

Article

Research on AI-Empowered Precision Training Strategies for Rural Teachers

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Abstract: With the rapid development of information technology, artificial intelligence (AI) has become increasingly prevalent in education, yet rural teacher training still faces challenges such as insufficient resources, homogenized content, and difficulty matching training to individual needs. Focusing on AI-empowered precision training for rural teachers, this study constructs an indicator system grounded in precision-training theory, designs an intelligent training framework, and pilots a system prototype in model rural schools. First, we gathered teachers' needs and existing pain points through questionnaires and interviews, then applied machine-learning algorithms to develop multidimensional profiles of teaching ability, subject-matter knowledge, and professional aspirations. Based on these profiles, we used recommendation systems and intelligent instructional-analytics technologies to deliver customized courses and practical guidance. Finally, an empirical analysis compared experimental and control groups on teaching effectiveness, satisfaction, and professional-growth rates. Results indicate that introducing an AI-driven precision training mechanism significantly enhanced teaching ability, increased participation by 25%, improved course-match accuracy by 30%, and effectively supported teachers' ongoing professional development. Theoretical and practical optimization strategies and paths for broader adoption are proposed, offering reference for training-program innovators.

Keywords: artificial intelligence; rural teachers; precision training; intelligent recommendation; professional development

1. Introduction

Rural education has long been constrained by a shortage of qualified teachers, limited training resources, and underdeveloped professional-development pathways, resulting in clear lags in instructional innovation, subject-knowledge updates, and educational-technology adoption. Meanwhile, AI technologies — particularly in big-data analytics, intelligent recommendation, and natural-language processing — have matured rapidly, offering unprecedented support for personalized, precision-based learning. Introducing AI into rural teacher training can overcome geographic and time barriers by constructing multidimensional teacher profiles based on instructional behaviors, knowledge structures, and development intentions, thereby enabling tailored precision training. Such an approach not only enhances training efficiency and outcomes but also provides continuous, intelligent support for rural teachers' ongoing professional growth, promoting educational equity and balanced quality.

This study aims to develop an AI-empowered precision-training system for rural teachers, encompassing three primary objectives. First, through questionnaire surveys and in-depth interviews, we identify rural teachers' training needs and pain points to establish a data foundation for profiling. Second, we design and implement an intelligent training framework based on machine-learning and recommendation algorithms to gen-

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erate multidimensional teacher profiles — covering instructional competence, subject literacy, and professional intention — and to deliver personalized courses and guidance. Third, we conduct a controlled experiment in representative rural schools to quantitatively assess training outcomes and, based on these findings, propose optimization strategies and scalable deployment paths. The results enrich precision-training theory and offer actionable technical and methodological guidance for education authorities and training institutions seeking to enhance rural teachers' capabilities.

2. Literature Review

2.1. *Advances in AI Applications for Educational Training*

In recent years, AI's role in educational training has developed from isolated modules to ecosystem-scale solutions. Early work focused on expert-system-based tutoring and automated grading — systems like ALEKS and AutoTutor provided personalized feedback through rule-based inference — while intelligent question-answering and text-matching grading technologies were adopted by massive open online course (MOOC) platforms, ensuring basic quality control in online instruction. As machine-learning matured, researchers combined learner-behavior data with cognitive-diagnostic models to precisely characterize learning states [1]. For example, Knowledge Tracing models use sequential data to predict mastery of specific concepts and inform adaptive learning paths; Learner Profiling applies feature engineering and clustering to identify learner segments and tailor differentiated instruction and group collaboration [2].

With the advent of deep learning, AI applications in educational training have expanded to multimodal and complex scenarios. Natural-language-processing (NLP) techniques now enable robust essay scoring, oral-language assessment, and automated summarization, significantly improving language-subject efficiency. Image and video analysis have been explored for hands-on skills training and virtual simulations, providing learners immersive experiences via action recognition and real-time feedback. Meanwhile, recommendation systems and learning-analytics platforms refine content delivery by merging teacher-instruction data with student-learning trajectories for precision and visibility in training management. Cutting-edge research also investigates affective computing and reinforcement learning in instructional systems — such as emotion-recognition-triggered interventions and adaptive interaction strategies — infusing AI-driven education with dynamic responsiveness. Overall, AI-enabled educational training has evolved from single-function modules toward integrated, ecosystem-level solutions, laying a solid technical foundation for "teach-to-fit" and fine-grained management [3].

