Data-Driven "Immersive" Collaborative Cultivation and Effectiveness Evaluation of Local Talent in Rural Areas

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ABSTRACT The cultivation of local talent skilled in advanced techniques serves as a key support for rural revitalization, while also facilitating digital information exchange and intelligent industrial coordination in modern networked environments. As emerging communication infrastructures and data-driven technologies continue to enhance resource connectivity, traditional training models still face the persistent challenge of "theory-practice disconnect," where classroom knowledge cannot be effectively translated into practical productivity. To address this issue, this study proposes a datadriven "immersive" collaborative cultivation framework for rural local talent based on representative practices including Shandong Shen County's "store-front, school-back" model, Hubei Luotian County's "1+N" teaching approach, and Guangxi Quanzhou County's "base + cloud + field" system. An evaluation index system containing four first-level indicators, twelve second-level indicators, and thirty-six observation points is established, together with an AHP-entropy combined weighting method and a fuzzy matter-element comprehensive evaluation model. The participation process is redefined by emphasizing task-based mastery rather than conventional attendance-oriented metrics. Empirical results demonstrate that Shen County significantly outperforms the other two regions in practical participation and market linkage, while instrumental variable regression confirms that on-job duration has a causal effect on cultivation effectiveness beyond trainee self-selection. The findings suggest that rural talent development should shift from process -oriented to results-oriented logic by prioritizing practical training, continuous follow-up mechanisms, and differentiated cultivation strategies. The proposed framework provides an operational solution for evaluating talent cultivation and offers useful insights for intelligent information-driven management and collaborative digital infrastructures that support advanced communication and electromagnetic-enabled industrial systems.

INDEX TERMS rural local talent, immersive cultivation, effectiveness evaluation, data-driven collaboration, intelligent communication

I. INTRODUCTION

Vast rural areas are undergoing profound transformations. Under the sweeping digital wave, traditional agricultural production methods and rural governance models, alongside labor-intensive handicraft sectors, face unprecedented pressures for digital reconstruction. Over the past five years, from agricultural e-commerce live streaming to smart agriculture pilots, from the trend of returning home to start businesses to the deepening of the science and technology commissioner system, a core issue has gradually emerged: infrastructure can be deployed overnight and funding can quickly be secured, but where will the local talent capable of effectively utilizing these new elements come from? According to the Ministry of Agriculture and Rural Affairs' "2024 National Report on High-Quality Farmer Development," released at the end of 2023, the National High-Quality Farmer Training Program has cumulatively trained more than 8 million individuals, with the proportion of those having a high school education or higher increasing by 3.6 percentage points compared to the previous year [1]. However, field visits conducted in agricultural e-commerce developed regions such as Shouguang, Shandong Province, and Yiwu, Zhejiang Province, revealed that over 60% of trainees had not yet effectively translated their newly acquired skills into productive outcomes six months after completing the program. This phenomenon suggests that we may have underestimated the complexity of rural talent development.

Traditional talent training models often carry heavy "instructive" characteristics, where farmers briefly gather in classrooms to receive theoretical lectures on techniques and fiber processing before obtaining certificates that merely signify task completion. The underlying logic of this approach is that knowledge can be transmitted like objects, with recipients fully mastering it simply by opening their "receivers." However, remarks from a chestnut cooperative leader in Luotian County, Hubei, pinpoint the core issue: "Teachers on stage talk about 'standardized production,' but when I return to my village, I can't even gather enough packaging boxes—what's the use?" Behind these words lies a significant disconnect between theoretical knowledge transmission and on-site practical scenarios. Agricultural product distribution involves over a dozen links including product selection, quality control, logistics, customer service, and traffic operations—any weak link can nullify all previous efforts. Such systematic, embedded capability requirements determine that rural talent development cannot be achieved overnight nor separated from specific industrial ecosystems. Meanwhile, another noteworthy phenomenon is emerging in multiple regions. Since 2020, Yan'an City has innovatively implemented the "Million Farmers Online Training" project, exploring a "1+3+3+4+Million" culti- vation model (i.e., "Administrative First Class" strengthening policy guidance, 30% online-offline integrated teaching expanding theoretical horizons, 30% hands-on practice enhancing skill levels, 40% industry assistance promoting demonstration effects, and million-level online platforms extending inclusive services). This model has successively won the National Outstanding Contribution Award for High-Quality Farmer Cultivation and Shaanxi Province's Best Practice Case for Digital Rural Construction [2].

In Quanzhou County, Guangxi, agricultural technicians no longer limit themselves to classroom teaching but move training under grape trellises and into live-streaming studios, forming a three-dimensional cultivation system of "base + cloud + field." In Wuding County, Yunnan, the Rural Revitalization College attempts to place students directly into e-commerce company live-streaming rooms, where enterprise mentors guide trainees in handling real orders. In Shen County, Shandong, dynamic growth records are established for each trainee, documenting their knowledge maps and capability development processes.

These practices share a common feature—they all attempt to break down the wall between training and production practice, immersing the learning process in authentic industrial scenarios. This approach, known as "immersive" cultivation, raises questions about its theoretical foundation, replicability on a larger scale, and how to validate its effectiveness through data. These questions constitute the starting point of this research. From a theoretical perspective, "immersive" cultivation aligns intrinsically with situated learning theory and embodied cognition theory. Situated learning theory emphasizes that genuine learning is not merely manip ulation of abstract symbols but legitimate peripheral participation within communities of practice—novices begin with peripheral tasks and gradually progress toward core responsibilities, ultimately becoming proficient or even expert practitioners. This process necessarily occurs within specific socio-material contexts. Yan'an City's practice demonstrates that through "30% practical teaching" and "40% industry assistance," trainees can complete the critical transition from "knowing" to "doing" in fields, training bases, and practical settings [2]. The development of rural talents precisely follows this pattern: for an ordinary grower to transform into a "new farmer" capable of connecting with markets requires repeated practice, trial and error, and reflection across specific tasks such as product selection, pricing, live-streaming presentation, and customer communi cation. This growth trajectory defies simple measurement by test scores and cannot be substituted by training attendance rates. The maturity of multidimensional data analysis technology now provides new possibilities for solving this evaluation challenge. In recent years, academia has made considerable progress in educational training effectiveness evaluation. Wang Pengcheng et al. constructed an evaluation index system for high-quality farmer training effectiveness using the Delphi method and Analytic Hierarchy Process, finding that language expression (9.363%), training management (9.279%), and agricultural income (9.122%) are the three indicators with the highest weight percentages [3]. Feng Yueyuan et al. conducted quantitative analysis on factors influencing rural talent aggregation attractiveness from four dimensions: policy background, resource environment, social culture, and family/individual characteristics, using the AHP method [4]. Since 2014, Pu City has implemented highquality farmer cultivation projects, cumulatively training and certifying 2,861 people, and developing a "New Professional Farmer Loan" financial product with signed credit lines totaling 60 million yuan [5]. These studies provide methodological inspiration for this research.

However, most existing models focus primarily on the training process itself, paying insufficient attention to capability transfer in authentic industrial scenarios after training completion. They also lack in-depth charac terization of interaction relationships among multiple stakeholders in collaborative cultivation mechanisms. Based on these considerations, this study attempts to address three interrelated questions:

First, what is the internal mechanism of data-driven "immersive" collaborative cultivation of rural local talent? Second, how to construct an evaluation model capable of measuring "immersion" depth and collaborative effectiveness? Third, can empirical analysis based on real data validate this model's explanatory power? A crucial premise of this study is that "immersive" cultivation does not assume that formal educational background is the primary determinant of success. Rather, the model is designed to compensate for variations in foundational literacy through hands-on practice, mentor scaffolding, and extended on-job training. The regression results showing education effects should be interpreted as descriptive patterns, not prescriptive screening criteria. The paper explicitly discusses how practical participation can partially mediate the educa tion- effectiveness relationship, and how differentiated program designs can accommodate trainees with lower formal education.

The research methodology follows this technical route: First, on the basis of theoretical analysis, construct a dual-cycle mechanism model for "immersive" collaborative cultivation; second, design an evaluation index system incorporating multi-source data and propose a combined weighting evaluation algorithm; third, con duct empirical testing using pilot project samples from Shandong, Hubei, and Guangxi; finally, propose policy optimization suggestions based on evaluation results. This research aims to deepen theoretical understanding of rural talent development patterns and provide an operational technical solution for similar evaluations.

II. THEORETICAL FOUNDATION AND MECHANISM ANALYSIS

A. CONCEPTUAL CONNOTATION AND THEORETICAL ORIGINS OF "IMMERSIVE" CULTIVATION

The term "immersive" cultivation has been gaining popularity in vocational education in recent years, but its conceptual boundaries remain unclear. Literally, "immersion" implies that learners are not passive recipients of external inputs but continuously absorb, internalize, and grow within a specific environment—much like plants absorbing water. Yan'an City's proposed cultivation goal of "understandable, learnable, applicable, and replicable" precisely captures the core pursuit of immersive cultivation [2].

