perception of new-type agricultural business entities within such parks reflect not merely individual-level cognitive differentiation, but may also, at the aggregate scale, forge divergent transformation pathways inside niche spaces, which generate “leading areas” and “lagging areas” in the uptake of sustainable practices. From the theoretical framework of Agricultural Innovation Systems (AISs), Klerkx and Begemann [2] posit that innovation is co-created by multi-stakeholder networks covering academia, industrial sectors, civil society and public authorities; interactive coordination among these actors underpins the institutional foundation of food system transformation. By synthesizing the dual theoretical lenses of MLP and AISs, a core proposition can be formulated: actors' subjective perceptions and strategic choices form the logical starting point for unpacking spatial differentiation in agricultural sustainability transitions.

However, when taking subjective cognition as the analytical object, rigorous clarification of core concepts is required. The core construct of the present study, innovative perception, must be sharply differentiated from the widely adopted term innovation adoption. Innovation adoption denotes tangible operational measures—including technological upgrades and organizational restructuring—carried out by new-type agricultural business entities; it represents the tangible external outcome generated after adoption takes place.

By contrast, innovative perception refers to systematic cognition and attitudinal inclinations formed by decision-makers drawing on industrial experience alongside policy and market contexts, serving as the prior psychological prerequisite that drives innovative behavior. The two constructs form a sequential causal pathway of “perception–behavior”, a logic rooted in the core tenets of Schumpeter’s innovation theory: the generation of innovative practices inevitably relies on preliminary cognitive accumulation and evaluative judgment [3]. A systematic review by Dessart et al. [4], together with research from Läpple & Kelley [5] and Wollni & Andersson [6], further confirms that cognitive factors, including perceived cost–benefit evaluation and risk perception, act as proximal antecedents of real adoption intentions, which delivers cross-country empirical evidence from behavioral economics to validate the mechanism whereby cognitive evaluation shapes innovative adoption.

Nevertheless, heterogeneous innovative perception among operators within industrial parks may plausibly translate into divergent green-production decisions. Whether and to what extent such perceptual gaps ultimately manifest in tangible behavioral and sustainability-related outcomes remains an open empirical question. Addressing this would necessitate outcome-level metrics alongside longitudinal tracking, which constitutes a key avenue for future inquiry.

From a transdisciplinary analytical lens, empirical research undertaken by Dimitriadis, Koursaros, and Savva [7] covering eight core global industrial sectors confirms that eco-labels suppress asset market valuations and push up risk premiums in the early innovation phase due to steep compliance burdens; yet, as market penetration rises and fixed costs are amortized over time, such labels eventually drive substantial growth in market share. This “short-run penalty, long-run premium” temporal asymmetric pattern uncovers a universal rule: innovation payoffs hinge on whether an actor’s individual endowments can support sustained operation amid periods of cost pressure. The research further identifies that mature, steady manufacturing industries and high-margin technology segments suffer milder adverse shocks from eco-certification, while revenue-sensitive finance and real estate sectors exhibit far more pronounced negative asymmetry and price volatility. Such cross-sector heterogeneous outcomes echo, across disciplinary boundaries, the divergent innovative responses of new-type agricultural business entities with varied endowments inside characteristic agricultural industrial parks.

1.2. Research Gaps

A systematic review of the domestic and international literature concerning agricultural innovation identifies two dominant research strands, both of which contain prominent research gaps. The first stream centers on micro-level behavioral drivers behind farmers’ uptake of sustainable farming practices; questionnaire-based surveys are widely adopted to extract cognitive, social, and contextual variables shaping adoption choices. Nevertheless, such works mostly rely on cross-sectional data confined to individual samples and fail to extend their analytical scope to unpack spatial differentiation features at the aggregated township level. The second strand adopts analytical tools, including the Geodetector model [8,9], to explore the spatial differentiation of agricultural innovation, yet these investigations predominantly revolve around industrial economic laws and geographic patterns, with scarce integration of theoretical frameworks rooted in sustainability transitions theory [2].

From an industrial contextual perspective, extant empirical work overwhelmingly targets annual field crops. By contrast, empirical evidence centering on China’s unique characteristic tea industrial parks, which adopt townships as the aggregation unit and integrate sustainability transitions theory, remains extremely limited. Current scholarly

outputs cannot resolve the core scientific question: How are spatial gradients in innovative perception associated with township-level differentiation, and what potential implications might these spatial associations hold for sustainable agricultural transition—including ecological governance and livelihood advancement—within industrial parks? This unresolved question creates a vital research vacancy that the present study aims to fill.

1.3. Research Objectives and Questions

To fill the abovementioned theoretical research gaps, this study selects the Anhua National Modern Agricultural Industrial Park as the research case. Based on field questionnaire data collected from 363 new-type agricultural business entities, we construct a four-dimensional measurement indicator system for innovative perception, covering innovation cognition, innovation purpose, innovation need, and innovation intention. Factor analysis is adopted to compute township-level composite scores of innovative perception. Combined with the natural-breaks method and GIS spatial analysis techniques, we further unpack multi-scalar spatial differentiation patterns along the hierarchical scale of the whole park, core zone, and demonstration zone down to individual townships. Moreover, the Geographical Detector model is adopted to quantify the independent explanatory capacity and interactive coupling effects of seven factor dimensions (decision-maker characteristics, basic attributes of decision-making subjects, knowledge base, cognitive evaluation, park environment, macro-level and micro-level policy environment, and market environment) underlying the observed spatial differentiation. Ultimately, grounded in sustainability transitions theory, this research elaborates the potential theoretical and practical implications of the spatial gradient of innovative perception for sustainable agricultural transition within the park.

This study intends to answer three layered, progressively in-depth core research questions: (1) What spatial differentiation characteristics of innovative perception emerge among new-type agricultural business entities within the modern agricultural industrial park across three spatial tiers: the core zone, the demonstration zone, and individual townships? (2) Which single factors and pairwise factor interactions possess statistically significant stratified explanatory power over variations in innovative perception? (3) What potential implications do the observed spatial associations in innovative perception carry for sustainable agricultural transition within the park, and how can these spatial patterns inform the design of targeted differentiated governance policies?

Table 1 summarizes the matching relationships among the study's analytical logic, research objectives, research hypotheses, and empirical analysis, as well as the empirical approaches adopted and corresponding expected and actual verification outcomes. Objective 1 focuses on characterizing the spatial pattern of innovative perception. Objective 2 applies the Geographical Detector to conduct statistical tests for all formulated research hypotheses. Objective 3 draws on the quantitative results to interpret the observed spatial associations and distill differentiated policy implications, including their potential implications for sustainable agricultural transition.

Table 1. Matching relationships among research objectives, research hypotheses, empirical methods, and key empirical findings.

No.	Research Objectives	Research Hypotheses	Empirical Methods	Key Empirical Findings
1	Characterizing spatial differentiation patterns of innovative perception within the three-tier nested structure covering the whole study area, sub-zones, and townships		Actor analysis combined with ArcGIS-based (10.8) spatial visualization	Overall, the industrial park maintained relatively high values; the core zone scored significantly higher than the demonstration zone, and townships presented a core-periphery gradient pattern
2	Identifying driving factors and factor interaction effects	H1: Individual endowments of decision-makers H2: Spatial and scale characteristics of business entities H3: Park institutional-environment perception H4: Decision-makers' innovative value perception H5: External institutional and market environment	Geographical Detector (single-factor detection + interaction detection)	Hypothesis H1 was fully supported; several variables under H2, H3, H4 and H5 showed non-significant results. The interaction effect between age and innovation applicability was the strongest, with a spatially stratified explanatory power (q) of 0.961
3	Uncovering mechanisms behind development gaps and proposing differentiated policy recommendations		Comprehensive qualitative mechanism interpretation	Disparities in innovative perception originate from spatial imbalances in individual endowment, institutional supply, and market-related resources, giving rise to five differentiated governance-oriented policy recommendations

1.4. Research Hypotheses

As a platform anchored in large-scale planting and breeding and marked by the agglomeration of modern production factors, the modern agricultural industrial park acts as a pivotal vehicle for agricultural supply-side structural reform and forms the core carrier of rural industrial revitalization [10–13]. New-type agricultural business entities, mainly consisting of specialized large households and family farms, stand for contemporary organizational forms of agricultural production and operation and function as the core engine advancing new quality productive forces in agriculture [14–16]. Innovative perception, defined as systematic cognition and attitudinal inclinations toward innovation activities formed by such entities, originates from established theoretical frameworks and presents as a four-dimensional innovation tendency within agricultural contexts; this construct directly shapes the responsiveness of new-type agricultural business entities to agricultural modernization progress [17–19].

The level of innovative perception stems from the joint effects of decision-makers' characteristics and the external environment. Combining established theories with field-survey data on dark tea production collected from the Anhua National Modern Agricultural Industrial Park, this study categorizes influencing factors into five theoretical dimensions: decision-makers' individual endowments, spatial and scale characteristics of business entities, the perceived institutional environment of the park, decision-makers' perceived value of innovation, and external institutional and market environment. Based on theoretical reasoning pertaining to each dimension, the following research hypotheses are put forward.

H1. *Individual endowments of decision-makers exert statistically significant explanatory power over the spatial differentiation of innovative perception.*

Age-based stratification generates divergent preferences for innovative adoption, and younger cohorts' greater receptiveness to emerging business models and novel technologies further corroborates this pattern. Drawing on established theoretical mechanisms, middle-aged new-type agricultural business entities accumulate long-run comparative returns from tea cultivation, yielding superior risk-bearing capacity; younger operators display heightened sensitivity to emerging business formats yet lack extended industrial practical experience as a frame of reference; meanwhile, highly educated decision-makers gain access to more comprehensive information pipelines. Age, educational level, and dark tea farming experience collectively form heterogeneous assessments of innovation payoffs, ultimately giving rise to cognitive stratification across townships. Human capital theory proposed by Schultz posits that investments in human capital, such as educational attainment and farming experience, strengthen decision-makers' capacity to acquire information and assess innovation-related benefits and risks, serving as a core driver for the transformation of conventional agriculture. Drawing on this theoretical foundation, educational level, years of agricultural operation, and farming experience are widely adopted as core indicators to measure the human capital stock of new-type agricultural business entities [20]. Empirical research conducted by Li Zhi on entrepreneurial innovative consciousness verifies that age and occupational experience exert statistically significant impacts on innovative perception [21]. Empirical analysis by Tuolunay Maymayti and Zhu Meiling [22], which centers on agricultural-technology demands held by business entities, further confirms that younger decision-makers are more inclined to embrace innovative cognition.

Accordingly, Hypothesis 1 is formulated: Age, educational level, and dark tea planting experience of decision-makers exert statistically significant explanatory power over the spatial differentiation of innovative perception. Among new-type agricultural business entities, those of middle and advanced age with higher educational attainment and long-term dark tea planting experience demonstrate stronger capacity to recognize both economic and ecological benefits brought by innovation, which raises their likelihood of forming high-level innovative perception oriented toward sustainable development.

H2. *The spatial and scale characteristics of business entities significantly explain the spatial differentiation of innovative perception levels.*

From the perspective of scale effects, Green et al. [23] argued that magnitude effects shape actors' decision-making and judgment. Drawing on empirical evidence from agricultural industrial parks, Wang [9] further verified that operational scale positively boosts technology-adoption intentions, which supports the "scale-innovation cognition" transmission chain. When considering geographical proximity, discrepancies emerge between theoretical expectations and empirical observations. Friedmann's (1966) [24] core-periphery theory posits that regional innovation resources tend to agglomerate in core zones, whereas peripheral regions suffer factor siphoning and resource leakage. Accordingly, business entities located within core zones are expected to exhibit higher innovative perception levels. Empirical work by Yu [8] also suggests that farmers closer to technology centers report stronger adoption intentions. Nevertheless, existing empirical evidence reveals that the relationship between proximity to technology centers and planting-technology adoption intentions does not hold universally across industrial contexts. The net effect of spatial distance is moderated by contextual factors, including industry attributes and intra-park organizational integration. Such mismatches between theoretical inferences and heterogeneous empirical outcomes imply that the net effect of locational conditions on

innovative perception cannot be stipulated a priori. From the natural-location dimension, elevation acts as a fundamental production constraint. By altering temperature, frost-free periods and cultivation conditions, it constrains the available technological alternatives for tea plantations and indirectly shapes business entities' innovation willingness.

Based on the above reasoning, we propose the following hypothesis: operational scale should exert significant explanatory power for the spatial differentiation of innovative perception; the anticipated influences of elevation and locational conditions remain ambiguous, and their real-world effects will be tested via subsequent factor detection with the Geographical Detector.