2.2. *Current State and Core Challenges of Rural Teacher Training*

Despite increased investment by national and local authorities and the emergence of diverse training formats — centralized workshops, on-the-job learning, and online micro-courses — rural teacher training still grapples with the tension between broad coverage and shallow depth. Traditional centralized programs tend to emphasize policy dissemination and pedagogical lectures, featuring short durations, infrequent sessions, and weak follow-up, which fail to address rural teachers' varied needs in instructional practice, classroom management, and technology integration. While online training can transcend time and space constraints, it is hampered by inadequate equipment, unstable internet connections, and uneven digital literacy among teachers, resulting in low participation and subpar learning outcomes. Furthermore, training content often exhibits homogeneity, lacking stratified design tailored to rural contexts and individual career stages; this disconnect undermines the translation of training into sustained classroom improvements [4].

Against this backdrop, rural teacher training faces multiple core challenges. First, resource allocation is uneven: high-quality trainers and instructional materials cluster in urban areas, leaving rural teachers without access to expert demonstration and guidance.

Second, needs assessments are inadequate: without rigorous analysis and profiling to inform program design, training cannot precisely address teachers' weaknesses and aspirations. Third, evaluation and feedback mechanisms are underdeveloped: most programs rely solely on satisfaction surveys rather than quantifying changes in teaching behavior or student learning [5]. Finally, sustainability and incentive structures are lacking: after fulfilling mandated hours, rural teachers have few opportunities for further advancement or professional recognition, dampening motivation for lifelong learning. Overcoming these bottlenecks requires the introduction of data-driven, personalized recommendation, and intelligent analytics-centered precision-training mechanisms, shifting rural teacher development from blanket coverage toward refined customization [6].

2.3. Critical Review of Existing Rural Teacher Training Research

Although numerous studies have evaluated the short-term impact of rural teacher training — such as immediate gains in trainee satisfaction, improvements in pedagogical skills, and higher performance on post-training assessments — there remains a striking lack of systematic, long-term follow-up. Most existing literature relies on pre-and post-training comparisons or immediate survey feedback, overlooking how teachers sustain and apply new practices over months or years, and how these practices influence student outcomes in the long run. A handful of longitudinal investigations exist, but they tend to employ small sample sizes within single regions, limiting the generalizability of their findings across diverse rural contexts [7]. This gap in longitudinal evidence not only hampers the ability to assess the enduring effectiveness of different training models but also weakens the empirical foundation that program designers need to make informed, sustainable investments. To address this deficiency, the present study will conduct six-month follow-up interviews and classroom observations with participating teachers, integrating measures of student academic progress and teaching quality to deliver robust, long-term insights into rural teacher training effectiveness [8].

3. Theoretical Foundations and Framework Design

3.1. Precision-Training Theory and Indicator System

Precision training derives from the concepts of precision education and data-driven individualized support, emphasizing data-driven multidimensional profiling of individuals' needs, capabilities, and potential to create a closed feedback loop from "profile to program". Its theoretical underpinnings include:

- 1) adult-learning theory, which posits that teachers prefer self-directed, experiential, and problem-based learning.
- 2) differentiated-instruction theory, which advocates designing tiered, modular content based on learner readiness.
- 3) learner-profiling and path-optimization theory, which leverages big data and machine learning to identify learner characteristics and plan personalized learning pathways and resource allocation.

Integrating these theories into rural teacher training establishes an organically connected precision-training system spanning policy and practice [9].

Building on this foundation, we propose an indicator system for rural teachers' precision training with three dimensions: Competency Profiling: instructional design ability (e.g., setting learning objectives, integrating resources), classroom delivery ability (e.g., facilitating interaction, using multimedia), and reflective improvement ability (e.g., writing teaching journals, frequency of peer review). Knowledge Literacy: subject-matter expertise (assessed via tests and classroom observations), educational-technology fluency (e.g., proficiency in online platforms, micro-course creation), and pedagogical theory mastery (e.g., modern teaching methods). Intentions and Environment: willingness to continue learning (e.g., training-registration frequency, sustained engagement duration), collaboration and sharing propensity (e.g., forum posts and responses), and external support

environment (e.g., school internet bandwidth, hardware availability). Quantifying these indicators through data collection and modeling provides a robust basis for subsequent multidimensional profiling and recommendation decisions, ensuring training aligns precisely with teachers' actual needs [10].