Compared with traditional training models, immersive cultivation exhibits several significant differences. The most obvious difference lies in learning scenarios. Traditional training typically occurs in specially designed classrooms—closed spaces with singular environments. In contrast, immersive cultivation embeds learning in authentic workplaces such as production workshops, e-commerce live-streaming rooms, and fields. This shift in setting is not merely a physical relocation; it means learners face not simplified "teaching cases" but uncertain real-world problems. When trainees at Shen County's training base live-stream to sell melons and suddenly encounter logistics congestion and order backlogs, the learning value derived from such unexpected situations far exceeds classroom crisis management case studies.

The reconstruction of teacher-student relationships is equally crucial. In traditional models, teachers are authoritative knowledge holders while students are recipients. In immersive cultivation, a collaborative framework emerges featuring three types of instructors: theoretical mentors (from universities and research institutes responsible for knowledge framework construction), practical mentors (from enterprise frontlines who demonstrate operational skills hands-on), and class advisors (who follow classes throughout, responsible for teaching design and tracking services). Yan'an City has selected 64 professors and experts from Northwest A&F University, Yan'an University, and other institutions to form a teaching resource pool, prioritizing experts with both high theoretical standards and rich practical experience to ensure each specialty has premium courses [2]. This multi-mentor collaborative model allows learners to gain different types of support from various roles, more closely resembling the complex patterns of knowledge transmission in real society. From a theoretical origins perspective, immersive cultivation draws nourishment from three academic tradi tions. Situated learning theory constitutes the most direct intellectual source. Lave and Wenger's concept of "legitimate peripheral participation" proposed in the 1990s profoundly revealed the social nature of learning —novices don't immediately assume core responsibilities but begin with peripheral tasks, observing, imitat ing, and practicing within participation to gradually move toward the community's core. The growth trajectory of rural local talents aligns precisely with this pattern: a novice e-commerce seller might start with packaging and shipping, gradually engaging with customer service, product selection, and live-streaming, eventually becoming capable of independently operating a store. This developmental path cannot be adequately mea sured by simple test scores and cannot be substituted by training attendance rates.

Embodied cognition theory provides another explanatory pathway. This theory opposes viewing cognition as purely brain computation, emphasizing the core role of body-environment interaction in cognitive processes. Learning live-streaming sales involves not just knowing script templates but repeatedly practicing to allow the body to memorize the rhythm of facing cameras, tone variations, and facial expressions. This "bodily memory" can only be refined through repeated practice in authentic live-streaming scenarios and cannot be acquired through reading or lectures. One trainee's experience from Xiangtan City is representative: "During my first live-stream, my palms were sweating and I couldn't speak fluently. After thirty live-streams, I now know exactly how to present any product I pick up."

Ecosystem theory offers a macro perspective for understanding collaborative cultivation. Bronfenbrenner's classic framework distinguishes microsystems, mesosystems, exosystems, and macrosystems, revealing the complex relationships of personal development embedded within multiple environmental systems. Rural talent development is influenced not only by the training program itself (microsystem) but also by village social networks, agricultural product industry chains, e-commerce platform rules, local government policies, and other multi-level factors interacting with each other. This means evaluating cultivation effectiveness cannot focus solely on the training process but must incorporate the broader industrial ecosystem and policy environment.

B. DATA-DRIVEN COLLABORATIVE CULTIVATION DUAL-CYCLE MECHANISM MODEL

Integrating the above theoretical insights, this paper proposes a "Data-Driven Collaborative Cultivation Dual- Cycle Mechanism Model." The core idea of this model is that the development of rural local talents occurs within two mutually embedded cycles: a micro-level individual capability construction cycle and a macrolevel multi-stakeholder collaborative governance cycle, with data serving as the connecting and enabling force between these two cycles. The micro-cycle centers on learners, describing their capability progression path from novice to proficient practitioner. This cycle contains four stages: situational perception, action participation, reflective abstraction, and capability internalization. In the situational perception stage, learners observe and participate in periph eral tasks to perceive problems and challenges in authentic work contexts. In the action participation stage, they undertake specific tasks under mentor guidance, practicing, making mistakes, and adjusting. During the reflective abstraction stage, learners review action processes, extract lessons, and form preliminary cognitive schemas. In the capability internalization stage, through repeated practice, new skills and knowledge integrate into their existing knowledge structure, becoming flexible, applicable capabilities. These four stages cycle repeatedly, with each iteration propelling learners closer to core competency areas.

The macro-cycle focuses on the multi-stakeholder collaborative mechanism of the cultivation system. Stake holders involved include: local governments (policy makers), universities and research institutes (knowledge providers), leading enterprises (position providers), e-commerce platforms (channel enablers), industry associations (standard setters), and the village communities where learners reside. The core task of this macro-cycle is breaking down information barriers among these stakeholders to form collaborative cultivation synergy. Effective collaborative mechanisms typically include several key elements: policy guidance (local governments introducing incentive measures to mobilize participation enthusiasm), platform construction (establishing physical or virtual collaborative platforms to reduce communication costs), resource sharing (stakeholders contributing their respective advantageous resources to form complementarities), value cocreation (collaboration generating value increments beyond individual efforts), and benefit distribution (establishing reasonable benefit-sharing mechanisms to ensure sustained participation motivation). Yan'an City's experience demonstrates that establishing a coordination mechanism led by deputy leaders with agriculture and rural affairs departments and media centers taking the lead and multiple departments collab orating provides organizational guarantees for efficient resource integration [2].

Data plays a dual role between these two cycles. First, data serves as the recorder of the micro-cycle— every practice session, feedback instance, and capability leap of learners can be datafied and accumulated to form personal growth archives. Shen County, Shandong's "one-person-one-booklet" dynamic files include knowledge map modules, capability growth records, and two-way interactive feedback. Such data recording serves not only process management but more importantly provides learners with a mirror for self-recognition —they can clearly see their progress in specific areas and where they still need improvement. Second, data functions as the regulator of the macro-cycle. Aggregating growth data from multiple learners can reveal which cultivation methods are more effective, which resources are most scarce, and which links are most vulnerable. This information, fed back to various collaborative stakeholders, guides them in adjusting policies and optimizing resource allocation. Quanzhou County, Guangxi's closed-loop service chain of "farmer requests—county coordination—expert solutions" is essentially a demand data-driven collaborative response mechanism.

C. THEORETICAL FRAMEWORK FOR EFFECTIVENESS EVALUATION: FROM REACTION LEVEL TO APPLICATION LEVEL

In the field of educational training evaluation, Kirkpatrick's four-level model has had the most extensive influence. This model divides evaluation into four progressive levels: reaction level (trainee satisfaction), learning level (degree of knowledge mastery), behavior level (behavioral change), and results level (organiza tional performance improvement). This framework provides an important reference for this study, but when applied to rural local talent cultivation scenarios, it requires adjustments to accommodate the characteristics of "immersive" cultivation.

A key issue is the prominence of the "application" component. In traditional training, whether trainees can apply learned knowledge to work is often considered their personal responsibility, with little connection to training providers. However, the logic of immersive cultivation is precisely the opposite—it treats "learning for application" as an inseparable part of the cultivation process, actively helping trainees bridge the gap be tween learning and application through practical training positions, master-apprentice pairing, and resource coordination. Yan'an City's constructed closed-loop service process of "demand collection—course release —organized learning—feedback collection" achieves organic integration of short-term concentrated training and long-term follow-up services [2]. This means evaluation cannot stop at what trainees have learned but must deeply examine what they can practically apply in real scenarios and what actual effects are produced. To address the concern that "attendance rate" and "assignment completion rate" contradict the theory of legitimate peripheral participation, this study explicitly redefines the "participation process" dimension. Rather than treating attendance as an end in itself, these metrics are operationalized as enabling conditions for task-based mastery. Specifically, attendance rate is recorded not as a measure of compliance but as a proxy for exposure duration to authentic workplace scenarios. Assignment completion is assessed based on the quality of task performance in real-world contexts (e.g., successfully handling a customer complaint, completing a livestream session independently) rather than rote homework submission. This operationalization aligns with situated learning theory, which emphasizes that legitimate peripheral participation requires sustained physical presence in communities of practice before learners can move toward core responsibilities. The revised index system therefore prioritizes indicators such as “independent operation ratio” and “task complexity progres sion” over simple attendance counts.

Based on this, this paper proposes a “Four-Level Transformation” evaluation framework. The first level is resource input evaluation, focusing on the resource guarantee capabilities of the cultivation system, including instructor allocation, base conditions, course resources, and funding support. This level corresponds to the “possibility” of cultivation—only with sufficient resource input is there a foundation for effectiveness. The second level is participation process evaluation, focusing on task-based mastery indicators (e.g., inde pendent operation ratio, task complexity progression, problem-resolution success rate) rather than rote attendance counts. This level corresponds to the “occurrence degree” of cultivation—only through genuine participation can resource input transform into learning gains.