H3. *The perceived institutional environment of the industrial park exerts significant explanatory power for the spatial differentiation of innovative perception levels.*

This hypothesis focuses on business entities' subjective perceptions regarding institutional supply within industrial parks. Its theoretical foundation integrates two frameworks: mission-oriented agricultural innovation systems (MAISs) and Rogers' innovation-diffusion theory. Klerkx and Begemann [2] posit that industrial parks function as niche-mediating innovation platforms. Whether objective institutional inputs such as park policies and training programs can be translated into innovative behavior hinges critically on operators' differentiated perceptions, evaluations, and participatory practices. Following the progressive "cognition–evaluation–behavior" logic, this study adopts three independent indicators: park awareness, representing operators' breadth of knowledge regarding park policies and technical resources corresponding to the information-acquisition level; service level, referring to subjective satisfaction evaluations of park training and supporting services at the attitudinal-judgment level; and service intensity, denoting the objective annual frequency of operators' actual participation in park training and consultation activities at the practical-behavioral level. These three observational dimensions are conceptually distinct, with clear theoretical boundaries and no overlapping constructs. In terms of case-specific spatial characteristics, the core zone features a relatively higher coverage density of agricultural technical services and a higher concentration of special supporting policies for the dark tea industry, whereas the demonstration zone exhibits certain gaps in service accessibility. Consequently, business entities located in these two types of zones show marked differences in institutional perceptions and participation frequency.

Turning to the empirical literature, Yu [8] indicates that the technical-service level of industrial parks exerts no significant influence on technology-adoption willingness, while training intensity generates significantly positive effects on both technology-adoption willingness and actual adoption behavior. Cheng [25] found that higher participation in training or lectures exerts positive effects on residents' health perceptions. Although that study belongs to the field of public-health research, the facilitating effect of training-participation frequency on individual perceptions demonstrates cross-domain generality, which provides indirect supporting evidence for using service intensity as a proxy for behavioral participation in this study. The above-mentioned findings imply hierarchical heterogeneity in park institutional supply: the influence pathway of superficial information awareness may be weaker than that of in-depth behavioral participation. Nevertheless, concrete hierarchical disparities remain to be identified through empirical tests.

Building on the above theoretical reasoning, we derive subordinate theoretical expectations under H3: service intensity and park awareness exert significant explanatory power over the spatial differentiation of innovative perception; given conflicting conclusions reported in the existing literature regarding service level, its anticipated influence on the spatial differentiation of innovative perception remains indeterminate and is open to subsequent empirical testing.

H4. *Decision-makers' perception of innovation value exerts significant explanatory power for innovative perception levels.*

The perceived innovation value of decision-makers is split into two core dimensions: knowledge reserves and subjective evaluation of innovation outcomes. The existing literature has verified their dual effects on innovative thinking from the knowledge foundation and innovation cognition perspectives, respectively. From the knowledge endowment dimension, fundamental knowledge accumulation facilitates the cultivation of innovative perception and improves the practical outcomes of innovative activities [26–28]. Specifically, knowledge diversity expands the boundary of innovation resources accessible to business operators and strengthens their comprehensive innovation capacity, while knowledge specialization deepens decision-makers' logical understanding of industrial innovation [29,30]. Digital access channels further advance integrated innovation by broadening knowledge acquisition pathways and boosting resource integration efficiency [31].

In terms of innovation cognitive evaluation, innovation novelty and applicability interact synergistically [32]. Innovation novelty helps raise the output value and operational performance of innovative schemes, whereas innovation applicability magnifies the practical benefits brought by novel innovations [33,34]. Moreover, perceived innovation novelty and perceived applicability jointly act as core psychological drivers that motivate decision-makers to adopt innovative practices [35].

Based on the above theoretical deduction, we propose the following hypotheses: Knowledge diversity and knowledge specialization, together with perceived innovation applicability, exert significant explanatory power over the spatially stratified heterogeneity of innovative perception; by contrast, perceived innovation novelty presents no significant explanatory capacity for such spatial stratification, and perceived innovation applicability serves as the core perceptual factor that stimulates operators' willingness to carry out sustainable production innovation.

H5. *External institutional and market environments exert significant explanatory power over the spatially stratified heterogeneity of innovative perception.*

Institutional policies and market conditions constitute two core external drivers shaping the evolution of innovative perception among new-type agricultural business entities. Existing scholarship has thoroughly discussed their effects from the dimensions of policy instruments, market competition, and factor endowments. In terms of policy regimes, policy frameworks standardize industrial innovation orientations and reshape operators' innovation expectations, thereby exerting direct impacts on their innovative cognition [36]. Macro industrial policies delineate industrial development trajectories and build cross-regional innovation ecosystems to consistently stimulate operators' innovation incentives [37]. By contrast, micro supporting policies deploy targeted instruments, including special innovation grants, technical consultation, and entrepreneurial subsidies, to cut innovation trial-and-error costs and facilitate the translation of innovation willingness into practical actions [38–40]. From a market perspective, end-consumer demand and industrial competition generate persistent innovation-driven signals that push business entities to renew their innovative perception [41,42]. Labor market talent reserves can provide fundamental factor support for industrial innovation [37,39].

Accordingly, the following hypotheses are proposed: both macro-level policies and micro-level policies within the policy environment exert significant explanatory power over the spatially stratified heterogeneity of innovative perception; consumer markets, industrial markets, and labor markets within the market environment possess significant explanatory capacity for such spatially stratified heterogeneity.

2. Materials and Methods

2.1. Overview of the Case Study Area

The Anhua National Modern Agricultural Industrial Park was founded in 2018 and approved as one of the second batch of national-level parks in 2019. The industrial park is located in the north-central part of Hunan Province, within the main range of the northern section of Xuefeng Mountain, bordering 8 counties (cities/districts), including Dingcheng District and Taoyuan County (Figure 1). It governs 23 townships and 448 administrative villages (communities), with a total area of 4950 km². Distinctively, it is the sole national-level industrial park nationwide that specializes in dark tea as its core leading industry. In 2021, its regional GDP reached 26.091 billion yuan; the total output value of agriculture, forestry, animal husbandry, and fishery was 9.691 billion yuan; and the per capita disposable income of rural residents was 12,109 yuan. The dark tea planting area reached 360,000 mu (approximately 59,300 acres) in 2021, with a comprehensive industrial output value of 23 billion yuan, and its dark tea output has ranked first across China for 15 consecutive years.

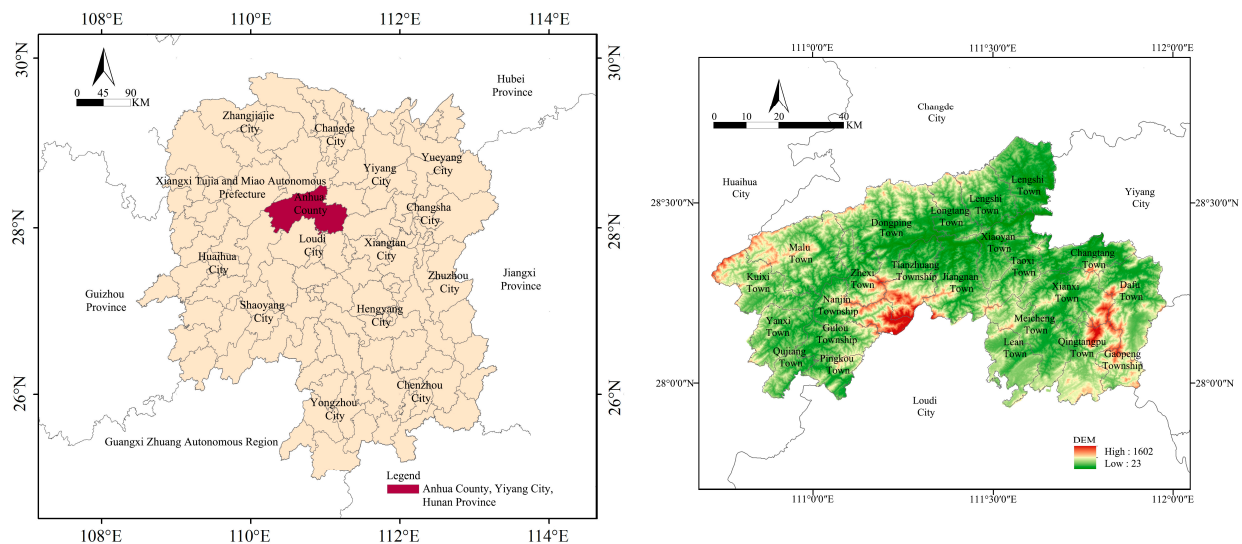


Figure 1. Location map of Anhua National Modern Agricultural Industrial Park.

The park boasts prominent industrial agglomeration advantages. Through policy support such as financial subsidies and technical training, the park has fostered four types of new-type agricultural business entities: planting enterprises, farmer cooperatives, family farms, and large growers. After on-site surveys and verification in 2022, and excluding invalid entities, 363 valid samples of dark tea planting entities were identified. Specifically, there were 76 planting enterprises, 205 farmer cooperatives, 58 family farms, and 24 large-scale growers. In terms of their respective proportions, planting enterprises accounted for 20.9%, farmer cooperatives for 56.5%, family farms for 16.0%, and large-scale growers for 6.6% (Table 2). These entities, by engaging in large-scale and specialized production, coupled with technological and organizational innovation, have become the core driving force for the high-quality development of the dark tea industry.

The robust industrial and economic foundation of Anhua Industrial Park provides sufficient fiscal support for innovation-oriented policy interventions within the park boundary. From a spatial matching perspective, the average score of innovative perception in the core zone calculated in this study reaches 4.209, which is statistically markedly higher than the value of 3.726 recorded in the demonstration zone. Under the unified territorial layout of the park, the core zone agglomerates a large number of leading enterprises and professional technical service stations, granting local business entities more accessible

channels for ecological tea cultivation training and integrated production-marketing cooperation. By contrast, the demonstration zone suffers from inadequate industrial supporting facilities and insufficient supply of innovative resources, resulting in an overall lower level of innovative perception among operators. This evidence reveals that regional economic indicators cannot be interpreted as isolated statistical figures; instead, they indirectly shape the innovative perception of township-level business entities via spatially uneven allocation of policy inclinations and industrial supporting resources. Such spatial differentiation logic further delivers structural evidence for the formulation of tiered, differentiated support policies within the industrial park.

Table 2. Number of new-type agricultural business entities engaged in dark tea planting in 2022.

Variable Name	Planting Enterprises	Farmer Cooperatives	Family Farms	Large-Scale Growers	Total
Quantity	76	205	58	24	363
Proportion (%)	20.9	56.5	16.0	6.6	100

2.2. Delineation of the Research Scope

Based on the spatial association characteristics of the dark tea industry and regional radiation logic, the radiation scope of the Anhua National Modern Agricultural Industrial Park is divided into three tiers: the primary radiation area includes seven counties (cities/districts) surrounding Anhua County: Taojiang, Heshan, Taoyuan, Shimen, Yuanling, Baojing, and Guzhang; the secondary radiation area comprises the rest of Hunan Province excluding the primary radiation area; and the potential radiation area comprises all dark tea production regions outside Hunan Province (Figure 2). Based on the planned layout, industrial agglomeration intensity, and development orientation of the industrial park, the core zone of the Anhua National Modern Agricultural Industrial Park includes nine townships and towns, including Yangjiaotang, Jiangnan, and Malu, while the demonstration zone of the Anhua National Modern Agricultural Industrial Park includes 14 townships and towns, including Meicheng, Pingkou, and Gulou (Figure 3).

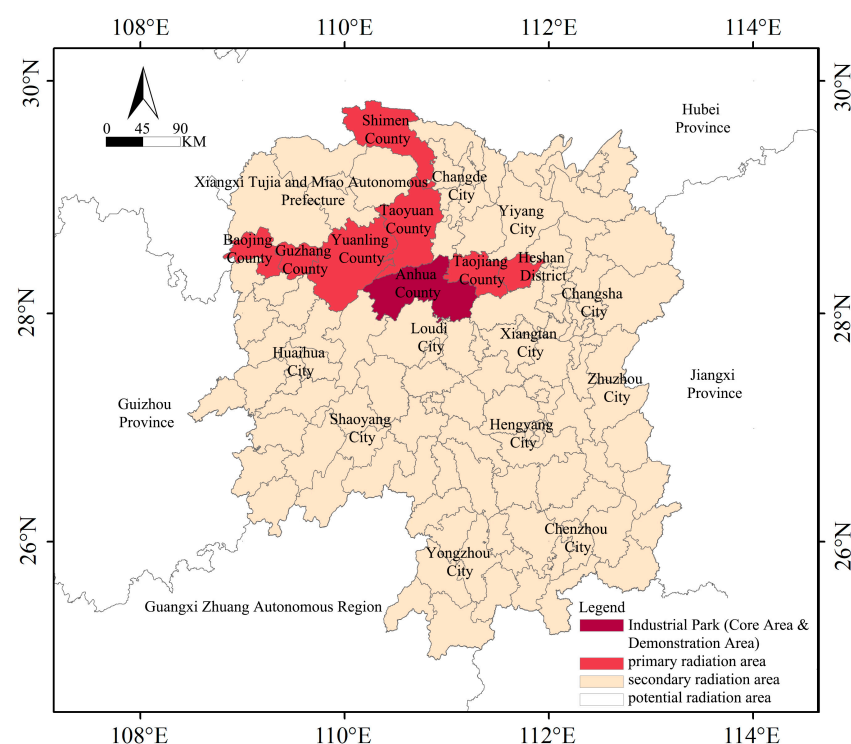


Figure 2. The radiation scope of the Anhua National Modern Agricultural Industrial Park.