3.2. AI-Empowered Training Framework

The AI-empowered precision-training system for rural teachers comprises five interconnected modules: data-collection, profiling-analysis, recommendation-decision, training-delivery, and feedback-evaluation. In the data-collection layer, we harvest multi-source inputs — online questionnaires, teaching logs, classroom videos, and platform activity — to capture teaching behavior, content, and environmental context, supplemented by school-based surveys and interviews for rich structured and unstructured data. In the profiling-analysis layer, we clean and integrate this data, apply feature engineering and deep-learning models to build an educational data warehouse, and employ classification and clustering algorithms to generate competency, knowledge, and intention profiles, precisely characterizing individual differences [11].

Within the recommendation-decision layer, a hybrid algorithm combining collaborative filtering and content-based recommendation dynamically generates personalized training plans — pushing suitable micro-courses, thematic seminars, and school-based research activities. An intelligent-instruction analytics module monitors teachers' progress and interaction in real time, automatically adjusting course difficulty and resource allocation. The training-delivery layer, hosted on a unified intelligent-training platform, supports online learning, virtual simulations, and collaborative communities; teachers self-select recommended courses, submit assignments, and share reflections, achieving a "learn-practice-assess" closed loop. Finally, the feedback-evaluation layer integrates learning-outcome models with student-performance metrics to quantify training impact; a visual dashboard relays results to both administrators and teachers, guiding iterative strategy refinement and resource reallocation to sustain the precision-training ecosystem [12].

4. Research Methods

4.1. Data Sources, Sample, and Variable Selection

This study took several rural primary schools in three districts of a province in East China as the sampling frame. By combining stratified random sampling with convenience sampling, a total of 120 on-the-job teachers from 10 rural schools were selected as the research subjects. The data sources mainly include three parts: The first is the behavior log based on the intelligent training platform, which is used to obtain the online learning duration, course browsing records and assignment submission situations of teachers; The second is structured questionnaire surveys, covering basic information of teachers (such as age, educational background, and teaching experience), training needs and satisfaction evaluations; The third is the semi-structured interview record. Through in-depth interviews with 20 representative teachers, it supplements the training pain points and environmental constraints that are difficult to quantify in the platform logs and questionnaires [1].

In terms of variable selection, based on the index system constructed in Chapter Three, this study divides the variables into two major categories: independent variables and dependent variables. The independent variables include: the ability profile dimension (such as the score of teaching design ability, the frequency of classroom interaction), the knowledge literacy dimension (the test score of subject professional knowledge, the proficiency of information operation), and the willingness and environment dimension (the online participation rate, the number of school-based research and training activities, and the network bandwidth level). The dependent variable is mainly based on the training effect, including learning satisfaction (Likert scale score), improvement of knowledge

mastery (difference between the pre-test and post-test), and the application rate of classroom practice (comprehensive score of interviews and teaching observations). Furthermore, to control the confounding effect, this paper also introduces the personal characteristics of teachers (gender, age, educational level) and the hardware conditions of schools (teaching equipment allocation index) as control variables to ensure the robustness of the model estimation results [13].

4.2. Algorithm Model Design and Implementation Process

To achieve precise matching and personalized recommendations for rural teachers, we designed a hybrid algorithm that combines collaborative filtering with content-based recommendation. First, numerical and categorical features from the competency and knowledge profiles were preprocessed using standardization and one-hot encoding to map heterogeneous data into a unified feature space. Simultaneously, we tokenized, embedded, and performed topic extraction on teacher interaction logs and interview texts to construct a textual-feature matrix. In the collaborative-filtering module, we built a teacher-course matrix and calculated user similarity using cosine similarity to identify teacher cohorts with similar learning behaviors. In the content-based module, we trained a gradient-boosted decision-tree (GBDT) regression model that predicts each course's suitability score based on course metadata and teacher-profile features. A weighted-fusion strategy then combined these two recommendation scores, balancing behavioral similarity with profile matching [14].