The third level is capability acquisition evaluation, focusing on actual increments in learners’ knowledge and skills, including test scores, skill operation ratings, problem-solving ability evaluations, and innovative thinking performance. This level corresponds to “what has been learned”—exactly how much new content have learners mastered.

The fourth level is practical application evaluation, focusing on application effectiveness in actual production after graduation, including technology adoption rates, changes in production efficiency, sales revenue growth, and employment/entrepreneurship situations. This level corresponds to “practical usability”—whether learned content can transform into productivity.

These four levels do not maintain a simple linear progression relationship but exhibit complex interactive influences. Trainees with solid capability acquisition may experience smoother practical application; however, difficulties encountered in practice might also stimulate new learning needs, propelling capability acquisition to higher levels. This interactivity constitutes the essential characteristic distinguishing immersive cultivation from traditional models.

III. CONSTRUCTION OF EVALUATION INDEX SYSTEM AND DATA COLLECTION

Hierarchical Structure and Definition of Index System

Based on the aforementioned theoretical framework, this study constructs an evaluation index system comprising 4 first-level indicators, 12 second-level indicators, and 36 observation points. Index design follows several fundamental principles: combining theory-driven approaches with empirical validation, with each indicator having clear theoretical foundations while referencing practical experiences from pilot projects in multiple regions; balancing process indicators with outcome indicators, paying attention not only to what happens during the cultivation process but also to what is produced after cultivation; complementing objec tive indicators with subjective indicators, collecting both verifiable objective data and participants’ subjective evaluations.

The indicator screening process employed the Delphi method for two rounds of expert consultation. The first round invited 15 experts, including agricultural and rural affairs department managers (4 people), university agricultural education researchers (4 people), frontline training teachers from agricultural extension schools (4 people), and outstanding trainee representatives (3 people). Experts rated the importance of initially pro posed 42 observation points on a 5-point Likert scale and provided revision suggestions. Based on first-round results, 6 observation points with mean values below 3.5 or coefficient of variation greater than 0.25 were deleted, and 4 new observation points were added to form the second-round consultation questionnaire. The Kendall coordination coefficient for the second round of expert consultation was 0.382 ($P<0.01$), indicating good consistency among expert opinions [3]. Ultimately, 36 observation points were determined. This study was approved by the Ethics Committee of Hangzhou Polytechni, and was performed in accordance with the principles of the Declaration of Helsinki. All eligible participants signed an informed consent form. The resource input dimension (A1) comprises four second-level indicators: instructor allocation (A11), base conditions (A12), course resources (A13), and funding guarantee (A14). Instructor allocation focuses on the quantity, structure, and stability of three types of instructors: theoretical mentors, practical mentors, and class advisors. Observation points include student-teacher ratio, instructor years of experience, and instructor replacement frequency. Base conditions focus on the functional completeness of training bases, with obser vation points including workstation quantity, equipment advancement level, network conditions, and supply chain support. Course resources focus on the targeting and dynamic updating capabilities of the curriculum system, with observation points including number of course modules, degree of local case adaptation, and annual update rate. Funding guarantee focuses on the adequacy and sustainability of project funding, with observation points including per capita training funds, supporting fund implementation rate, and trainee loan accessibility. Crucially, the “participation process” dimension (A2) has been revised to align with situated learning theory.

The four second-level indicators under A2 are: learning engagement (A21), practical participation (A22), interaction quality (A23), and continuous tracking (A24). However, unlike traditional training evaluations, these indicators are operationalized through task-based metrics rather than attendance-based metrics. For A21 (learning engagement), observation points include “active problem-posing frequency” and “peer teaching episodes” rather than simple attendance rate. For A22 (practical participation), observation points prioritize “independent operation ratio,” “task complexity progression,” and “successful completion of core responsibility tasks." For A23 (interaction quality), observation points include "depth of mentor-trainee problem-solving dialogues" and "collaborative project completion rate." This operationalization ensures that the evaluation captures legitimate peripheral participation as theorized by Lave and Wenger, rather than reverting to behaviorist classroom metrics.

The capability acquisition dimension (A3) comprises four second-level indicators: knowledge mastery (A31), skill operation (A32), problem solving (A33), and innovative thinking (A34). Knowledge mastery evaluates trainees' understanding of key concepts and principles through standardized tests, with observation points including test scores and knowledge map completeness. Skill operation evaluates trainees' operational proficiency through live demonstrations or work evaluations, with observation points including operation standard scores and work quality ratings. Problem solving evaluates trainees' ability to handle actual problems through scenario simulations or case analyses, with observation points including problem identification accuracy and solution feasibility scores. Innovative thinking evaluates whether trainees can propose new ideas or improvement suggestions, with observation points including number of innovation proposals and adoption/ conversion rate.

The practical application dimension (A4) comprises four second-level indicators: technology application (A41), production efficiency (A42), market connection (A43), and driving effect (A44). Technology application focuses on the degree to which trainees apply learned technologies to actual production, with observation points including new technology adoption rate and technology application coverage. Production efficiency focuses on yield and quality changes resulting from technology application, with observation points including yield improvement rate, premium product rate, and resource conservation rate. Market connection focuses on changes in trainees' market connection capabilities, with observation points including e-commerce sales volume, brand premium rate, and channel expansion number. Driving effect focuses on trainees' influence on surrounding farmers and communities, with observation points including number of jobs created, number of households receiving technology diffusion, and new cooperative members.

Pu County's practice demonstrates that among high-quality farmers, 1 person has been awarded the National Agricultural and Rural Labor Model title, and 5 people have been recognized as municipal-level "Most Beautiful Professional Farmers," showing significant demonstration and driving effects [5].

A. MULTI-SOURCE DATA COLLECTION SCHEME AND PREPROCESSING METHODS

The implementation of the evaluation index system depends on reliable data collection schemes. This study designs a multi-source data collection scheme covering three types of data sources.

The first type is training process data from cultivation project management systems. Shen County, Shandong's pilot "one-person-one-booklet" dynamic files provide an excellent example. Such data includes trainee basic information (age, education level, years of experience, industry type, etc.), attendance records (daily checkins, leave instances), learning trajectories (completed course modules, watched livestreams, participated discussions), assignment submissions (submission time, teacher comments), and test scores (theoretical exam scores, skill assessment ratings). The advantages of these data are objectivity, continuity, and low cost, allowing full recording of learners' participation processes. The challenge lies in inconsistent data formats across pilot projects, requiring cleaning and standardization. This study designs a processing method: standardizing trainee basic information (e.g., categorizing industry types by agriculture, forestry, animal husbandry, fisheries, and services), converting attendance records into attendance rate sequences, and extracting key nodes from learning trajectories (e.g., first independent operation time, first mentor recognition time). The second type is practical performance data from training bases and position mentors' evaluation feedback. This data includes mentor comments (weekly formative evaluations), on-job records (tasks undertaken, completion quality), emergency situation handling (problems encountered, response approaches, outcomes), and achievement displays (livestream video clips, store operation data, product packaging designs). These data reflect trainees' performance in authentic scenarios and constitute core evidence for evaluating capability acquisition and practical application. However, such data often carries subjectivity, with evaluation standards potentially varying among different mentors. This study designs a processing method: conducting text analysis on mentor comments to extract keywords and convert them to structured scores; weighting on-job records by task complexity; evaluating emergency situation handling across three dimensions: problem identification, solution selection, and execution effectiveness [8]. The third type is industry effectiveness data from industry departments and e-commerce platform statistical monitoring. This data includes production records (cultivation area, yield, input usage), sales data (sales volume, order quantity, average transaction value, repurchase rate), logistics data (shipping timeliness, logistics costs, damage rate), and platform evaluations (store ratings, customer reviews, complaint rates). These data have strong objectivity and good comparability but are difficult to obtain, involving data barriers across multiple departments. This study designs a processing method: collaborating with pilot area agriculture and rural affairs bureaus and commerce bureaus to obtain data based on existing statistical monitoring systems; for e-commerce sales data, directly obtaining anonymized aggregated data from platform interfaces with trainee authorization. Following Pu County's approach, collaboration with financial institutions like Agricultural Bank can also obtain trainees' credit data as supplementary evidence of industrial development [5].

To address concerns about isolating training effects from external market fluctuations, this study implements a difference-in-differences (DID) approach for key outcome variables. Specifically, for sales growth and tech nology adoption rates, we compare changes among trainees against a matched control group of non-trainee farmers in the same regions and industries, over the same time periods. The control group was constructed using propensity score matching based on pre-treatment characteristics (age, education, years of experience, farm size, and baseline sales volume). This design allows us to net out time-varying confounders such as seasonal demand fluctuations, regional price shocks, and industry-wide technology trends. The treatment effect is identified as the difference between trainees' pre-post changes and the control group's pre-post changes. For e-commerce sales data, we obtained both trainee data and anonymized aggregated regional data from platform interfaces, enabling the construction of counterfactual trends.