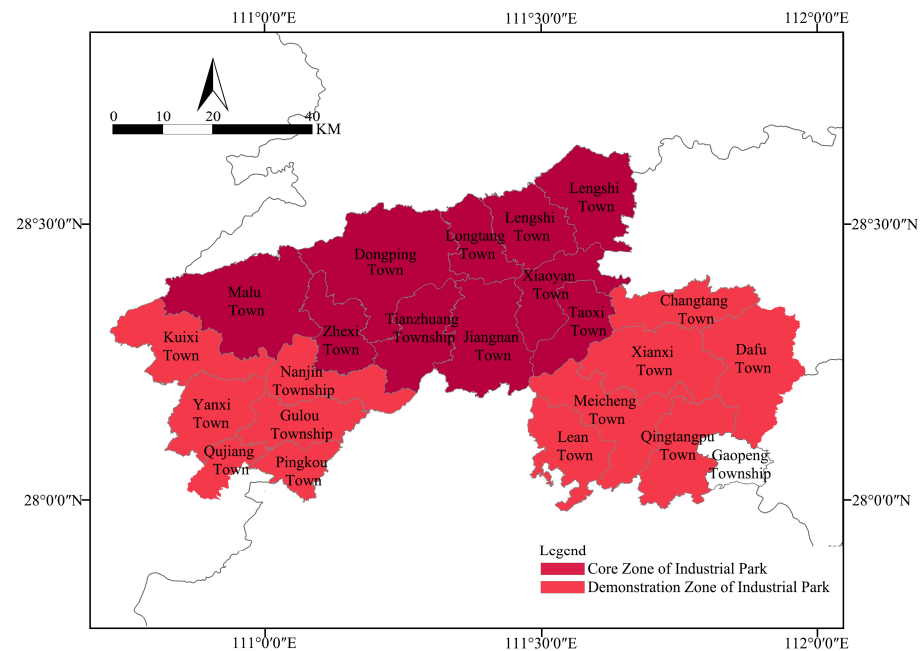


Figure 3. The scope of the core zone and demonstration zone of Anhua National Modern Agricultural Industrial Park.

Following preliminary data collection, a pre-survey, and field investigations in counties and districts surrounding Anhua County, it was found that the scale of tea cultivation in these adjacent areas remains limited, and the number of new-type agricultural business entities engaged in dark tea planting in each county and district is insufficient to support a robust sample. Therefore, after careful consideration, the core zone and demonstration zone of the Anhua National Modern Agricultural Industrial Park were selected as the study area for this paper.

2.3. Data Sources

2.3.1. Spatial Data Materials

Digital Elevation Model (DEM) data with a 30 m resolution were obtained from the Geospatial Data Cloud. The longitude and latitude coordinates of 363 new-type agricultural business entities were collected from positioning information provided by WeChat Location and the Two Steps Outdoor Assistant application.

2.3.2. Socioeconomic Statistical Data

At the macro level, these include statistical yearbooks and tea industry development plans for seven counties (cities and districts), such as Taojiang and Taoyuan, sourced from the statistical bureaus and departments of agriculture and rural affairs of the respective counties; at the micro level, they encompass lists of tea enterprises in Anhua County and household farm records obtained from the Anhua County Tea and Tourism Industry Development Service Center, the Rural Revitalization Bureau, and other relevant institutions. These data were further integrated with the China Rural Statistical Yearbook, the Anhua County Statistical Yearbook, and statistical reports at the township and village levels to form a complete data chain.

2.3.3. Other Relevant Materials Include Textual Documents Pertaining to Urban and Rural Planning and Industrial Parks

Regarding urban and rural planning, these materials encompass the “Overall Plan for Hunan Anhua Economic Development Zone (2017–2030),” the “Overall Urban Plan for

Anhua County, Hunan Province (2016–2030),” the “Regulatory Detailed Plan and Urban Design for Anhua Dark Tea Industrial Park,” the “Hunan Anhua Dark Tea Industry Development Plan (2014–2020),” the “Overall Plan for Anhua Dark Tea Modern Agricultural Industrial Park (2017–2020),” and other textual documents such as overall plans, layout plans, and tourism development plans for various townships and towns and villages. These documents were sourced from the Anhua Natural Resources Bureau and the Anhua County National Modern Agricultural Industrial Park Management Committee. For industrial parks, the relevant documents include application materials for the Hunan Anhua Dark Tea Characteristic Industrial Park, the creation plan for the Anhua County Modern Agricultural Industrial Park in Hunan Province, the Anhua County Tea and Tourism Industry Development Plan, and the Anhua Dark Tea High-Quality Development Action Plan. These materials were sourced from the Anhua County Tea and Tourism Industry Development Service Center, the Anhua County National Modern Agricultural Industrial Park Management Committee, and the Anhua County Economic Development Zone Management Committee.

2.4. Stratified Sampling and Sample Representativeness Assessment

This study yielded 363 valid questionnaires. All 22 townships with valid responses had no fewer than two valid samples, which satisfied the minimum sample threshold required for township-level aggregation analysis. The compositional structure of new-type agricultural business entities was consistent with official business-entity ledgers. Surveyed decision-makers were predominantly middle-aged and possessed extensive practical experience in dark tea cultivation, indicating good overall sample representativeness. Detailed statistics on township-level sample distribution and sample demographic profiles are provided in Supplementary Materials: see Tables S1 and S2 in Supplementary Material S1.

2.5. Construction of the Indicator System for Measuring Innovative Perception

2.5.1. Definitions of the Four Core Dimensions and Their Progressive Logic

Innovation cognition sits at the starting point of the psychological transmission chain. It is defined as “the foundation of innovative perception, serving as its prerequisite and safeguard and built upon a certain knowledge base and evaluation level.” This dimension captures survey subjects’ basic understanding of innovation and addresses the question of “whether they understand innovation”, laying the cognitive groundwork for subsequent evaluation and intention formation. The definitions and progressive inter-relationships among the four dimensions are elaborated below.

Innovation purpose constitutes the second link in the psychological transmission chain and represents the value-orientation dimension. It refers to “the ends toward which innovative means or methods are directed to attain specific goals or realize certain values.” This dimension measures decision-making subjects’ innovation-motivation orientation and expected benefits, answering the question of “why innovate”.

Innovation need—situated at the third stage of the psychological transmission chain—corresponds to the behavioral-pathway dimension. It is defined as “the behavioral pathway that actors must follow to achieve specific goals or realize certain values”. This dimension captures the concrete needs perceived by subjects for pursuing innovation goals and addresses the question “Through what means is innovation pursued?”. The key distinction from innovation purpose is as follows: purpose denotes value orientation (what), whereas need denotes the behavioral pathway (how). At the operationalization stage, purpose-oriented items use willingness-framed phrasing such as “Do you wish to ...?”, while need-oriented items adopt utility-judgment phrasing such as “Do you need ...?” or “Do

you consider ... beneficial?”. These two constructs are clearly distinguishable in both conceptual domain and measurement wording and exhibit no conceptual overlap.

Innovation intention represents the terminal node of the psychological transmission chain and belongs to the behavioral-tendency dimension. It is defined as “the affective attitude and inclination toward performing a given behavior, acting as the precondition and foundation for behavioral generation”. This dimension gauges subjects’ behavioral inclination to engage in innovative activities under given conditions and answers the question of “whether one is willing to innovate”.

Collectively, these four dimensions follow the psychological-transmission logic of “cognition → purpose → need → intention”, fully covering the complete pre-behavioral cognitive chain ranging from exposure to innovation-related information to the formation of behavioral inclination. This progressive logic is consistent with the classical “cognition → attitude → behavioral intention” transmission pathway within the Technology Acceptance Model (TAM) [43].

2.5.2. Basis for the Four-Dimensional Measurement Framework and Comparison with Existing Research

Grounded in the complete and continuous psychological evolutionary chain of innovative perception—“cognition–purpose–need–intention”—this paper establishes three screening and evaluation criteria for dimension selection for indicator construction. First, clarity of dimensional conceptual boundaries: each dimension must represent an independent psychological construct with no conceptual overlap. Second, operational feasibility for agricultural questionnaire surveys: dimensions shall lend themselves to questionnaire-based measurement targeting new-type agricultural business entities engaged in dark tea production. Third, consistency of analytical boundaries: the analysis must be strictly confined to the level of innovative perception and must not extend to innovative behavior, consistent with the “perception-to-behavior” staged research framework adopted in this study.

Guided by the above criteria, this paper systematically reviews existing dimensional frameworks proposed in prior studies. In the five-dimensional framework reported by Wang et al. [44], the affective and psychological dimensions cannot be independently measured within structured questionnaires and thus fail to satisfy practical survey requirements. The three-dimensional framework developed by Li [21] places excessive emphasis on means-oriented consciousness that leans toward actual behavioral outcomes, exceeding the analytical boundary of perception-level research. The two-dimensional framework from Zhang [45] suffers from a thin structural design and omits dimensions specific to agricultural operators, such as income-growth motives and policy-related demands. Although the four-dimensional framework proposed by Ni [46] conforms to the complete psychological chain of perception formation, it merges value goals and implementation pathways into a single module, which gives rise to conceptual ambiguities.

Overall, notable limitations exist within the two-, three-, and five-dimensional frameworks mentioned above. Accordingly, this study revises and further disaggregates Ni’s four-dimensional framework by separating innovation purpose and innovation need into two independent constructs, finally constructing a four-dimensional measurement system consisting of innovation cognition, innovation purpose, innovation need, and innovation intention.

Within this measurement system, innovation cognition constitutes merely a sub-dimension of innovative perception. Innovative perception represents a composite latent variable synthesized from the four dimensions via factor analysis; the two maintain a subset-to-superset relationship, which precludes concerns over endogeneity or circular reasoning. Two methodological points further rule out such logical risks. First, the four extracted

common factors remain mutually independent with no nested relationships following varimax rotation in factor analysis processing. Second, the 18 explanatory factors input into the Geographical Detector model are external influencing factors (e.g., decision-maker characteristics, knowledge base, and cognitive evaluation). These predictors are external driving forces rather than constituent components of the dependent-variable innovative perception and are therefore not incorporated as parts of the dependent variable. Hence, the logical fallacy of “explaining an outcome by its own components” is absent from the analytical design.

2.5.3. Design, Source and Localization of Measurement Items

Based on the sequential psychological-transmission logic elaborated above, 20 five-point Likert-scale measurement items were developed and assigned to the four dimensions. Each item corresponds to only one single independent latent construct, with no cross-dimensional conceptual overlap:

- (1) Innovation Cognition (5 items): Measures operators’ fundamental understanding of dark tea cultivation, organizational-mode innovation, and potential innovation-related risks;
- (2) Innovation Purpose (4 items): Captures respondents’ goal-orientation toward realizing self-value and other expected outcomes through innovation;
- (3) Innovation Need (5 items): Evaluates respondents’ perceived practical utility of diverse innovation implementation approaches, focusing on behavioral pathways;
- (4) Innovation Intention (6 items): Describes operators’ subjective behavioral tendencies to pursue innovation under varying policy and resource conditions.

All measurement items were localized and revised according to field-survey data obtained from the local dark tea industry.

The formal scale was adapted and integrated from multiple well-established domestic and international measurement instruments. Items for cognitive traits were revised from Schaefer’s Creativity Attitude Scale and Basadur and Hausdorf’s Ideation-Preference Scale. Items reflecting value orientation and behavioral intention drew upon Costa and McCrae’s NEO Personality Inventory and Li Zhi’s Innovation-Consciousness Scale [21,47–49]. Items for innovation-need-related implementation pathways were newly developed based on semi-structured field interviews with stakeholders in the Anhua dark tea industry. This supplementary development addresses the limitation of mainstream foreign scales, which lack items concerning agricultural operators’ income-growth needs and industrial adaptation requirements. This four-dimensional framework retains the core latent constructs of classical scales while conforming to the practical characteristics of the local dark tea industry. The complete wording, item codes, dimension assignment, and theoretical sources of the 20 measurement items are provided in Supplementary Materials S2: see Table S3.

2.5.4. Reliability and Validity Testing

In the reliability and validity testing, the Cronbach’s α coefficients for innovation cognition, innovation purpose, and innovation need all exceeded 0.8, whereas the α coefficient for innovation intention fell within the range of 0.7–0.8. Corrected item–total correlation (CITC) values for all 20 measurement items were greater than 0.4. The removal of any individual item did not yield an increase in the corresponding Cronbach’s α coefficient, indicating satisfactory internal consistency for each dimension. The KMO value reached 0.897, and Bartlett’s test of sphericity was statistically significant ($p < 0.05$). Four common factors were extracted via varimax rotation, with a cumulative variance contribution rate of 63.867%, which confirms the satisfactory construct validity of the scale. Robustness checks of the four-dimensional measurement structure of innovative perception are provided in Table S1 in Supplementary Material S2.

2.6. Research Methods

The independent variables in this study consist of 18 indicators grouped into five dimensions: decision-makers' individual endowments, spatial and scale characteristics of new-type agricultural business entities, perceived institutional environment of the industrial park, decision-makers' perceived innovation value, and the external institutional and market environment. The dependent variable refers to the township-scale level of innovative perception, which is represented by the mean innovative perception score of new-type agricultural business entities within each township. Definitions, coding schemes, and theoretical sources for all variables are presented in Table 3.

Table 3. Variable definitions and coding descriptions.

Dimensions	Variable Name	Variable Definition	Coding	Theoretical Basis
Individual endowments of decision-makers	Age	Age of decision-maker	Mean age of decision-makers of new-type agricultural business entities in each township and town	Human Capital Theory
	Educational level	Educational level of the decision-maker	1 = Primary education or below, 2 = Junior high school education, 3 = Senior high school/secondary vocational education, 4 = College education, 5 = Bachelor's degree or above, mean value	Human Capital Theory
	Tea Planting experience	Years of tea planting experience of the decision-maker	1 = Less than 1 year, 2 = 1–2 years, 3 = 3–5 years, 4 = 6–10 years, 5 = More than 10 years, mean value	Learning by Doing
Spatial and scale characteristics of business entities	Operation scale	Tea plantation scale (mu, 1 mu $\approx$ 0.0667 ha)	1 = Less than 100 mu, 2 = 101–200 mu, 3 = 201–500 mu, 4 = 501–1000 mu, 5 = More than 1000 mu, mean value	Economies of Scale Theory
	Elevation	Elevation of new-type agricultural business entities (m)	Mean elevation of new-type agricultural business entities in each township and town	Agricultural Location Theory
	Locational condition	Is it located in the core area of the industrial park?	0 = demonstration zone, 1 = core zone	Core and Periphery Theory
Park institutional-environment perception	Park cognition	How familiar are you with modern agricultural industrial parks?	1 = Not familiar at all, 2 = Not familiar, 3 = Neutral, 4 = Familiar, 5 = Very familiar	Diffusion of Innovations Theory
	Service satisfaction	How satisfied are you with the service level of the industrial park?	1 = Very dissatisfied, 2 = Dissatisfied, 3 = Neutral, 4 = Satisfied, 5 = Very satisfied	SERVQUAL
	Service Intensity	How many times have you attended training organized by the government or an industrial park?	1 = 0 times, 2 = 1 time, 3 = 2 times, 4 = 3 times, 5 = 4 times or above	Human Capital Investment Theory

Table 3. *Cont.*

Dimensions	Variable Name	Variable Definition	Coding	Theoretical Basis
Decision-makers' innovative value perception	Knowledge diversity	How knowledgeable are you about the dark tea industry?	1 = Not familiar at all, 2 = Not familiar, 3 = Neutral, 4 = Familiar, 5 = Very familiar	Knowledge-Based View
	Knowledge specialization	How well do you understand the knowledge related to innovations in dark tea?	1 = Not familiar at all, 2 = Not familiar, 3 = Neutral, 4 = Familiar, 5 = Very familiar	Absorptive Capacity Theory
	Innovative novelty	How satisfied are you with the tea organization and the novelty of its technological innovation?	1 = Very dissatisfied, 2 = Dissatisfied, 3 = Neutral, 4 = Satisfied, 5 = Very satisfied	Creative Cognition Theory
	Innovative applicability	How satisfied are you with tea industry organizations and technological innovation in terms of their applicability to the development of the tea industry?	1 = Very dissatisfied, 2 = Dissatisfied, 3 = Neutral, 4 = Satisfied, 5 = Very satisfied	Task–Technology Fit
External institutional and market environment	Macro-level policies	How satisfied are you with the level of support from the park's various policies?	1 = Very dissatisfied, 2 = Dissatisfied, 3 = Neutral, 4 = Satisfied, 5 = Very satisfied	Institutional Change Theory
	Micro-level policies	How satisfied are you with the various subsidies and the level of financial and fiscal support provided by the park?	1 = Very dissatisfied, 2 = Dissatisfied, 3 = Neutral, 4 = Satisfied, 5 = Very satisfied	Externality and Agricultural Support Policy
	Labor market	How would you rate the ease or difficulty of hiring various types of labor in the park?	1 = Difficult, 2 = Relatively difficult, 3 = Neutral, 4 = Relatively easy, 5 = Easy	Dual Economy Theory
	Consumer market	To what extent do you think consumer demand plays a role in driving innovation among new-type agricultural business entities?	1 = No effect, 2 = little effect, 3 = Moderate effect, 4 = Relatively great effect, 5 = Great effect	Demand–Pull Innovation Theory
	Industrial market	How would you rate the extent to which the dark tea industry market drives its innovation?	1 = No effect, 2 = little effect, 3 = Moderate effect, 4 = Relatively great effect, 5 = Great effect	Competition and Innovation

Variable selection followed the principle of “theoretical framework priority, support from empirical literature, and case-specific adaptation”, and the theoretical foundations for each indicator are summarized in Table 3. This paper clarifies that park cognition (within the institutional-environment dimension of independent variables) and innovation cognition (a sub-dimension of the four-dimensional innovative perception construct, i.e., the explained variable) are two distinct measurement constructs. Park cognition reflects new-type agricultural business entities' acquisition of information on industrial-park policy resources, while innovation cognition denotes cognitive processing oriented toward

innovation itself. The questionnaire items for these two constructs are assigned to separate questionnaire modules with no overlapping measurement content.

At the factor analysis stage, all extracted common factors are mutually independent. Importantly, innovation cognition was not included among the set of independent variables input into the Geographical Detector model. Accordingly, there exists no risk of circular reasoning arising from explaining an outcome using components of that very outcome. Detailed differentiations between these constructs and a full elaboration of the theoretical transmission logic for each dimension are provided in Supplementary Materials S3.

Factor Analysis and Geographical Detector Model

(1) Factor Analysis

Factor analysis, a classic latent-variable dimension-reduction technique, was adopted in this study to compute the township-level composite score of innovative perception. Building on well-established innovation measurement instruments, a locally adapted 5-point Likert scale was developed based on field surveys of the Anhua dark tea industry. Z-score normalization was applied to the dataset to remove dimensional differences. Screening criteria were set as follows: Cronbach's $\alpha \geq 0.7$, CITC ≥ 0.4 , KMO > 0.7 , and factor loading ≥ 0.4 . Principal-component extraction combined with varimax orthogonal rotation was performed to extract common factors whose eigenvalues exceeded 1. Objective weighting based on each factor's variance contribution rate was implemented to obtain the composite score of innovative perception, which avoids bias introduced by subjective weighting schemes. The core computational formulas are shown in Equations (1)–(4).

$$y_i = \frac{x_i - \bar{x}}{s} \quad (1)$$

$$\text{where } \bar{x} = \frac{1}{n} \sum_{i=1}^n x_i, s = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2}$$

$$\begin{cases} x_1 = a_{11}F_1 + a_{12}F_2 + \cdots + a_{1m}F_m + a_1\varepsilon_1 \\ x_2 = a_{21}F_1 + a_{22}F_2 + \cdots + a_{2m}F_m + a_2\varepsilon_2 \\ \cdots \\ x_n = a_{n1}F_1 + a_{n2}F_2 + \cdots + a_{nm}F_m + a_n\varepsilon_n \end{cases} \quad (2)$$

where $F_1, F_2, \dots, F_m$ denote m factors; $x_1, x_2, \dots, x_n$ represent n standardized original variables (with $m < n$); and ε denotes the specific factor.

$$X = AF + \alpha\varepsilon \quad (3)$$

where A denotes the factor loading matrix and F denotes the extracted common factors.

$$C = m_1F_1 + m_2F_2 + m_3F_3 + \cdots + m_nF_n \quad (4)$$

where C denotes the innovative perception score; m and n denote the weights of the first- and second-level indicators; and $F_1, F_2, \dots, F_n$ represent the final scores of x measurement indicators for the four dimensions: innovation cognition, innovation purpose, innovation need, and innovation intention. Detailed procedures for the complete factor analysis workflow, scale processing, and weight-calculation steps adopted in this study are provided in Supplementary Materials S4.

(2) Geographical Detector

This study employs the Geographical Detector to calculate the spatially stratified explanatory power, q , of influencing variables [50]. This model is well-suited for the small-

sample size and mixed-type independent variables adopted in this work; it is insensitive to multicollinearity and supports factor interaction analysis. Model prerequisites include a continuous dependent variable, discretization of continuous independent variables, and a minimum of two samples within each stratum. This study applied the GD package in R to iterate over five discretization methods with classification levels ranging from three to five. The optimal discretization solution was selected according to the maximum-q criterion. This selection strategy entails the risk of q-value overestimation, which this study mitigates via cross-check robustness validation across multiple discretization schemes. Given the limited sample size, the statistic q ranges from 0 to 1, where higher values denote stronger spatial explanatory power; this threshold setting represents an established practice for small-sample exploratory research. The core computational formula for the q-statistic is given in Equation (5), and the formula for the significance F-test is provided in Equation (6). The q-statistic merely reflects the strength of spatially stratified association and cannot establish causal relationships. Detailed elaborations on the rationale for adopting the Geographical Detector and discretization protocols and the justification for the selected significance threshold are available in the Supplementary Materials S4.

$$q = 1 - \frac{\sum_{h=1}^L N_h \sigma_h^2}{N \sigma^2} = 1 - \frac{SSW}{SST} \quad (5)$$

$$SSW = \sum_{h=1}^L N_h \sigma_h^2, \quad SST = N \sigma^2$$

$$F = \frac{N-L}{L-1} \frac{q}{1-q} \sim F(L-1, N-L; \lambda) \quad (6)$$

$$\text{where } \lambda = \frac{1}{\sigma^2} \left[\sum_{h=1}^L \bar{Y}_h^2 - \frac{1}{n} \left(\sum_{h=1}^L \sqrt{N_h} \bar{Y}_h \right)^2 \right].$$

In the above equation, λ is the non-centrality parameter and $\bar{Y}_h$ is the mean of stratum h .

2.7. Method Robustness

This study performed robustness tests for both the analytical methods adopted and the resulting empirical conclusions. Factor analysis extracted common factors based on Z-score standardization and the eigenvalue criterion, which avoided bias arising from subjective weighting. Nevertheless, score stability was limited at the small-township scale. The Geographical Detector, which is insensitive to multicollinearity, quantified the explanatory intensity of spatial differentiation; however, it suffered from sample- and scale-related constraints as well as inherent limitations for causal inference. Common-method bias was effectively mitigated via procedural controls during questionnaire administration, multi-source data cross-validation, and factor structure tests. The Jenks natural-breaks classification was appropriate for spatial pattern identification, yet its thresholds were relative and vulnerable to the modifiable areal unit problem (MAUP). The empirical conclusions exhibited satisfactory internal reliability. Even so, given the uniqueness of the study case, single-period cross-sectional data, and restrictions in sample coverage, the generalizability of these findings to other contexts remained bounded. Full methodological details and robustness-related results are provided in the Supplementary Materials S5.

3. Results

3.1. Spatial Differentiation Characteristics of Innovative Perception Levels

The first part of this section calculates the composite scores of innovation perception at multiple scales—the entire Anhua Industrial Park, the core/demonstration zone, and individual towns—systematically delineating both the overall mean level of innovation

awareness among new-type agricultural business entities and the spatial differentiation pattern characterized by a “core–periphery” gradient. Innovative perception scores of new-type agricultural business entities in Anhua National Modern Agricultural Park were calculated based on indicator weights and standardized indicator values. These scores were then categorized into five levels using the ArcGIS natural-breaks method: low level (0.010–3.333), relatively low level (3.340–3.720), medium level (3.730–3.940), relatively high level (3.950–4.260), and high level (4.270–4.620).

3.1.1. Industrial-Park Innovative Perception Level Characteristics

To reflect the level of innovative perception of new-type agricultural business entities in the industrial park, this level was measured using factor analysis (Table 4).

Table 4. Industrial-park innovative perception level.