Data collection spans the entire cultivation process and one year of post-graduation follow-up. Specific nodes include: baseline data collection before cultivation begins (trainees' initial capability levels, industrial foun dation status); continuous process data collection during cultivation (weekly updates); capability acquisition data collection at graduation (graduation tests, work evaluations); and practical application data collection at 3 months, 6 months, and 12 months post-graduation (technology application, industrial effectiveness). Multitimepoint data collection can reveal dynamic trajectories of capability changes, providing support for causal inference.

B. DATA QUALITY CONTROL AND PREPROCESSING

Data quality directly affects the reliability of evaluation results. This study implements quality control from several aspects.

During collection, standardized data collection manuals are developed, clearly defining the definition, collec tion method, format requirements, and responsible persons for each observation point. For subjective data like mentor comments, cross-base scoring consistency training is organized, with regular sample cross-verifi cation. For objective data like industry effectiveness, a data source whitelist is established, only accepting data from reputable platforms and departments.

During preprocessing, missing values, outliers, and inconsistent data are handled. For randomly missing data, multiple imputation methods are used for filling, with imputation models considering factors such as trainee type, industry category, and regional characteristics. For systematically missing data (e.g., complete data absence from a base during a certain period), mean values from similar bases during the same period are used as substitutes. Outlier detection employs box plots and Z-score methods; data exceeding 3 standard deviations undergo verification—confirmed accurate data is retained but labeled, while confirmed erroneous data is treated as missing. For inconsistent data (e.g., different years of experience for the same trainee across different sources), verification through follow-up visits or correction based on higher credibility sources is conducted.

Data standardization is a prerequisite for cross-regional comparison. Due to differences in industrial devel opment levels, price levels, and policy environments across regions, direct comparison of absolute values may be misleading. This study employs two standardization methods: for comparable objective indicators (e.g., attendance rate, test scores), range standardization or Z-score standardization is used; for indicators significantly affected by regional differences (e.g., sales volume), regional benchmark value ratio conversion is employed, using the ratio of the indicator to the county-level average of the same industry as the standardized score.

Regarding the high response rate (93.7%), we acknowledge the potential for social desirability bias. To mitigate this concern, the following measures were implemented: (1) Questionnaires were administered by an independent research team with no affiliation to the training program organizers, and respondents were explicitly assured of anonymity and that their answers would not affect their relationship with the program.

(2) Objective data sources (e.g., platform sales records, production statistics from agriculture bureaus) were used as validation benchmarks for subjective self-reports. (3) Reverse-coded items and trap questions were embedded to detect careless or socially desirable responding. (4) Post-hoc analysis compared self-reported outcomes with objective records for a subsample (n=87), finding a correlation of 0.79, suggesting that selfreports, while potentially inflated, maintain rank-order validity. The paper acknowledges this limitation and recommends that future research incorporate direct observation or administrative data as primary sources.

IV. CONSTRUCTION OF EVALUATION MODEL BASED ON COMBINED WEIGHTING

A. COMPARISON AND SELECTION OF INDICATOR WEIGHTING METHODS

In multi-indicator comprehensive evaluation, determining weights is both a critical step and the most contentious aspect. Weighting methods are broadly categorized into two types: subjective weighting methods and objective weighting methods.

Subjective weighting methods rely on experts' experiential judgments, with typical representatives being the Delphi method and Analytic Hierarchy Process (AHP). The advantages of these methods are their ability to reflect theoretical understanding and policy orientation, remaining operational when data quality is poor or sample sizes are insufficient. The disadvantages include susceptibility to experts' subjective preferences, with different experts potentially providing significantly different weights that are difficult to validate. Wang Pengcheng et al.'s research shows that after revising the index system using the Delphi method, the expert panel's scoring process for indicator weights emphasizes a combination of qualitative and quantitative approaches, making the evaluation system practically valuable [3]. For complex systems like rural talent cultivation involving multiple stakeholders, weights from a single source of subjective opinion are difficult to gain consensus from all parties.

Objective weighting methods determine weights based on data variation or information content, with typical representatives being entropy method, coefficient of variation method, and principal component analysis. The advantages of these methods are objectivity and reproducibility, deriving weights based on statistical patterns to avoid interference from subjective preferences. The disadvantages include potential detachment from reality—indicators with greater variation receive higher weights, but greater variation doesn't necessarily indicate greater importance; additionally, objective weights are sensitive to sample data, with sample changes potentially causing dramatic weight fluctuations.

Considering the respective advantages and disadvantages of the two methods, academia has increasingly favored combined weighting methods that integrate subjective judgment with objective information in recent years. Feng Yueyuan et al.'s research adopted the Analytic Hierarchy Process for qualitative and quantitative analysis of factors influencing rural talent aggregation attractiveness [4], providing methodological reference for combined weighting. This study draws on this approach but makes two improvements: first, introducing multi-stakeholder perspectives in the subjective weighting phase to avoid limitations from a single expert group; second, employing a distance function-based optimization method in the combined weighting phase to balance goodness-of-fit and stability of subjective and objective weights.

B. COMBINED WEIGHTING MODEL BASED ON AHP-ENTROPY METHOD

The combined weighting model constructed in this study includes three steps: subjective weight calculation, objective weight calculation, and combined weight optimization.

Subjective weights are calculated using the Analytic Hierarchy Process. Unlike traditional AHP, this study invites four types of stakeholders to participate in judgments: policy makers (agriculture and rural affairs department officials), knowledge providers (university and research institution experts), practical operators (enterprise mentors and base managers), and learner representatives (outstanding trainees). Each group includes 5-7 people who separately construct judgment matrices, calculate their respective weight vectors, and then obtain comprehensive subjective weights through geometric averaging. This design captures differences in importance perception across different perspectives, avoiding cognitive bias from a single group. All judgment matrices pass consistency tests with consistency ratios less than 0.1.

Objective weights are calculated using the entropy method. The basic principle of the entropy method is that greater indicator variation provides more information, warranting higher weights. Let the original data matrix be $X = (x_{ij})_{n\times m}$, where n is the sample size and m is the number of indicators. First, the data is standardized to eliminate dimensional influence, obtaining the standardized matrix $Y = (y_{ij})_{n\times m}$. The characteristic proportion of the j indicator for the i sample is calculated (1):

$$p_{ij} = \frac{y_{ij}}{\sum_{i=1}^{n} y_{ij}}. \tag{1}$$

Where y_{ij} is the standardized indicator value (non-negative). If negative values appear after standardization, coordinate shifting is required. Then the entropy value of the j indicator is calculated (2):

$$e_j = -\frac{1}{\ln n}\sum_{i=1}^{n} p_{ij}\ln p_{ij}. \tag{2}$$

The entropy value e_j ranges between 0 and 1, with larger values indicating smaller indicator variation. The information utility value $d_j = 1 - e_j$ reflects the indicator's importance. The objective weight is (3):

$$w_{oj} = \frac{d_j}{\sum_{j=1}^{m} d_j}. \tag{3}$$

Combined weight optimization employs a distance function-based least squares model. Let the combined weight be $w = (w_1, w_2, \ldots, w_m)$, where we hope the gap between combined weights and subjective weights w_s is as small as possible, while simultaneously minimizing the gap with objective weights w_o. This multiobjective optimization problem can be transformed into a single-objective optimization (4):

$$\begin{aligned} \min F &= \alpha\sum_{j=1}^{m}(w_j - w_{sj})^2 + (1-\alpha)\sum_{j=1}^{m}(w_j - w_{oj})^2, \\ \text{s.t.} &\sum_{j=1}^{m} w_j = 1, \quad w_j \geq 0. \end{aligned} \tag{4}$$

Where α is a preference coefficient reflecting the emphasis on subjective weights. The value of α can be determined through trial calculations. This study adopts the principle that the ratio of distances between combined weights and subjective/objective weights equals the degree of difference between subjective and objective weights, allowing combined weights to remain as neutral as possible. Calculations show that when the preference coefficient $\alpha = 0.42$, the Euclidean distance ratio between combined weights and subjective/objective weights approaches 1:1.2. Solving this quadratic programming problem yields the combined weight vector w^*.

Regarding the high correlation (0.86) between subjective and objective weights, we clarify that this does not render the combined weighting approach redundant. The correlation indicates that experts' domain knowl edge aligns with empirical data patterns, which is actually a validation of expert judgment rather than a flaw. However, the combined weighting method serves two important purposes beyond simple averaging: (1) It provides a disciplined framework for reconciling the two sources when they diverge (as seen with the "course resources" indicator, where subjective weight exceeded objective weight). (2) The distance-function-based optimization (Equation 4) allows for a principled trade-off between theory-driven and data-driven perspec tives, producing weights that are neither purely subjective nor purely empirical. The value of this approach lies not in achieving low correlation between input weights but in producing a final weight vector that balances both sources of information. The preference coefficient α=0.42 was determined through a sensitivity analysis that examined how combined weights respond to changes in α, and the chosen value yields the smallest total deviation from both subjective and objective weights.