Region	Mean	Standard Deviation	Minimum	Maximum
Industrial park	3.955	0.684	1	5

Measurements indicated that the industrial park’s level of innovative perception had a mean score of 3.955, a standard deviation of 0.684, a minimum value of 1, and a maximum value of 5. According to the evaluation criteria, the score of 3.955 falls within the range of 3.950 to 4.260, indicating that the current level of innovative perception in the industrial park is high (Figure 4).

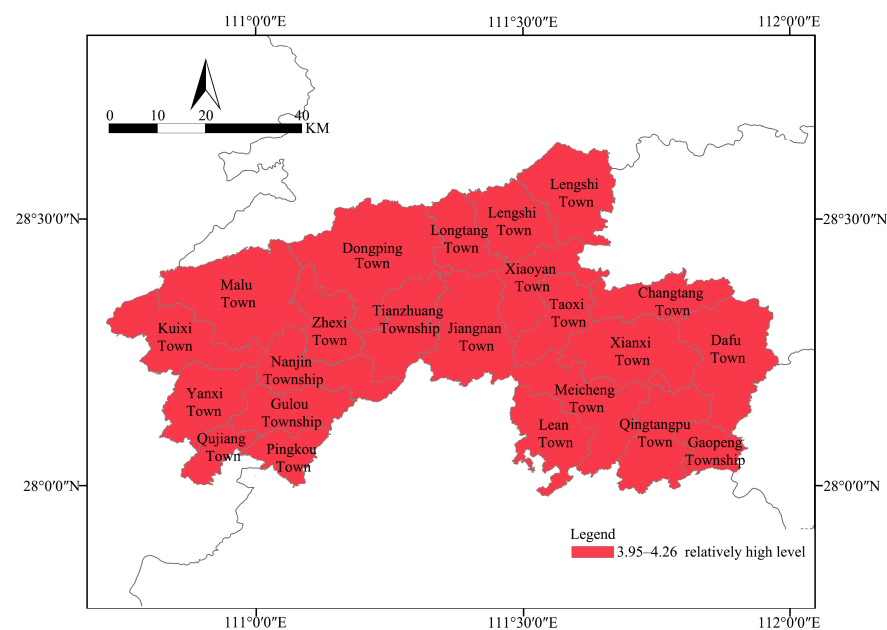


Figure 4. Overall innovative perception level of the industrial park.

This figure enables full-domain spatial visualization of innovative perception using classification outputs from the Jenks natural-breaks method. It overcomes the limitation of Table 4, which only reports the overall mean value of the Anhua industrial park (3.955). Whereas Table 4 delivers merely an aggregated numerical statistic, this figure intuitively visualizes the spatial pattern: innovative perception across the whole study area generally remains at a relatively high level, with low-value patches scattered inside two sub-regions of the demonstration zone. From a macro-spatial viewpoint, the figure corroborates the quantitative statistical outcomes presented in Table 4, whereby the region-wide numerical characteristics and spatial pattern evidence mutually reinforce one another.

3.1.2. Characteristics of the Level of Innovative Perception in the Core and Demonstration Zones of the Industrial Park

To reflect the differences in the level of innovative perception across regions of the industrial park, its core and demonstration zones were compared (Table 5).

Table 5. The level of innovative perception in the core and demonstration zones of the industrial park.

Region	Mean	Standard Deviation	Minimum	Maximum
Core zone	4.209	0.244	3.928	4.622
Demonstration zone	3.726	0.193	3.327	4.062

The core zone's mean level of innovative perception was 4.209, higher than the overall value of 3.955. Its standard deviation was 0.244, lower than the overall standard deviation of 0.684. Its minimum was 3.928, above the overall minimum of 1, while its maximum was 4.622, below the overall maximum of 5. In contrast, the demonstration zone had a mean innovative perception level of 3.726, lower than the overall mean of 3.955. Its standard deviation was 0.193, lower than the overall standard deviation of 0.618. Its minimum was 3.327, above the overall minimum of 1, and the maximum was 4.062, below the overall maximum of 5. Overall, the core zone exhibited a higher level of innovative perception than the demonstration zone, indicating regional differences (Figure 5).

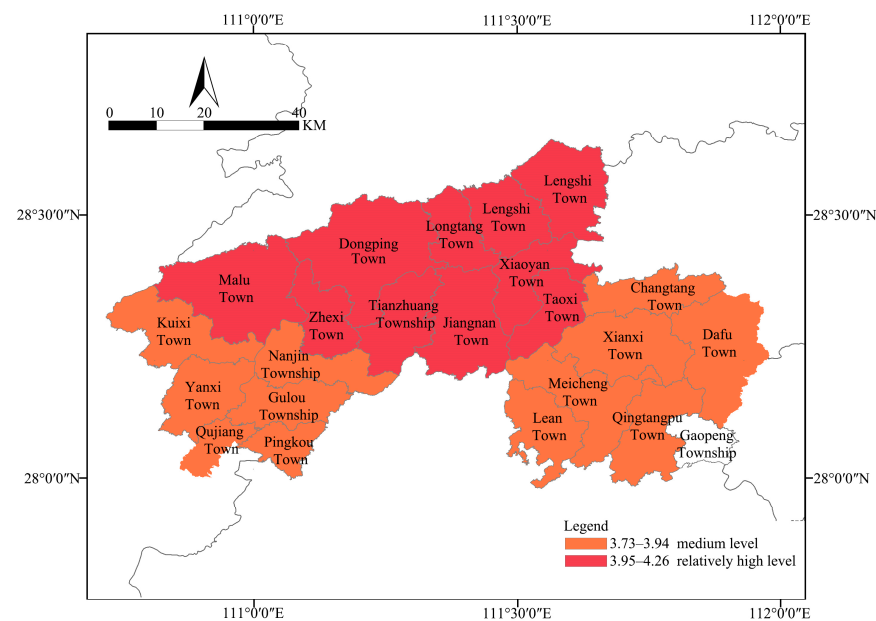


Figure 5. Characteristics of the level of innovative perception in the core and demonstration zones of the industrial park.

While Table 5 merely quantifies the mean difference between the two groups and cannot intuitively reflect their spatial distribution patterns, this figure visualizes the spatial differentiation characteristics via color-coded classification: contiguous high-value clustering within the core area and the predominance of low-to-medium values across the demonstration area. It provides visual evidence for the numerical gap, showing that the core-area mean (4.209) is markedly higher than that of the demonstration area (3.726). In this way, the figure corroborates the grouped statistical outputs from Table 5 from a spatial morphology perspective, such that regional disparities are not characterized by numerical metrics alone.

3.1.3. Township-Level Characteristics of Innovative Perception in the Industrial Park

A comparative analysis of differences in innovative perception levels among townships in the industrial park was performed. The results are shown in Table 6.

At the township scale, the mean innovative perception level varied significantly. Tianzhuang Township had the highest mean (4.622), while Gulou Township had the lowest (3.327). Of the five categories, three townships (Tianzhuang, Longtang, and Jiangnan) fell into the high level (4.270–4.620), accounting for 13.63%; six townships (including Lengshi, Dongping, and Malu) were at the relatively high level (3.950–4.260), accounting for 27.27%; five townships (including Xiaoyan, Taoxi, and Xianxi) were at the medium level (3.730–3.940), accounting for 22.73%; seven townships (including Zhexi, Kuixi, and Changtang) were at the relatively low level (3.340–3.720), accounting for 30.43%; and only one township, Gulou Township, fell into the low level (0.010–3.330), accounting for 4.35%.

Table 6. Descriptive statistics of innovative perception at the township level within the industrial park.

Township/Town	Mean	Standard Deviation	Minimum	Maximum	N
Gulou Township	3.327	0.531	2.302	3.869	6
Kuixi Town	3.553	0.661	2.322	4.521	7
Changtang Town	3.585	0.669	2.594	4.536	11
Dafu Town	3.636	0.445	2.968	4.571	10
Qingtangpu Town	3.661	0.736	2.110	4.887	9
Pingkou Town	3.668	0.519	2.896	4.699	4
Meicheng Town	3.686	0.982	1.000	4.780	17
Qujiang Town	3.715	0.677	1.669	4.880	7
Lean Town	3.777	0.659	1.936	4.852	6
Taoxi Town	3.853	0.687	2.610	4.704	10
Nanjin Township	3.862	0.530	2.901	4.777	11
Dongping Town	3.928	0.456	3.044	4.509	22
Yangjiaotang Town	3.943	1.335	2.032	4.702	2
Zhexi Town	4.010	0.581	2.966	4.918	14
Xianxi Town	4.057	0.555	3.502	4.612	31
Yanxi Town	4.062	0.808	2.879	4.785	15
Xiaoyan Town	4.065	0.493	2.764	4.547	23
Malu Town	4.104	0.488	3.598	5.000	47
Lengshi Town	4.256	0.421	3.195	4.847	15
Longtang Town	4.469	0.199	4.103	4.813	13
Jiangnan Town	4.480	0.476	3.362	4.851	41
Tianzhuang Township	4.622	0.270	3.442	4.929	42

N = number of valid questionnaires per township (see Table S1 in Supplementary Materials S1); townships with $n < 10$ are treated as exploratory units. Gaoming Township is not listed because no valid questionnaires were collected there.

Compared to the overall level of innovative perception in the industrial park, nine townships, including Tianzhuang, Jiangnan, and Zhexi, exceeded the overall level, while thirteen townships, including Yangjiaotang and Dongping, fell below it. Within the core zone, seven townships, including Tianzhuang, Jiangnan, Longtang, and Lengshi, exceeded the overall level, with only two townships, Dongping and Yangjiaotang, falling below the overall level. In the demonstration zone, only two townships, Xianxi and Yanxi, exceeded the overall level, and the remaining eleven townships, including Nanjin and Taoxi, fell below it (Figure 6).

Table 6 presents discrete mean-value statistics for the 22 townships, which hinders intuitive recognition of spatial adjacency between high- and low-value observations. By mapping each township's score to its corresponding administrative unit, this figure clearly illustrates the clustering pattern: the three high-value townships of Tianzhuang, Jiangnan, and Longtang are spatially contiguous and concentrated within the core zone, whereas low-value townships are scattered across the demonstration zone. This visualization validates the

gradient grouping pattern reported in Table 6, intuitively interprets the township-scale “core–periphery” spatial differentiation pattern, and addresses the analytical limitation of tabular outputs, which fail to reflect agglomeration effects generated by geographical proximity.

Based on the above analysis, the level of innovative perception among new-type agricultural business entities exhibits multi-scale spatial differences: the industrial park as a whole is at a relatively high level; the core zone is also at a relatively high level, while the demonstration zone is at a medium level; and at the township scale, a “core–periphery” gradient distribution is observed.

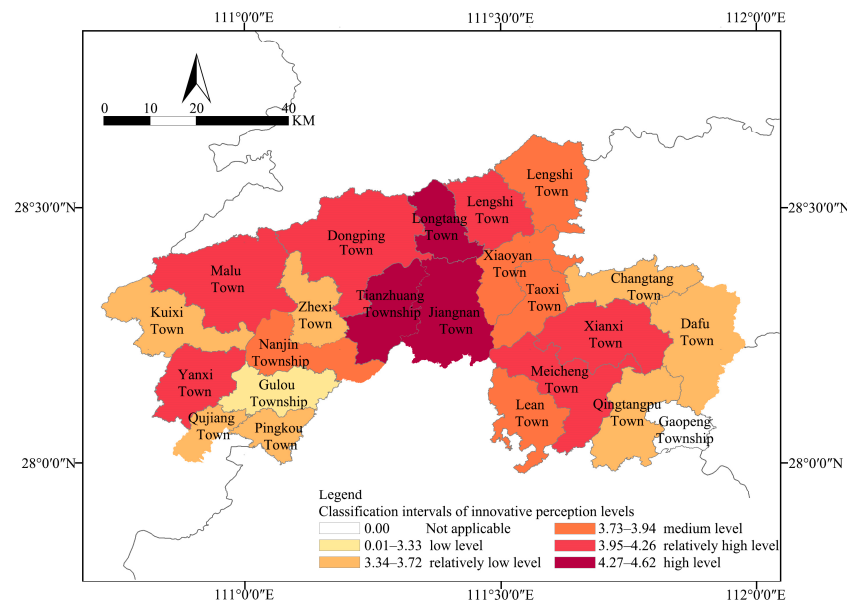


Figure 6. Township-level characteristics of innovative perception in the industrial park.

3.2. Factor Detection and Interaction Analysis

This section provides a unified account of the statistical evaluation framework adopted throughout this paper.

Spatial classification: The Jenks natural-breaks method was applied to stratify township-level innovative perception scores. This algorithm minimizes within-group variance and maximizes between-group variance, making it well-suited for depicting gradient-based differentiation across townships.