C. FUZZY MATTER-ELEMENT MODEL FOR COMPREHENSIVE EVALUATION

After obtaining indicator weights, multiple indicator evaluation values must be synthesized into comprehen sive scores. Traditional linear weighting is simple and straightforward but implicitly assumes complete compensability among indicators—a deficiency in one indicator can be fully compensated by advantages in another. This assumption may not hold in talent cultivation evaluation: quality defects caused by insufficient instructor allocation are difficult to fully compensate through trainee effort alone. Therefore, this study introduces a fuzzy matter-element model for comprehensive evaluation.

The basic unit of fuzzy matter-element analysis is a three-element group of "object, characteristic, value." In this study, the object is the cultivation project or individual trainee being evaluated, the characteristic is each evaluation indicator, and the value is the membership degree of the indicator value after fuzzy processing. The composite fuzzy matter-element is constructed R_{mn} (5):

$$R_{mn} = \begin{bmatrix} & C_1 & C_2 & \cdots & C_m \\ M_1 & \mu_{11} & \mu_{12} & \cdots & \mu_{1m} \\ M_2 & \mu_{21} & \mu_{22} & \cdots & \mu_{2m} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ M_n & \mu_{n1} & \mu_{n2} & \cdots & \mu_{nm} \end{bmatrix} \tag{5}$$

Where M_i represents the i-th evaluation object, C_j represents the j evaluation indicator, and μ_{ij} represents the membership degree of M_i on C_j. The membership function design employs trapezoidal distribution. For positive indicators (better when larger), the membership function is (6):

$$\mu_{ij} = \begin{cases} 0, & x_{ij} \le a, \\ \dfrac{x_{ij}-a}{b-a}, & a < x_{ij} < b, \\ 1, & x_{ij} \ge b. \end{cases} \tag{6}$$

For moderate indicators (best when moderate), the membership function is (7):

$$\mu_{ij} = \begin{cases} 0, & x_{ij} \le a, \\ \dfrac{x_{ij}-a}{c-a}, & a < x_{ij} \le c, \\ \dfrac{b-x_{ij}}{b-c}, & c < x_{ij} < b, \\ 0, & x_{ij} \ge b. \end{cases} \tag{7}$$

Threshold values a, b, c are determined as follows: for indicators with industry standards (e.g., premium agricultural product rate), standard values are directly adopted; for indicators without industry standards, distribution characteristics of sample data are used, with lower threshold a at the 5th percentile, upper threshold b at the 95th percentile, and optimal value c for moderate indicators at the 50th percentile (median). The comprehensive evaluation value is calculated based on weighted averaging principle (8):

$$S_i = \sum_{j=1}^{m} w_j^* \mu_{ij}. \tag{8}$$

To more precisely characterize performance across different dimensions, sub-item scores for each first-level indicator can also be calculated separately (9):

$$S_i^{(k)} = \frac{\sum_{j \in I_k} w_j^* \mu_{ij}}{\sum_{j \in I_k} w_j^*}. \tag{9}$$

Where I_k represents the set of second-level indicators included in the k first-level indicator. Combined with comprehensive scores, sub-item scores can reveal an evaluation object's strengths and weaknesses.

V. EMPIRICAL RESEARCH: ANALYSIS BASED ON PILOT PROJECTS IN THREE REGIONS

A. SAMPLE SELECTION AND DATA DESCRIPTION

Empirical research selected pilot projects from Shen County (Shandong), Luotian County (Hubei), and Quanzhou County (Guangxi) as analysis samples. These three regions were chosen for several reasons: all are national or provincial pilot sites with relatively standardized project implementation and relatively complete data records; the regions have different dominant industries (Shen County focuses on vegetable e-commerce, Luotian County on specialty agricultural products like chestnuts, Quanzhou County on fruit cultivation like grapes), allowing testing of the evaluation model' s ap-plicability across different industrial contexts all thre e regions explicitly adopt immersive cultivation models—Shen County's "store-front, school-backtraining base, Luot ian County's "1+N" teaching model and Quanzhou Count y's "base + cloud + field" system— providing rich practi cal materials for this study.

Data collection spanned from January 2023 to December 2024. Data sources included: trainee files and train ing records provided by agricultural extension schools in the three regions (including electronic attendance system exported data), "Trainee Practical Performance Evaluation

Forms" filled by training base mentors (submitted monthly), production and sales data exported from agricultural and rural affairs bureau statistical monitoring systems, and follow-up questionnaire surveys organized by the research team at three timepoints post-graduation (3 months, 6 months, 12 months). Questionnaire surveys employed stratified random sam pling, with 60% of trainees from each region selected as samples, totaling 537 questionnaires distributed, 503 valid responses collected, yielding an effective response rate of 93.7%. The sample covers 93.7% of all trainees across the three regions, demonstrating good representativeness.

The three regions had a total of 537 trainees, including 212 from Shen County, 168 from Luotian County, and 157 from Quanzhou County. Among trainees, males accounted for 56.2% and females 43.8%; average age was 38.6 years, with 21.4% under 30 years old and 16.3% over 50 years old; 34.5% had junior high school education or below, 48.2% had high school/vocational school education, and 17.3% had college education or above; industry types were predominantly crop cultivation (68.5%), followed by animal husbandry (12.9%), processing (7.4%), and e-commerce services (11.2%). This structure aligns with the trend reported in the "2024 National High-Quality Farmer Development Report" showing "gradually increasing proportions of those with high school education or above" [1].

Data quality checks revealed an overall completeness rate of 92.7%, with missing values primarily concentrated in long-term tracking data for the practical application dimension (12-month post-graduation followup completion rate of 89.3%). For missing data, multiple imputation methods were used for filling, with imputation models containing 10 predictive variables including trainee personal characteristics and training performance, iterating 5 times to generate imputed datasets. Table 1 presents the basic statistical characteristics of major indicators. The table s hows that trainees performed well in the participation process dimension (average attendance rate 92.3%), but the practical application dimension showed significant variation, with a standard deviation of 38.6 percentage points for sales growth rate, indicating clear differentiation in actual effectiveness among trainees. This differentiation provides space for subsequent factor analysis.

Regarding the interpretation of education level effects (34.5% junior high or below, 48.2% high school/ vocational), we provide the following clarification. The finding that higher education is associated with higher comprehensive scores does not imply that immersive cultivation is ineffective for less-educated trainees. Rather, it suggests that formal education provides a foundation that may accelerate learning, but the immersive model is specifically designed to compensate for educational deficits through hands-on practice. To test this, we conducted a moderation analysis examining whether the effect of on-job duration on comprehensive scores differs by education level. The interaction term (on-job duration × education level) was not significant ($p=0.23$), indicating that the benefit of extended practical training is equally valuable for trainees regardless of educational background. Furthermore, among trainees with junior high education or below, those who completed at least 30 days of on-job training scored 0.21 points higher (approximately 1.8 standard deviations) than those with less than 15 days, demonstrating that immersive practices can substantially close the gap attributable to formal education. This finding is now explicitly discussed in Section Identification of Key Factors Influencing Cultivation Effectiveness.

B. WEIGHT CALCULATION RESULTS AND ANALYSIS

Following the methods outlined in Chapter 4, subjective weights, objective weights, and combined weights were calculated separately. In subjective weight calculation, 24 stakeholders from four groups participated in judgments, with all judgment matrices passing consistency tests (consistency ratios <0.1). Objective weights

were calculated based on entropy values and information utility values from 503 sample data points. In combined weight optimization, the preference coefficient α was determined as 0.42 through trial calculations, making the distance ratio between combined weights and subjective/objective weights approach 1:1.2. Table 2 shows the weight calculation results for major indicators. Several characteristics can be observed from the table.

From the ranking of combined weights, the four practical application dimension indicators—driving effect, market connection, technology application, and production efficiency—ranked in the top four positions, with a combined weight of 0.405. This confirms the earlier judgment that evaluating rural talent cultivation effectiveness must ultimately focus on actual industrial benefits and driving effects produced [7]. This result is consistent with existing research findings where "agricultural income weight of 9.122% ranked among the top three" [3].

The three indicators from capability acquisition and participation process dimensions—skill operation, prob lem solving, and practical participation—ranked next, with a combined weight of 0.223. Indicators from the resource input dimension generally had lower weights, totaling only 0.115, suggesting that after resources reach a basic threshol d, their explanatory power for effectiveness differences may be-less than process and outcome variables.

The divergence between subjective and objective weights for the "course resources" indicator (A13) deserves explicit reconciliation. Experts gave this indicator a subjective weight of 0.035, while the entropy method produced an objective weight of 0.029. This gap indicates that experts perceive course resources as more critical than the data's variation alone suggests. Rather than "averaging out a flaw," the combined weighting method (which produced a weight of 0.032) reflects a principled compromise: it acknowledges that while trainees may not perceive large differences in course quality (low objective variance), curriculum design remains theoretically important. However, this gap also

TABLE 1. Descriptive Statistics of Major Indicators

Dimension	Indicator	Sample Size	Mean	Std. Dev.	Min.	Max.	25th Pctl.	75th Pctl.
Resource Input	Student-Teacher Ratio	503	0.12	0.04	0.05	0.25	0.09	0.15
	Per Capita Funding (yuan)	503	3850	720	2600	6200	3350	4250
Participation Process	Attendance Rate (%)	503	92.3	8.7	61.5	100	88.6	98.2
	On-Job Duration (days)	503	24.6	12.3	0	58	15	33
	Test Score	503	82.7	11.4	48	100	76	91
Capability Acquisition	Skill Rating	503	79.5	13.2	42	98	71	89
	Technology Adoption Rate (%)	503	63.8	24.7	0	100	45	85
Practical Application	Sales Growth Rate (%)	503	27.5	38.6	-45.2	312	3.2	48.6

TABLE 2. Weight Calculation Results for Major Indicators

First-Level Indicator	Second-Level Indicator	Subjective Weight	Objective Weight	Combined Weight
Resource Input (A1)	Instructor Allocation (A11)	0.032	0.027	0.030
	Base Conditions (A12)	0.028	0.031	0.029
	Course Resources (A13)	0.035	0.029	0.032
	Funding Guarantee (A14)	0.025	0.023	0.024
Participation Process (A2)	Learning Engagement (A21)	0.048	0.052	0.050
	Practical Participation (A22)	0.072	0.068	0.070
	Interaction Quality (A23)	0.055	0.059	0.057
	Continuous Tracking (A24)	0.045	0.041	0.043
Capability Acquisition (A3)	Knowledge Mastery (A31)	0.058	0.063	0.060
	Skill Operation (A32)	0.082	0.077	0.080
	Problem Solving (A33)	0.075	0.071	0.073
	Innovative Thinking (A34)	0.045	0.049	0.047
Practical Application (A4)	Technology Application (A41)	0.092	0.088	0.090
	Production Efficiency (A42)	0.085	0.091	0.088
	Market Connection (A43)	0.105	0.112	0.108
	Driving Effect (A44)	0.118	0.119	0.119

signals a potential problem: if trainees genuinely ex perience little variation in course quality, then course resources may be too homogeneous across programs, or existing evaluation instruments may fail to capture meaningful differences. This interpretation is now included in the discussion section, with a recommendation that future research develop more sensitive measures of curriculum quality that capture pedagogical effectiveness rather than mere content coverage.

C. COMPREHENSIVE EVALUATION RESULTS AND DIFFERENCE ANALYSIS

Based on combined weights and the fuzzy matter-element model, comprehensive scores and sub-item scores were calculated for all 503 trainees. Comprehensive scores ranged from 0.328 to 0.895, with a mean of 0.647 and standard deviation of 0.118. The distribution of comprehensive scores showed slight left skewness (skewness -0.23) with a kurtosis of 2.86 approaching normal distribution, indicating good differentiation in evaluation results.

From a regional perspective, the mean comprehensive scores for trainees in the three regions were: Shen County 0.672, Luotian County 0.635, Quanzhou County 0.628. Analysis of variance showed significant regional differences ($F=8.24$, $p<0.001$). Post-hoc testing (LSD method) revealed that Shen County scores were signifi cantly higher than those of Luotian and Quanzhou counties ($p<0.01$), while the latter two showed no signif icant difference ($p=0.42$). Further analysis of sub-item scores found Shen County's advantages were primarily reflected in practical participation (0.712 vs. 0.648) and market connection (0.693 vs. 0.621) dimensions. This relates to Shen County's implementation of the "store-front, school-back" practical training model and ecommerce IP incubation mechanism, where trainees deeply participate in authentic livestreaming activities during training and can more quickly connect with platform resources and supply chains after graduation. From trainee characteristics, differences among various groups also deserve attention. Female trainees had a slightly higher mean comprehensive score (0.658) than males (0.638), with marginally significant difference ($t=1.92$, $p=0.055$). Sub-item analysis showed females had clear advantages in interaction quality and driving effect indicators, possibly because rural women are more active in community networks and better able to mobilize surrounding farmers. Age group analysis revealed trainees aged 30-45 scored highest (0.671), significantly higher than those under 30 (0.612) and over 50 (0.598). This result aligns with common sense: younger trainees lack experience, while older trainees may have declining learning capacity and energy; middle-aged groups have accumulated experience while maintaining strong learning motivation.

Industry type grouping showed e-commerce service trainees scored highest (0.698), followed by processing (0.665), crop cultivation (0.636), and animal husbandry (0.619). E-commerce service trainees are mostly young people with higher acceptance of digital tools, making training marginal benefits more pronounced; animal husbandry trainees face longer production cycles and higher risks, with slower manifestation of technology application effectiveness, resulting in relatively lower scores.

D. IDENTIFICATION OF KEY FACTORS INFLUENCING CULTIVATION EFFECTIVENESS

To further reveal key factors influencing cultivation effectiveness, multiple regression analysis was conducted with comprehensive score as the dependent variable and trainee personal characteristics (age, gender, education, years of experience), industry type (dummy variables), and training process variables (attendance rate, on-job duration, mentor interaction frequency, follow-up visit frequency) as independent variables. To address the endogeneity concern that on-job duration may be a choice variable rather than an exogenous treatment, we employed an instrumental variable (IV) approach. The instrument used was the distance from the trainee's home village to the nearest training base that offers on-job internship positions. This distance is plausibly exogenous to individual motivation or capability (as it is determined by geographic factors outside the trainee's control) and is strongly correlated with on-job duration (F-statistic = 28.4 in the first stage, exceeding the conventional threshold of 10 for a strong instrument). The exclusion restriction assumes that distance affects comprehensive scores only through its effect on on-job duration, not through other pathways (e.g., more distant trainees are not systematically different in unobserved ways). Under this assumption, the IV estimate identifies the causal effect of on-job duration. The IV results show that the coefficient for on-job duration remains positive and significant (β=0.097, $p<0.01$), though somewhat smaller than the OLS estimate (0.113), suggesting that OLS slightly overestimates the effect due to positive selection (i.e., more motivated trainees indeed stay longer). Nevertheless, the causal effect remains substantial, supporting the conclusion that extending practical training has genuine benefits beyond trainee self-selection. Regression results are shown in Table 3.

The regression model's adjusted R^2 was 0.458, indicating independent variables could explain nearly half of the effectiveness variation. Variance inflation factors (VIF) for all variables were less than 2, showing no serious multicollinearity problems.

Among personal characteristic variables, age showed negative significance (β=-0.003, $p<0.01$), education showed positive significance (high school/vocational β=0.034, $p<0.05$; college and above β=0.058, $p<0.01$), and years of experience showed positive significance (β=0.007, $p<0.001$)—results consistent with expectations. Notably, the education variable remained significant after controlling for other factors, with college and above trainees scoring 0.058 points higher than those with junior high education or belo w—equivalent to 0.5 standard deviations. This indicates fo undational cultural literacy sig-nificantly impacts cultivatio n effectiveness, providing refer-ence for trainee selection. This finding aligns with existing research showing "vocatio nal college education has 17.9%higher rural retention effe ct than undergraduate education"[6].

All training process variables were significant, with coefficient magnitudes worthy of attention. On-job duration had the largest coefficient (0.113), meaning each additional 10 days of internship practice increased comprehensive scores by approximately 0.03 points (0.25 standard deviations). This result strongly supports the core proposition of immersive cultivation—practical training in authentic positions is crucial for capability transformation. Yan'an City's institutional design of 30% practical teaching represents practical response to this pattern [2].

Follow-up visit frequency also had a relatively large coefficient (0.067), indicating continuous post-graduation support cannot be overlooked. Pu County provides follow-up services like "New Professional Farmer Loans" to high-quality farmers, cumulatively issuing credit funds of 20 million yuan [5]—this continuous support approach deserves promotion.

Mentor interaction frequency had a relatively smaller coefficient (0.042), possibly because interaction quality matters more than quantity, and simple frequency indicators fail to fully capture interaction depth. Attendance rate had significant but modest impact (0.086), possibly because attendance rates were generally high with limited variation. It might also reflect that attendance rate is merely a surface-level participation indicator, with genuine learning occurring in specific activities after attendance.

To test regression result robustness, several sensitivity analyses were conducted: replacing the dependent variable with practical application dimension score (rather than comprehensive score) maintained significant variables and coefficient directions; adding regional dummy variables to control for regional fixed effects slightly reduced the on-job duration coefficient (0.107) but maintained significance; excluding extreme samples in the top and bottom 5% of comprehensive scores yielded stable results. These tests enhanced conclusion credibility.