Single-factor detection: The q-value quantified the spatially stratified explanatory power of independent variables for township-level innovative perception scores. A one-tailed F-test at $p < 0.1$ denoted statistically significant spatial association. Model outputs were interpreted as having spatially stratified explanatory power, and no causal inference was drawn.

Interaction detection: All pairwise combinations of the 18 independent variables were exhaustively computed, yielding q-values for all 153 interaction pairs with no manual filtering. Key coupling combinations were identified exclusively according to the relative magnitude of q-values. Except for four interaction groups that presented a weakened two-factor interaction effect, the remaining 149 groups exhibited two-factor enhancement, including non-linear enhancement.

Robustness test: Cross-computations were performed across five discretization algorithms with classification levels ranging from 3 to 5. A stable q-value threshold gap of approximately 0.4 was observed between high- and low-explanatory-power variables. Thirteen out of the 14 significant variables satisfied the stricter criterion of $p < 0.05$; only tea planting experience was significant at the 10% level ($p = 0.071$), and the rank order of core variables remained unaffected by perturbations to discretization schemes. The multi-factor

coupling-driven mechanism uncovered via interaction detection maintained robustness across cross-validation of alternative discretization schemes.

Furthermore, this study explicitly defines the interpretive boundaries of the Geographical Detector model. The Geographical Detector analysis was performed on subjective-perception data derived from single-period cross-sectional questionnaire surveys. The q -statistic generated by the model only characterizes spatially stratified correlations between each independent variable and innovative perception scores and cannot support rigorous causal inference. The subsequent text only reports the magnitude of variable explanatory power and features of collaborative factor coupling and does not establish causal relationships between variables. Constrained by cross-sectional data, the model cannot capture long-term dynamic evolutionary relationships between variables. All mechanistic interpretations are restricted to association patterns under the static spatial configuration of the Anhua industrial park in the study period; no long-term time-series extrapolation was undertaken.

This section adopts the Geographical Detector model to quantitatively identify driving-factor effects and comprises two analytical components. The first component is single-factor detection, which differentiates statistically significant variables with high explanatory power from non-significant variables and compares disparities in the spatially stratified explanatory power of factors across dimensions. The second component is two-factor interaction detection, which extracts the globally strongest coupling combination and summarizes the intrinsic mechanisms behind multi-factor collaborative interactions.

(1) Data processing.

The Geographical Detectors require categorical variables for analysis. However, the raw data in this study were continuous numerical variables. Accordingly, the GD package implemented in R was applied to perform optimal-parameter-based classification. Calculations were carried out to determine the classification method and intervals that maximized the q -value, and factor detection together with factor interaction detection were implemented based on these outputs. The `gdm` routine from the GD package in R was called to select the optimal transformed classification approach for each indicator according to the maximum- q criterion. Candidate discretization approaches included equal-interval, natural-breaks classification, quantile, geometric-interval, and manual-interval methods. Under the constraint of 3–5 classification levels, the optimal classification interval was further determined. The q -values of each numerical independent variable under alternative classification methods and interval settings were compared comprehensively, and the classification scheme producing the highest q -value was chosen to process raw-indicator data. The discretization approach and number of classification levels finally adopted for each variable are presented in the Supplementary Materials S4: see Table S1.

This method is subject to the following accuracy-related limitations. First, the q -value maximization criterion selects parameters based on the present sample dataset and lacks independent-sample validation, which entails a certain risk of overfitting. Second, continuous within-group variation information is discarded after stratification, potentially underestimating the genuine spatially stratified explanatory power of some gradual variables. Third, several indicators feature sparsely distributed township samples under extreme strata, which may impair the estimation accuracy of local q -values. Accordingly, only computational outputs obtained under the optimal discretization condition are reported in the subsequent results. As the robustness of core conclusions against alternative discretization schemes has already been confirmed via multi-method comparative checks above, systematic bias stemming from reliance on a single discretization approach can be prevented. In the following discussion, single-factor q -values are interpreted prudently; emphasis is placed on the relative-importance ranking of variables instead of comparisons of their absolute values.

(2) Factor Detection Analysis

For factor detection analysis, the township-level mean level of innovative perception among new-type agricultural business entities was set as the dependent variable. Eighteen indicators covering five dimensions (individual endowments of decision-makers, spatial and scale characteristics of business entities, park institutional-environment perception, decision-makers' innovative value perception, and external institutional and market environment) were adopted as independent variables, and factor detection computation was implemented via the Geographical Detector. The corresponding outcomes are shown in Table 7.

Table 7. Factor detection results.

Dimensions	Metric Name	q Value	Significance (Sig)
Individual endowments of decision-makers	Age	0.892	0.011
	Educational level	0.748	0.001
	Tea planting experience	0.667	0.071
Spatial and scale characteristics of business entities	Operation scale	0.569	0.040
	Elevation	0.342	0.985
	Locational condition	0.648	0.000
Park institutional-environment perception	Park cognition	0.570	0.829
	Service satisfaction	0.650	0.010
	Service Intensity	0.693	0.029
Decision-makers' innovative value perception	Knowledge diversity	0.623	0.005
	Knowledge specialization	0.594	0.005
	Innovative novelty	0.629	0.935
	Innovative applicability	0.795	0.000
External institutional and market environment	Macro-level policies	0.666	0.009
	Micro-level policies	0.477	0.034
	Labor market	0.168	0.923
	Consumer market	0.673	0.005
	Industrial market	0.447	0.027

The factor detection results were grouped into four tiers according to the magnitude of spatially stratified explanatory power.

First-tier core high-explanatory-power variables ($q \geq 0.7$, significant at the 1% or 5% significance level): age ($q = 0.892$, the highest overall q -value across all variables, significant at the 5% level), innovative applicability ($q = 0.795$, significant at the 1% level), and educational level ($q = 0.748$, significant at the 1% level). These variables represented the fundamental core factors driving the spatial differentiation of innovative perception. Second-tier secondary-significant variables ($0.5 \leq q < 0.7$, significant at the 5% or 10% significance level) covered nine indicators: service intensity, macro-level policies, consumer market, tea planting experience, service level, locational condition, knowledge diversity, knowledge specialization, and operation scale, which exerted auxiliary supporting effects on the spatial patterns of innovative perception. Two indicators fell into the weak-but-significant category ($q < 0.5$, $p < 0.1$): micro-level policies ($q = 0.477$) and industrial market ($q = 0.447$; despite limited explanatory power, their statistical influences remained valid). Non-significant weak explanatory variables ($p > 0.1$): elevation, park cognition, innovative novelty, and labor market. These indicators showed no statistically significant association with the spatial stratification of township-level innovative perception.

(3) Factor Interaction Analysis

This observation aligns with the core logic of the Geographical Detector, in which interacting factors jointly account for spatial stratification. Of particular note, the interaction between age and innovation applicability yields a q -value of 0.961, representing the

strongest pairwise spatial association observed within the present sample. As q-values characterize sample-specific descriptive metrics of spatially stratified explanatory power derived from 23 township-level units and are susceptible to stratum-level sample-size effects, this finding should be interpreted as a robust qualitative coupling pattern instead of a quantitatively precise effect-size estimate. This spatial association can be tentatively interpreted from the following two perspectives.

From the perspective of the age dimension, single-factor detection results returned a q-value of 0.892 ($p < 0.05$), ranking age first in explanatory power among the 18 independent variables. Within our sample, middle-aged business entities aged 41–60 years accounted for 78.51%. Among the full sample, respondents with 6 or more years of tea planting experience accounted for 78.9%, which allowed them to make intuitive comparisons of long-term economic and ecological benefits brought by technologies, including organic-fertilizer substitution and ecological tea-garden management. Their judgments regarding innovation applicability were rooted in long-term practical experience.

For the innovation applicability dimension, its single-factor q-value reached 0.795 ($p < 0.001$), second only to age in explanatory power. This result aligns with a non-linear enhancement pattern: the interaction q-value of 0.961 for age $\times$ innovation applicability surpasses the respective individual q-values (0.892 for age and 0.795 for innovation applicability). Furthermore, when paired in interaction with other indicators, the q-values for age, educational level, and innovation applicability all exceed 0.8. Given the descriptive nature of the Geographical Detector q-statistic and its susceptibility to stratum-specific sample-size effects, we interpret this observed coupling pattern as indicative rather than confirmatory; mechanistic explanations for this interplay remain a hypothesis requiring larger sample sizes and individual-level modeling for formal empirical verification. It also suggests that improving decision-makers' personal competencies and their perception of innovation effectiveness constitutes a core pathway for elevating innovative perception levels among new-type agricultural business entities. The two-factor interaction heatmap generated in this study adopts a q-value-based color gradient to highlight this core interaction combination (Figure 7).

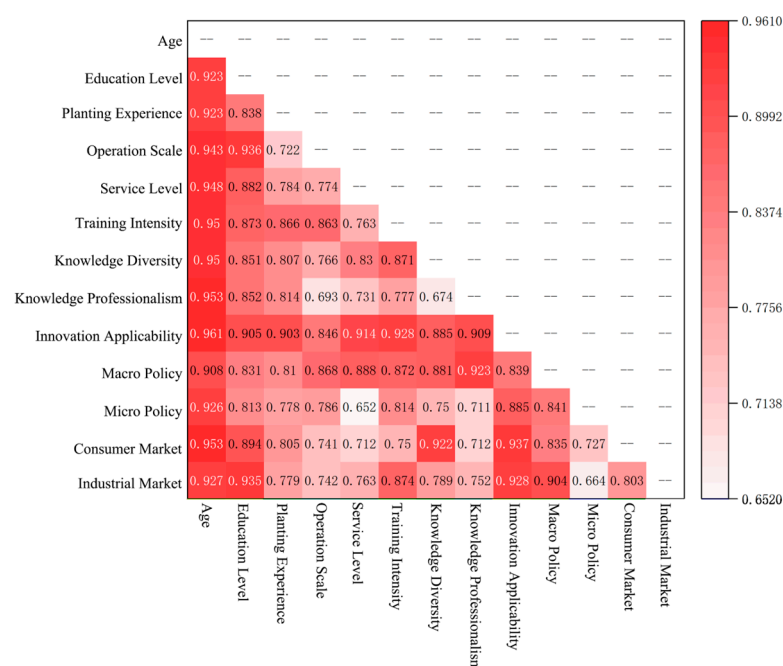


Figure 7. Two-factor interaction explanatory power.

3.3. Analysis of Influencing Factors

(1) Impact of Individual Endowments of Decision-Makers on the Level of Innovative Perception

The influence of decision-maker characteristics on the regional level of innovative perception exhibits significant heterogeneity. “Age” and “farming experience” are statistically significant at the 10% level, while “educational level” is significant at the 1% level. This indicates that average age is significantly positively correlated with the regional level of innovative perception at the 10% level. Older decision-makers possess a stronger economic foundation and greater risk resistance capability. In contrast, although younger decision-makers are more inclined to adopt new technologies, they lack comparative experience in innovation. Farming experience is also significantly positively correlated with the regional level of innovative perception at the 10% level. Longer farming tenure indicated that dark tea planting accounted for a larger share of household income, which strengthened operators’ willingness to increase household income through innovation.

Furthermore, decision-makers with rich farming experience held more in-depth insights into dark tea planting techniques and organizational innovation and better recognized the value of such innovations. Educational level delivered significant spatially stratified explanatory power for regional innovative perception at the 1% level. Decision-makers from new-type agricultural business entities with higher educational attainment were more receptive to novel ideas. They held stronger demands for technical learning, technological renewal, as well as innovation and entrepreneurship. Benefiting from richer knowledge reserves, wider exposure, and better command of emerging technologies and new concepts, they also possessed improved risk awareness and risk-resilience capacity.

(2) Impact of the Spatial and Scale Characteristics of Business Entities at the Level of Innovative Perception

Operation scale was statistically significant at the 5% level, location conditions was statistically significant at the 1% level, whereas elevation showed no statistical significance. Operation scale exerted significant spatially stratified explanatory power over regional innovative perception at the 5% level. New-type agricultural business entities with larger tea planting scales generally achieved higher tea yields and income, accompanied by a more solid innovation foundation and higher innovation awareness. This finding accorded well with our field-survey observations. Operators with large planting scales usually possessed relatively comprehensive strengths and were more motivated to improve competitiveness through innovation. Location conditions produced significant spatially stratified explanatory power for regional innovative perception at the 1% level. New-type agricultural business entities were strongly conditioned by geographic setting; entities located in geographically advantageous positions benefited from more obvious radiation spill-over effects. According to the field survey, new-type agricultural business entities within the industrial-park core zone demonstrated a deeper understanding of park-related innovations. They obtained new information and technologies through more direct channels compared with counterparts in the demonstration zone. By contrast, elevation exhibited no significant spatially stratified correlation with regional innovative perception. A plausible explanation is that elevation values were derived from the registered addresses of new-type agricultural business entities rather than the actual planting bases. Registered addresses usually correspond to enterprise factory premises or farmers’ residential sites. Mean elevation disparities across townships were minor and insufficient to generate a statistically meaningful spatially stratified association.