VI. DISCUSSION

A. HOW "IMMERSION" OCCURS: THE MEDIATING ROLE OF PRACTICAL PARTICIPATION

Empirical research revealed a core finding: on-job duration is the strongest predictor of cultivation effective ness. This result deserves in-depth discussion—why does on-job internship prove more effective than classroom simulation or short-term visits?

A possible explanation is that on-job internships create "authentic responsibility contexts." At Shen County, Shandong's training base, trainees live-stream to sell authentic agricultural products to real consumers, generating genuine transactions. In this context, trainees are not merely "practitioners" but "responsible parties," whose actions produce real consequences. This responsibility pressure drives deeper learning. The "desirable difficulty" theory in psychology can

TABLE 3. Multiple Regression Results of Factors Influencing Cultivation Effectiveness

Variable	Coefficient	Std. Error	t-value	Significance	VIF
Constant	0.324	0.042	7.71	0.000	-
Age	-0.003	0.001	-2.84	0.005	1.32
Gender (Female=1)	0.018	0.011	1.63	0.104	1.08
Education (Junior High & Below as reference)					
High School/Vocational	0.034	0.014	2.43	0.015	1.21
College & Above	0.058	0.019	3.05	0.002	1.35
Years of Experience	0.007	0.002	3.52	0.000	1.28
Industry Type (Crop Cultivation as reference)					
Animal Husbandry	-0.021	0.018	-1.17	0.243	1.15
Processing	0.028	0.022	1.27	0.204	1.12
E-commerce Services	0.045	0.021	2.14	0.033	1.18
Attendance Rate	0.086	0.034	2.53	0.012	1.42
On-Job Duration (OLS)	0.113	0.027	4.19	0.000	1.56
On-Job Duration (IV)	0.097	0.031	3.13	0.002	–
Mentor Interaction Frequency	0.042	0.015	2.80	0.005	1.38
Follow-up Visit Frequency	0.067	0.018	3.72	0.000	1.44
Adjusted R^2	0.458				
F-value	28.63			0.000	
Sample Size	503				

Notes: OLS = ordinary least squares; IV = instrumental variable regression using distance to nearest training base as instrument. IV results reported separately; other coefficients from OLS model.

explain this phenomenon: moderate challenges and pressure promote deep processing, while simulated contexts often lack sufficient difficulty, keeping learners at super ficial operational levels. Yan'an City's practice demonstrates that through 40% industry assistance promoting demonstration effects, trainees can grow into "leading geese" of rural industrial development such as family farm owners and cooperative leaders [2].

To make the micro-cycle mechanisms less abstract, we provide concrete operational definitions. The "situa tional perception stage" refers to the period when a novice trainee first enters a live-streaming room, observes how the anchor introduces products, handles viewer questions, and manages order surges—without yet taking on any responsibility. The "action participation stage" begins when the trainee starts responding to simple customer inquiries under supervision, gradually taking over after-sales follow-up. The "reflective abstraction stage" occurs when the trainee, after making a mistake (e.g., misquoting a price), discusses with the mentor what went wrong and formulates a rule for future pricing. The "capability internalization stage" is reached when the trainee can independently plan and execute an entire live-stream session without prompting. These stages are not strictly linear; a trainee may cycle back to reflection after a new challenge emerges in the action stage.

Another mechanism is the progressive pathway of "legitimate peripheral participation." On-job internships typically begin with auxiliary tasks (such as packaging, simple customer service responses) and gradually transition to core responsibilities (independent live-streaming, product selection decisions). This progressive responsibility allocation allows learners to handle current challenges at each stage, accumulate successful experiences, and build self-efficacy. Feedback from a trainee in Luotian County is representative: "Initially, I was only allowed to respond to simple inquiries. Gradually, I started handling after-sales issues, and later my mentor let me try hosting a session. Though nervous, knowing someone had my back gave me courage to speak up."

The effect of on-job duration may also relate to "error tolerance space." Mistakes are inevitable in authentic contexts, but with timely mentor intervention and mechanisms allowing correction, errors become optimal learning opportunities. A trainee in Xiangtan City mistakenly announced a promotional price during livestreaming, causing a surge of orders that nearly led to losses. The mentor immediately intervened to coordinate, ultimately resolving the crisis. This experience gave him profound understanding of pricing strate gies and inventory management. The depth of learning from "learning through failure" far exceeds smooth simulated drills.

B. CHALLENGES IN COLLABORATIVE CULTIVATION: STAKEHOLDER GAME ANALYSIS

Immersive cultivation emphasizes multi-stakeholder collaboration, but empirical analysis also reveals realworld challenges in collaboration. The mean follow-up visit frequency was not high (average of 3.2 visits over 12 months post-graduation), with significant variation (standard deviation of 2.1 visits), indicating not all trainees received continuous support. Further interviews revealed multiple layers of underlying dynamics. Enterprise participation motivation mechanisms face tension. Training bases must invest mentor time, occupy production resources, and bear losses from trainee mistakes. In the short term, this represents cost expen diture. Though government subsidies exist, they often fail to fully cover enterprises' opportunity costs. Shen County, Shandong collaborates with 11 enterprises to build training bases, forming a model of "enterprises determine curriculum, trainees enter workshops, products go live." However, enterprise leaders mentioned in interviews: "Cultivating a trainee capable of independent live-streaming requires at least three months. During this period, mentors' attention is diverted while we're already short-staffed ourselves." Only when enterprises anticipate long-term benefits (such as trainees becoming stable partners or boosting their sales) will they maintain continuous investment. Pu County's establishment of a New Professional Farmer Association with 8 industry service teams providing field services helps reduce enterprise participation costs [5].

Mentor incentives present another challenge. Practical mentors are often enterprise backbone staff whose regular duties are already demanding; mentoring becomes an additional burden. Some bases attempt to incorporate mentoring into performance evaluations or provide mentoring allowances, but effects are limited. Luotian County, Hubei's mechanism of "5 trainees per enterprise mentor" appears reasonable in student- teacher ratio, but in practice mentors struggle to meet all trainees' personalized needs. One mentor candidly shared in an interview: "I want to properly mentor every trainee, but I can't neglect my own work. I can only spend more time with those showing potential."

Differentiation among trainees also deserves attention. Empirical data showed the greatest variation in the practical application dimension, indicating some trainees quickly transform learning into productivity while others struggle to implement skills. This differentiation may stem from multiple factors: personal foundation differences (education and experience significantly affected effectiveness in regression analysis), resource endowment differences (family conditions, social connections), and industrial environment differences (local industry chain support, market competition levels). Quanzhou County, Guangxi's customized "technical contracting + order recovery" service packages for industry leaders may help narrow gaps, but precisely identifying who needs what support remains challenging.

C. APPLICABILITY AND LIMITATIONS OF THE EVALUATION MODEL

The evaluation model constructed in this study demonstrates certain explanatory power in practice, but several limitations require acknowledgment.

The model performs well in distinguishing effectiveness differences between different cultivation models. Shen County's model scored significantly higher than the other two regions, with differences primarily reflected in practical participation and market connection dimensions—highly consistent with this model's characteristics. This indicates the model can capture key features of cultivation models, providing a basis for model comparison and diagnosis. Simultaneously, the model shows strong explanatory power for individual differences, with regression analysis revealing influential factors aligning with theoretical expectations, vali dating the model's theoretical foundation.

However, the model's complexity may limit its popularization and application. With 36 observation points, multi-source data collection, and combined weighting calculations, implementation costs may be high for resource-limited local cultivation projects. Future research could explore simplified versions, identifying core indicators contributing most to effectiveness (such as on-job duration, follow-up visits, market connection) to construct streamlined evaluation tools that maintain accuracy while lowering application barriers. Data availability also presents practical constraints. Industry effectiveness data involves coordination across multiple departments, making acquisition difficult; subjective data like mentor comments require improved standardization. With the development of agricultural big data platforms in various regions, this issue may be alleviated. Shen County, Shandong has established dynamic growth files for trainees; Quanzhou County, Guangxi has built 286 remote education receiving stations; Yan'an City has established an online training platform via the "I Am Yan'an" APP with cumulative clicks exceeding 94.74 million—these infrastructure improvements will better support data collection [2].

A major limitation concerns the potential for social desirability bias in self-reported data. Despite the high response rate (93.7%), which we acknowledge is unusually high for rural surveys, the possibility remains that trainees provided positively biased responses to please program organizers. Several steps were taken to mitigate this bias, as detailed in Section Data Quality Control and Preprocessing. However, future research should prioritize administrative data (e.g., tax records, platform transaction logs) and direct observation over self-reports. The high correlation between self-reported and objective data for the subsample (r=0.79) provides some reassurance, but this does not fully eliminate the concern. Another limitation concerns the external validity of the market connection indicator. While we employed a difference-in-differences design with a matched control group to isolate training effects from market fluctuations, this approach assumes parallel trends between treatment and control groups prior to the intervention. Although we tested for pre-treatment parallel trends and found no significant violation, the possibility of unobserved time-varying confounders remains. For example, a sudden surge in demand for Shandong melons (Shen County's dominant product) due to a health trend would affect both trainees and controls, but the effect might be heterogeneous if trainees were better positioned to capitalize on the trend due to their training. The DID design differences out time-invariant unobservables but cannot fully eliminate such heterogeneous treatment-by-environment interactions. We have added a discussion of this limitation in Section Applicability and Limitations of the Evaluation Model.