(3) Impact of Decision-Makers’ Innovation-Value Perception on the Level of Innovative Perception

Among the four variables within the innovation-value-perception dimension, both knowledge diversity and knowledge specialization were statistically significant at the 1% level and yielded substantial spatially stratified explanatory power. In terms of knowledge diversity, new-type agricultural business entities whose decision-makers possessed richer knowledge reserves, practical experience, and industry-related resources demonstrated deeper comprehension of the dark tea sector. This further enhanced their awareness of industry-relevant innovation and accelerated the formation and improvement of innovative perception levels. Regarding knowledge specialization, deeper understanding and mastery of the dark tea industry among decision-makers facilitated the expansion of both the breadth and depth of industry-related practice, stimulated stronger innovation willingness, and consequently fostered higher levels of innovative perception.

For cognitive-evaluation variables, innovation applicability was significant at the 1% level, whereas innovation novelty showed no statistical significance. Innovation applicability exhibits spatially stratified explanatory power with regard to elevating innovative perception levels. For new-type agricultural business entities, technological and organizational innovations that were simple, practical, easy-to-operate, and produced tangible benefits were more readily accepted, promoted, and disseminated. Survey evidence indicated that decision-makers first made practical judgments regarding innovation applicability for dark tea planting technologies and organizational innovations, including considerations of operational complexity, ease of implementation, risk controllability, and benefit clarity. Innovation novelty showed no statistically significant association with regional innovative perception levels. One plausible explanation is that decision-makers of new-type agricultural business entities attached limited importance to the novelty of dark tea planting technologies. They held clear practical goals and prioritized whether innovations suited their own production conditions and could generate tangible benefits, which represented their primary concern reflected in field surveys. Additionally, evaluating innovation novelty itself imposes relatively high cognitive requirements on respondents.

(4) Impact of Park Institutional-Environment Perception on the Level of Innovative Perception

Of the three variables in the park institutional-environment-perception dimension, service level and service intensity reached statistical significance at the 10% level, while park cognition was non-significant. Service level exhibited significant spatially stratified explanatory power for regional innovative perception at the 10% level. The service quality delivered by the industrial park constituted a key factor shaping regional innovative perception levels. New-type agricultural business entities that gave higher ratings to park services displayed greater recognition of the park and higher receptiveness toward new concepts and new technologies promoted by park authorities, which helped nurture their innovation awareness and raise their levels of innovative perception.

Service intensity also delivered significant spatially stratified explanatory power for regional innovative perception at the 10% level. Business entities that participated in more park-organized training activities demonstrated higher innovative perception levels. This observation can be interpreted as follows: dark tea planting technologies promoted by the park were mainly disseminated via technical training and demonstration bases operated by new-type agricultural business entities, while organizational-innovation initiatives were popularized through park policy outreach and entity-led demonstration effects. Increased training frequency and prominent demonstration effects broadened decision-makers' knowledge scope and improved the general applicability of relevant techniques. Meanwhile, decision-makers could directly observe the practical effects and benefits brought by new technologies, which stimulated their intrinsic innovation motivation.

Park cognition showed no statistical significance in relation to innovative perception levels. A potential reason is the relatively short establishment history of the agricultural

industrial park. Compared with industrial-oriented parks, its functional positioning was relatively scattered and less focused. Field surveys revealed that most new-type agricultural business entities broadly equated the industrial park with government agencies. They conflated the park's institutional role with government functions and lacked a clear understanding of the conceptual definition of an agricultural industrial park.

(5) Impact of the External Institutional and Market Environment on the Level of Innovative Perception

Of the two variables belonging to the external institutional dimension, macro-level policies were statistically significant at the 1% level, and micro-level policies were statistically significant at the 5% level. Macro-level policies delivered significant spatially stratified explanatory power for the level of innovative perception at the 1% level, indicating that macro-level policy frameworks could substantially elevate innovative perception levels among business entities. For new-type agricultural business entities, stronger governmental policy backing, higher subsidy support, and more flexible institutional mechanisms collectively contributed to improved innovative perception outcomes. Field-survey evidence showed that technical-innovation-related decisions made by dark tea planting new-type agricultural business entities, such as adopting new crop varieties or participating in cooperatives, were closely associated with governmental policy support.

Micro-level policies yielded significant spatially stratified explanatory power for the level of innovative perception at the 5% level, demonstrating that micro-level policy measures also exhibit strong spatially stratified explanatory power with regard to boosting innovative perception levels. Targeted policy instruments, including various governmental subsidies as well as fiscal and taxation incentives, markedly fostered diverse innovative behaviors among new-type agricultural business entities, which in turn helped raise regional innovative perception levels.

Among the three variables within the market-environment dimension, the consumer market was statistically significant at the 1% level and the industrial market was statistically significant at the 5% level, whereas the labor market showed no statistical significance. Specifically, the consumer market exhibited significant spatially stratified explanatory power for regional innovative perception levels at the 1% level. Diversified dark tea consumption demands, consumer attitudes, and market competition drove new-type dark-tea-related business entities to increase innovation investment to satisfy market requirements, thereby lifting their innovative perception levels. The industrial market produced significant spatially stratified explanatory power for regional innovative perception levels at the 5% level. Within the highly competitive dark tea industrial context, product innovation, technological innovation, and institutional innovation continuously pushed new-type agricultural business entities to advance their innovative perception levels. The labor market showed no statistically significant spatially stratified explanatory power with regard to regional innovative perception levels. A plausible explanation lies in the homogeneous talent structure of the labor pool within the industrial park: most technical personnel acquired know-how from intergenerational inheritance or learning-by-doing practices, resulting in a shortage of personnel equipped with innovative thinking and professional skills. Moreover, field-survey findings revealed that most new-type agricultural business entities lacked systematic employee-training and talent-development schemes. This constrained employees' acquisition of innovation-relevant skills and knowledge and consequently hampered improvements in innovative perception levels.

4. Discussion

The mean values of innovative perception across townships in Table 6 reveal a clear and stable hierarchy of groupings. Within the high-score tier, Tianzhuang Township (4.622),

Jiangnan Town (4.480), and Longtang Town (4.469) constituted the three highest-level townships across the study area, forming a distinct numerical break of more than 0.2 from the adjacent Lengshi Town (4.256) and showing prominent high-value agglomeration. At the low-value end, Gulou Township (3.327) represented the lowest value in the whole study area, followed closely by Kuixi Town and Changtang Town, which jointly formed a contiguous low-value distribution along the peripheral zone of the demonstration zone. In terms of spatial zoning matching, all high-level townships fell within the core area of the industrial park. In contrast, medium-low- and low-value townships, including Gulou, Kuixi, and Changtang, were concentrated in the demonstration zone. This grouping pattern corresponded well to the actual allocation of industrial factors within the park. The core zone gathered leading dark tea enterprises and standardized agricultural-technology service stations. It implemented targeted industrial support policies, enabling business entities to access innovation-demonstration scenarios through spatial proximity effects more readily. By contrast, the demonstration zone suffered from relatively weak industrial supporting infrastructure. Constrained simultaneously by the factor siphon effect originating from the core zone, high-quality industrial resources continuously flowed toward the core area. Remote mountain-fringe townships such as Gulou and Kuixi received the weakest factor radiation, which eventually produced a low-value depression of innovative perception across the whole study area. The quantitative outputs from factor detection were consistent with the spatial association patterns described above: age ($q = 0.892$, significant at the 5% level), innovation applicability ($q = 0.795$, significant at the 1% level), and educational level ($q = 0.748$, significant at the 1% level) served as core variables of the first explanatory-power tier. Among them, the interaction between age and innovation applicability yielded a q -value of 0.961, the strongest pairwise spatial association observed within the present sample; this interaction pattern was more pronounced in core-zone townships. In summary, the gradient of township-level innovative perception scores shown in Table 6 was not a random data distribution. Instead, it reflected a stable spatial pattern shaped by long-term park planning-and-layout effects and the spatially uneven allocation of innovation-related factors. It constituted an empirical manifestation of core-periphery theory from the perspective of innovative perception among new-type agricultural business entities.

Such spatial differentiation patterns were further supported by factor detection outputs. Individual endowment (age and educational level) and perception of innovation applicability acted as core factors accounting for spatial variations in innovative perception, and a notable interaction pattern was observed between these factors. Location conditions, service-supply intensity, operation scale, and decision-makers' knowledge reserves also presented significant spatially stratified correlations, supplying quantitative evidence for core-periphery-related cognitive differentiation. Benefiting from geographical-location advantages, the core zone aggregated industrial resources and agricultural-technology services, which fostered higher innovative perception levels among business entities. By comparison, business entities within the demonstration zone generally operated on small scales and possessed limited industrial-knowledge reserves. Insufficient supplies of training and policy resources were associated with the localized agglomeration of low innovative perception values. It is also noteworthy that mere awareness of the industrial-park concept could hardly improve innovative perception levels. Real improvements stemmed from business entities' practical participation in in-depth services, including training and technical guidance.

4.1. Interpretation of the Age $\times$ Innovation Applicability Spatial Association

The interaction between age and innovation applicability yields the largest q-value within our sample ($q = 0.961$). We interpret this outcome as the strongest observed spatial association among the examined pairwise combinations, rather than a precise quantitative estimate of causal magnitude. Two interpretive caveats should be noted. First, q-statistics from the Geographical Detector represent bounded metrics for stratified heterogeneity and are susceptible to inflation stemming from the maximum-q discretization criterion; this comparatively high value partially arises from our limited set of township-level analytical units ($n = 23$) and sparsely populated strata. Second, this finding is consistent with, but does not constitute conclusive evidence for, a coupling mechanism linking individual endowment and cognitive evaluation. This spatial association can be tentatively interpreted from the following two perspectives. From the age dimension, single-factor detection results returned a q-value of 0.892 ($p < 0.05$), ranking age first in explanatory power among the 18 independent variables. Within our sample, decision-makers of middle-aged business entities (41–60 years old) accounted for 78.51%, allowing them to make intuitive comparisons of long-term economic and ecological benefits brought by technologies such as organic-fertilizer substitution and ecological tea-garden management. Their judgments regarding innovation applicability were built upon long-term practical experience. From the innovation applicability dimension, its single-factor q-value reached 0.795 ($p < 0.001$), second only to age in explanatory power. This indicated operators' subjective evaluation of "whether innovative technologies fit local dark tea planting modes" was closely associated with innovative perception. A plausible interpretation is as follows: long-term farming experience among middle-aged business entities reinforced their positive judgments of eco-technology applicability; accumulated practical experience facilitated accurate identification of long-term technological benefits, and these judgments were associated with more favorable evaluations of innovation applicability and higher innovative perception levels. By contrast, even if young or elderly operators acknowledged technological applicability, improvements in innovative perception remained limited without long-term benefit-related practical references. This two-factor non-linear association pattern of "endowment (age) $\times$ cognitive evaluation (applicability)" is consistent with the core observation from the Geographical Detector interaction analysis: the spatial differentiation of innovative perception was more strongly associated with the joint configuration of individual life-cycle endowment and cognition of innovation-related benefits than with any single factor alone.

The interaction q-value of 0.961 for age $\times$ innovation applicability greatly exceeded the linear expectation derived from summing their respective individual q-values, consistent with a coupling pattern in which individual endowment and innovation-value perception jointly account for spatial variation in innovative perception. In other words, long-term planting experience among middle-aged business entities not only acted as a direct source of innovation-relevant knowledge but may also have strengthened the explanatory role of innovation cognitive evaluation for innovative perception through more accurate judgments of new-technology applicability. This finding was consistent with conclusions reported by Wollni and Andersson [6], who demonstrated that farmer-level farming experience exerted non-linear moderating effects on sustainable agricultural-technology adoption. It also echoed the theoretical viewpoints proposed by Klerkx et al. [2] concerning the co-evolution of agent endowment and cognitive evaluation within agricultural innovation systems.

4.2. Theoretical Implications and Policy Insights Drawn from Non-Significant Results

The four non-significant outcomes obtained in this study also delivered meaningful interpretive value.