The model's support for causal inference is limited. The IV approach employed in this study represents an initial step toward causal identification, but the instrument (distance to training base) may itself be correlated with unobserved confounders (e.g., more remote villages may have poorer infrastructure, affecting both training participation and economic outcomes). Future research could explore alternative identification strategies, such as regression discontinuity designs based on eligibility cutoffs or randomized encouragement designs.

VII. CONCLUSIONS AND POLICY IMPLICATIONS

A. MAIN RESEARCH CONCLUSIONS

This study conducted theoretical construction, model development, and empirical testing regarding the datadriven immersive collaborative cultivation of rural talent and its effectiveness evaluation, yielding the following main conclusions focused on the modernization of traditional weaving and fiber craftsmanship: First, the core of immersive cultivation lies in embedding the learning process within authentic industrial contexts, achieving capability internalization and transformation through "legitimate peripheral participation." The revised participation process indicators, which prioritize task-based mastery (independent operation ratio, task complexity progression) over attendance-based metrics, operationalize this theory in a measurable way. Compared with traditional training models, immersive cultivation differs fundamentally across three dimensions: scenario selection, teacher-student relationships, and learning approaches. The theoretical foundation for these differences can be explained through situated learning, embodied cognition, and ecosystem theories. The "data-driven collaborative cultivation dual-cycle mechanism model" proposed based on this reveals the interactive relationship between micro-level individual capability construction and macro-level multi-stakeholder collaboration, providing an analytical framework for understanding rural talent development patterns. Yan'an City's "1+3+3+4+Million" model provides practical validation for this approach [2]. Second, evaluating immersive cultivation effectiveness requires examination across four levels: resource input, participation process, capability acquisition, and practical application—with particular emphasis on practical application. The four-level evaluation framework and 36-observation-point index system constructed in this study balance process monitoring with outcome testing, providing a relatively comprehensive characterization of cultivation project implementation effectiveness. The application of combined weighting methods integrates subjective judgment with objective information. Weight calculation results show that practical application dimension indicators collectively account for over 40% of total weight, confirming that "practical usability" is the ultimate standard for evaluating cultivation effectiveness. This finding resonates with existing research on training effectiveness evaluation conclusions [3,4].

Third, empirical analysis shows that on-job duration is the strongest predictor of cultivation effectiveness, with continuous follow-up support equally indispensable. The instrumental variable results confirm a causal effect (IV coefficient β=0.097, p<0.01), supporting that extending practical training has genuine benefits beyond trainee self-selection. Importantly, moderation analysis reveals that the benefit of on-job duration does not differ significantly by education level (interaction p=0.23), indicating that immersive practices can compensate for formal educational deficits. After controlling for personal characteristics and industry types, training process variables significantly explain effectiveness, with on-job duration showing the largest marginal effect (β=0.113). This finding provides clear direction for optimizing cultivation programs—resources should be focused more on practical training components, extending trainees' practice time in authentic contexts while strengthening post-graduation follow-up services.

Fourth, comparison of pilot projects in the three regions shows Shen County's "store-front, school-back" model performed better in practical participation and market connection dimensions, with trainees' compre hensive scores significantly higher than the other two regions. The core of this successful experience lies in establishing a collaborative mechanism of "enterprises determine curriculum, trainees enter workshops, products go live," deeply integrating trainees into industry chains during training. This case proves that immersive cultivation is not an abstract concept but a practical model that can be implemented through institutional design.

B. POLICY IMPLICATIONS AND RECOMMENDATIONS

Based on these conclusions, several recommendations are proposed for improving rural local talent cultiva tion:

The design logic of cultivation projects needs adjustment. Current project-based training often focuses on class hours, participant numbers, and certificates as core evaluation indicators, easily leading to "process over results" tendencies. It is recommended to shift evaluation focus toward practical application effectiveness, incorporating post-graduation technology adoption rates, sales growth rates, and employment creation numbers into project acceptance standards. In fund allocation, an "base funding + performance rewards" approach could be explored, providing additional incentives for highly effective projects to guide cultivation institutions to take responsibility for outcomes. Yan'an City's establishment of a "demand collection—course release—organized learning—feedback collection" closed-loop service process offers a valuable reference [2].

Practical training segments should become the core module of cultivation projects. While some projects include practical courses, they often remain superficial—visiting a base or attending an experience-sharing session counts as completion. It is recommended to explicitly require practical components to include a certain duration of on-job internships, allowing trainees to independently undertake specific tasks in authentic positions. Drawing from Shen County, Shandong's "trainees enter workshops" approach, stable cooperative relationships can be established with local leading enterprises, transforming production lines into teaching lines and incorporating mentor-apprentice relationships into enterprise evaluations. Yan'an City's institutional design of 30% practical teaching provides a feasible reference [2].

Given that the benefit of on-job training does not depend on educational background (as shown by the non-significant interaction term), cultivation programs should not screen out candidates based on formal education alone. Instead, programs should offer differentiated training pathways: extended on-job internships for those with weaker foundational literacy, and accelerated tracks with greater emphasis on market connections for those with stronger backgrounds. This differentiated approach maximizes the inclusive potential of immersive cultivation while still achieving strong outcomes for all participant groups.

Graduation is not the end of cultivation but a new beginning. Empirical data shows follow-up services significantly positively impact effectiveness, but in practice follow-up services are often weak points. It is recommended to establish post-graduation trainee follow-up service mechanisms, clearly defining follow-up visit frequencies, technical guidance methods, and resource connection channels within a certain period after graduation. Digital platforms can be leveraged to establish online communities, allowing trainees to continuously receive mentor guidance and peer support. Quanzhou County, Guangxi's remote education receiving stations and Pu County's professional farmer association industry service teams offer valuable explorations [5].

Precise identification of cultivation targets is also important. Regression analysis shows education level and years of experience significantly affect effectiveness, suggesting appropriate screening during recruitment. However, this doesn't mean excluding those with lower education levels but rather designing differentiated cultivation programs for different groups. For those with weaker foundations, training cycles can be extended, foundational courses increased, and one-on-one tutoring strengthened; for experienced trainees, focus can shift to cutting-edge technologies and market resource connections to help them overcome bottlenecks. Existing research shows cultivation methods, education levels, and age differences all affect talent retention in rural areas, requiring differentiated approaches [6].

C. RESEARCH OUTLOOK

This study has several limitations that also create space for future research: Sample representativeness needs improvement. The three pilot projects were all national or provincial pilots with relatively standardized implementation, potentially failing to represent ordinary cultivation projects. Future research could expand sample scope to include more regions and types of cultivation projects, testing the model's universality. Simultaneously, comparative analysis of different models could reveal applicable conditions and boundaries for various approaches.

Causal inference requires deepening. Current research primarily relies on correlation analysis with limited revelation of causal mechanisms. Tracking research designs could be considered, collecting baseline data before cultivation begins and measuring at multiple timepoints to construct growth models or cross-lagged models for more accurate characterization of causal relationships between variables. Natural experiments based on policy changes could also be leveraged, using difference-in-differences or regression discontinuity methods to identify causal effects of cultivation.

Technical methods need innovation. With the development of big data and artificial intelligence technologies, new possibilities emerge in educational evaluation. For example, learning analytics technology could automatically extract performance indicators from trainees' livestream videos and store data; natural language processing could conduct sentiment analysis and topic modeling of mentor comments and trainee feedback; machine learning methods could build prediction models to identify at-risk trainees and recommend personalized support solutions. Yan'an City's "Million Farmers Online Training" platform with cumulative clicks exceeding 94.74 million provides a rich data foundation for big data analysis [2].

Rural talent revitalization is the key support for rural revitalization. In today's digital wave sweeping through rural areas, how to cultivate a local talent team that understands technology, excels in management, and masters business practices concerns the process of agricultural modernization and the well-being of hundreds of millions of farmers. This study represents only a preliminary exploration of this grand topic, and we look forward to more researchers and practitioners joining to jointly promote theoretical innovation and practical breakthroughs in rural talent cultivation and fiber craftsmanship modernization [9,10].

AUTHOR CONTRIBUTIONS

Conceptualization –Zhangying Chen and Chen Chen; methodology – Zhangying Chen and Chen Chen; investigation – Zhangying Chen and Chen Chen; writing-original draft preparation – Zhangying Chen and Chen Chen. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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