First, park cognition returned non-significant results ($p > 0.1$), while service intensity was statistically significant. Such a contrast challenges the intuitive assumption that raising operators' awareness of park policies and resources would improve innovative perception levels. Nevertheless, it is logically consistent with findings reported by Yu [8]: park technical-service levels exerted no significant effects on adoption willingness, whereas training intensity produced significant positive influences. Taken together, institutional supply within agricultural parks presents clear hierarchical differentiation. Superficial information awareness (i.e., park cognition) exhibited no statistical significance, whereas service intensity exerted significant explanatory power for innovative perception; in-depth behavioral participation represented by service intensity functions as the effective leverage. This result offers quantitative empirical support for the MAIS innovation-system theory proposition from Klerkx & Begemann [2], namely, that institutional supply can only generate real impacts when operators achieve in-depth perception and practical participation. Second, elevation yielded non-significant results ($p > 0.1$). Although the existing literature hypothesized that elevation, treated as a fundamental production constraint, would shape tea planting technology options via temperature, frost-season characteristics and cultivation conditions and further indirectly influence innovation willingness, dark tea plantations across Anhua were mostly distributed across mid- and low-mountain gentle-slope zones with comparable elevations. Mean elevation discrepancies among townships were minor; accordingly, natural terrain failed to generate stratified constraints. This non-significant result carries clear policy-relevant implications: spatial scheduling for mobile agricultural-technology services should be determined by distance rather than terrain, and resources ought not to be preferentially allocated to high-elevation townships merely because of their mountain-region attributes.

Third, innovative novelty likewise failed the significance test ($q = 0.629$, $p > 0.1$), whereas innovative applicability, belonging to the same cognitive-appraisal dimension, was highly significant at the 1% statistical level ($q = 0.795$, $p < 0.001$). This result contrasts with practical interpretative implications: park decision-makers exhibit limited concern for the novel attributes of dark tea planting technologies, with clear practice-oriented goals. Field surveys reveal that operators primarily evaluate technologies in terms of operational complexity, ease of implementation, risk controllability, and actual economic returns—these represent their core concerns—while attaching relatively little importance to technological novelty itself. Meanwhile, identifying genuine technological novelty imposes a relatively high cognitive threshold on technology adopters. The policy implication of this finding is that technology promotion and demonstration should prioritize applicability, emphasizing practical merits, including easy operation, low implementation barriers, rapid effects and tangible economic returns, instead of overemphasizing technological novelty. Novelty alone cannot serve as an effective lever to enhance innovative perception. Interaction-detection outputs further corroborate this interpretation: innovative applicability and age constitute the pairwise factor interaction combination with the strongest explanatory power ($q = 0.961$), suggesting that applicability, rather than novelty, is more closely associated with the spatial pattern of innovative perception.

Fourth, the labor pool exhibited the lowest explanatory power among the 18 indicators and was statistically non-significant ($q = 0.168$, $p > 0.1$). Nevertheless, the remaining two indicators within the market-factors dimension—namely, the consumer market ($q = 0.673$, significant at the 1% level) and the industrial market ($q = 0.447$, significant at the 5% level)—both passed significance testing. This null result can be attributed to structural features of the park-level labor force. The talent structure of local labor is relatively homogeneous; most technical practitioners acquire practical skills from intergenerational experience accumulation or “learning by doing”, and talents with innovative thinking and specialized

innovation competencies remain scarce. In addition, most new-type agricultural business entities invest insufficiently in staff training and capacity-building, making it difficult to acquire innovation-required skills and knowledge via the local labor pool. Consequently, cross-township disparities in labor-market conditions are inadequate to generate stratified constraints on innovative perception. This outcome does not indicate that human capital is negligible. Instead, it suggests that the labor-market transmission mechanism remains latent and to-be-activated. Policy interventions should avoid over-reliance on existing labor stock and prioritize improvements in human-capital quality; targeted measures, including technical training, talent recruitment and cultivation of innovative talents, can activate this transmission channel. In other words, the non-significant result for the labor pool acts as a vital diagnostic signal pointing to weaknesses within the park's innovation system, rather than evidence that labor-market effects can be disregarded. The above-mentioned non-significant findings indicate that agricultural-park policy design should avoid building upon untested intuitive assumptions. Analytical tools such as factor detection can help identify genuinely effective intervention levers and eliminate ineffective policy alternatives.

4.3. Dialogue with Existing Studies: Expected Outcomes and Interpretations for Industrial Heterogeneity

Regarding expected research outcomes, the strong explanatory power of educational level ($q = 0.748$) and innovation applicability ($q = 0.795$) supported core propositions from human-capital theory proposed by Schultz (1988) [20]. Statistically significant spatially stratified correlations for location conditions supplied empirical evidence for core-periphery theory (Friedmann, 1966) [24] at the micro-entity innovative perception level. Significant explanatory power detected for macro-level policies, micro-level policies, consumer markets and industrial markets validated theoretical expectations for institution-driven and market-driven innovation-related cognition. Unlike studies focusing on field-crop innovation adoption, which highlighted the prominent role of operation scale, this study found that human-capital-related variables possessed systematically higher explanatory power compared with operation-scale variables. Such divergence originated from the multi-year growth characteristics of the dark tea industry: operators needed to complete full planting cycles to form reliable judgments of long-term technological benefits. Experience accumulation within the temporal dimension imposed stronger constraints on innovative perception than operation-scale effects originating from the spatial dimension. This supplies new empirical evidence concerning cross-industry divergences within agricultural innovation geography. Limitations of this study should also be frankly acknowledged. Single-case cross-sectional data limited the cross-regional generalizability of conclusions and capabilities for interpreting dynamic evolutionary processes. Although township-level mean aggregation satisfied methodological prerequisites for the Geographical Detector, it masked disparities in innovative perception among individual business entities. Moreover, townships with comparatively small sample sizes (e.g., Gulou and Kuixi Town) suffered low robustness for factor score estimation and q -value computation. Future investigations may implement cross-case comparisons covering diverse industrial categories and multi-regional agricultural industrial parks. Combined with panel-dataset tracking for dynamic shifts in innovative perception, researchers can further test external validity and temporal stability for core conclusions drawn within this work.

4.4. Theoretical and Practical Implications

(1) Implement stratified training tailored to specific demographic groups and sub-areas. Age ($q = 0.892$) and educational level ($q = 0.748$) represent endogenous core variables within the first-tier group ranked by explanatory power. Within the total sample, decision-makers of middle-aged operators aged 41–60 years account for 78.51%, and this group

has long-term engagement in tea planting activities. Training programs for this cohort should place emphasis on comparisons of long-term economic and ecological benefits yielded by conventional and emerging dark tea technologies. Practical courses covering digital e-commerce and new-business-format operations should be supplemented for young operators, and for business entities with low educational attainment, paper-based lecture-only sessions ought to be replaced with field-based practical demonstrations as the core training modality. Training resources should be preferentially allocated to low-value townships in the demonstration zone to offset local gaps in innovative perception levels.

(2) Establish adaptability-testing carriers to improve operators' capacity for evaluating new-technology suitability. Innovation applicability ($q = 0.795$) ranks as the second most influential explanatory variable across the whole study area, and the interaction between age and innovation applicability ($q = 0.961$) represents the strongest pairwise spatial association observed in our sample. Comparative test fields for new technologies could be uniformly deployed in low-value townships of the demonstration zone to visually display yield and revenue gaps between innovative and conventional production modes over multiple cycles. A small-scale pilot-trial mechanism can be adopted to lower operators' trial-and-error costs associated with innovation. Experienced middle-aged growers from the core zone may be selected as technology-promotion ambassadors, translating long-term farming experience into standardized criteria for assessing innovation-related benefits, so as to narrow innovative perception gaps between the two zones.

(3) Optimize the spatial allocation of park service resources by shifting from general-scope publicity toward in-depth targeted services for the demonstration zone. Park cognition shows no significant explanatory power ($p > 0.1$), which indicates that simply disseminating information about the park concept cannot elevate innovative perception levels. Service intensity delivers significant spatially stratified explanatory power, whereas elevation does not constitute a constraint for spatial differentiation. Accordingly, budgets allocated for broad-reaching general publicity could be moderately reduced. More staff should be assigned to on-site posts at technical-service stations within the demonstration zone, and the duration of one-on-one field guidance ought to be extended. The deployment of mobile agricultural-technology services should be determined purely by township spatial distance rather than mountainous terrain conditions so as to balance service supply across the entire study area.

(4) Build a cross-regional driving mechanism led by leading farmer cooperatives within the core zone to mitigate the factor siphon effect. Both location conditions and operation scale exhibit significant explanatory power for spatial differentiation of innovative perception. Leading enterprises and professional cooperatives in the core zone could be encouraged to open technology-demonstration bases and mature production-marketing channels to entities in the demonstration zone in a targeted manner. On-site study tours for demonstration-zone operators based in the core zone can be organized on a regular basis. The application threshold for innovation-related subsidies for small-scale business entities should be lowered, reducing gaps in access to innovation resources caused by disparities in geographical location and operation scale.

(5) Formulate balanced innovation-incentive and market-linkage policies. Macro-level policies, micro-level policies, consumer markets, and industrial markets all passed statistical significance tests. The distribution pattern for universal subsidies can be adjusted by directly linking fiscal support to the actual adoption of new technologies and organizational innovations. A unified production-and-marketing docking platform for the industrial park should be constructed, opening channels for business entities from the demonstration zone to gain access to well-established core sales networks. In this way, market-driven effects can

function in a balanced manner across the whole region and alleviate resource imbalance among sub-areas.

4.5. Research Limitations and Future Directions

Drawing on 363 questionnaire responses collected from business entities within the Anhua National Modern Agricultural Industrial Park, this study uncovered township-scale spatial differentiation characteristics of innovative perception as well as its multi-factor spatial associations; nevertheless, several limitations should be acknowledged.

First are case-specific and sample-related constraints. This empirical analysis adopts a single-case design focusing on the Anhua industrial park, China's only park specialized in dark tea industries. Findings obtained within this mountainous perennial-tea-industry context cannot be directly generalized to other categories of agricultural industrial parks. The survey sample only includes planting-oriented new-type agricultural business entities and excludes traditional individual smallholder farmers, who account for roughly one-third of operators within the park. Such a sample composition may introduce bias when evaluating the overall level of innovative perception across the study area. Furthermore, individual-level questionnaire data were aggregated into township-level mean values for analysis. Although this aggregation enables effective identification of township-scale spatial patterns, it erases individual-level heterogeneity among business entities and fails to capture disparities in innovative perception at the individual-farmer level. Several townships (e.g., Gulou Township and Kuixi Town) have comparatively small sample sizes, which weakens the robustness of corresponding factor score estimates and q-statistic outputs. The seven townships with fewer than ten valid questionnaire responses are explicitly documented within Table 6 and treated as exploratory analytical units, from which no magnitude-driven quantitative inferences are drawn.

Second, there are inherent data- and model-driven limitations. This work relies exclusively on single-period cross-sectional data collected in 2022. Such data can only reflect static spatial correlations for a given time snapshot and cannot capture temporal shifts in innovative perception induced by policy and market dynamics, nor can they serve to disentangle temporal causal relationships among variables. As a variance-decomposition tool, the Geographical Detector can quantify variables' spatially stratified explanatory power, yet it cannot judge the sequence or causal direction of variable effects. Restricted by the limited total number of township units ($n = 23$), sample sparsity occurs within certain discrete stratification groups; hence, the generalizability of interaction-detection outcomes requires further validation using larger datasets. Relatedly, q-statistics from the Geographical Detector serve as descriptive metrics capturing spatially stratified explained variance. Accordingly, interaction outcomes such as the observed value of $q = 0.961$ should be interpreted as indicative qualitative coupling patterns instead of precise quantitative effect-size estimates. Moreover, multiple indicators originate from Likert-scale self-report questionnaires completed by operators. Accordingly, all analyses are built upon the mediating perspective of subjective respondent perceptions. Subjective perceptions do not equate to objective policy-market realities, which brings about potential risks of self-reporting bias. The present study assesses innovative perception as the cognitive prerequisite for sustainable farming practices, rather than measuring tangible sustainability-related outcomes per se. Whether and to what extent such perceptual gaps ultimately manifest in tangible behavioral and sustainability-related outcomes remains an open empirical question. Empirical tracing of the perception-to-behavior-to-outcome pathway would necessitate outcome-level metrics alongside longitudinal tracking, which constitutes a key avenue for future inquiry. Three avenues for future research are proposed to address the above-mentioned limitations. First, future studies could enlarge the research sample by incorporating traditional

individual smallholder farmers and carry out multi-case comparisons across different agricultural industrial parks so as to test the external validity of present findings under diverse industrial contexts. Second, long-term panel tracking surveys should be implemented to capture temporal evolutionary features of innovative perception and identify dynamic interaction relationships among variables. Third, multi-scale analytical frameworks that combine individual-level and aggregated-level perspectives can be adopted. Supplementary micro-analysis at the individual respondent level would allow deeper investigation of high-coupling interaction effects such as the pairing of age and innovation applicability, further enriching research concerning innovative perception among business entities within agricultural industrial parks.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/su18199727/s1>, S1: Stratified Sampling and Representativeness; S2: Four Factor Structure Robustness; S3: Variable Selection and Theoretical Basis; S4: Research Methods Factor Analysis and Geodetector; S5: Limitations and Common Method Bias; References [50–57] are cited in the Supplementary Materials S2 and S4.

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