The implementation proceeded in two stages. During offline training, we used the educational data warehouse and a Spark cluster to parallel-process raw logs and questionnaire data, producing feature tables for model training. We then leveraged Python libraries (scikit-learn, XGBoost) to perform cross-validation and hyperparameter tuning, selecting the optimal model parameters and exporting the trained models. For online deployment, these models were exposed via RESTful APIs on the intelligent training platform. The platform calls the profiling service to retrieve teachers' real-time profiles, feeds them into the recommendation service, and dynamically returns a list of tailored courses and learning resources. Finally, we ran A/B tests and real-time monitoring to track click-through rates, completion rates, and satisfaction scores; model weights and feature selections were iteratively adjusted based on this feedback to continuously optimize recommendation performance.

5. Empirical Analysis

5.1. System Prototype Design and Functional Modules

The system prototype adopts a browser-server (B/S) architecture. The front end uses responsive design to accommodate varying network conditions and device types in rural schools. The back end is organized as microservices, with each service exposing RESTful APIs for data exchange. The user interface is kept clean and intuitive: the home page displays an overview of the teacher profile, recommended courses, and a learning-progress dashboard, while a sidebar menu provides quick access to "My Profile", "Recommended Courses", "Online Learning", "Training Community", and "Feedback". To ensure scalability and high concurrency, back-end services are containerized, and structured data are stored in a relational database. Elasticsearch is used for efficient storage, retrieval, and analysis of logs and interview texts.

The prototype comprises the following core modules: Data Collection & Preprocessing: integrates online-learning logs, questionnaires, and interview records; performs cleaning, de-duplication, and formatting to produce standardized data for profiling. Profiling Analysis: uses machine-learning algorithms to generate dynamic competency, knowledge, and intention profiles, and provides visual reports. Intelligent Recommendation: applies the hybrid collaborative-filtering and content-based algorithm to push per-

sonalized courses and teaching-research activities. Online Learning & Interaction: supports video playback, practice exercises, assignment submission, and discussion forums, while capturing user-behavior data. Feedback & Evaluation: quantifies training effects through pre-and post-tests, satisfaction surveys, and classroom observations, and presents results in a visual dashboard to guide subsequent strategy optimization. Each module interlocks to form a closed loop from data collection to outcome evaluation, enabling precision training for rural teachers.

5.2. Training Effect Evaluation and Empirical Results

To evaluate the AI-empowered precision-training system's effectiveness, we employed a pre-test/post-test control-group design with 120 rural teachers randomly assigned to an experimental group ($n = 60$) and a control group ($n = 60$). The experimental group completed personalized courses and research interactions on the intelligent platform, while the control group received traditional centralized training. We assessed outcomes before and after training using three metrics: subject-knowledge test scores, teaching-satisfaction questionnaires, and classroom-practice observation ratings. Results show that the experimental group's knowledge scores rose from 70.4 to 85.7 (a 21.7% increase), whereas the control group improved from 69.9 to 76.2 (a 9.0% increase). Teaching satisfaction (5-point Likert scale) increased from 3.1 to 4.2 in the experimental group, compared to 3.0 to 3.4 in the control group. Classroom-practice application rates — measured by the proportion of training content applied in class — were 80.5% for the experimental group versus 61.3% for the control group. Independent-samples t-tests confirmed that all differences were statistically significant at $p < 0.05$, demonstrating that AI-driven precision training outperforms traditional methods in improving knowledge acquisition, satisfaction, and classroom-practice transfer. Moreover, participation and course-matching metrics improved markedly. The experimental group's online participation rate reached 96%, compared to 68% for the control group — a 28-percentage-point gain. Teachers' self-rated course-matching score averaged 4.3 out of 5 in the experimental group, 30% higher than the control group. Overall, the AI-empowered precision-training mechanism not only significantly enhances rural teachers' learning outcomes and satisfaction but also facilitates effective translation of training into classroom practice, offering a replicable and scalable technology pathway for their ongoing professional development.

6. Discussion

6.1. Strategy Optimization Paths Based on Empirical Findings

Building on our empirical results, precision-training strategies can be optimized in the following ways to further enhance rural teachers' training outcomes and sustain their professional growth. First, the teacher profiling system should be dynamically updated and enriched with multiple data sources. In addition to online learning logs and survey responses, it should integrate classroom recordings, student feedback, and school-based research outputs to create richer profile dimensions, enabling the recommendation engine to more accurately recognize teachers' proficiency and needs. Second, the hybrid recommendation algorithm's weighting and feature selection ought to be fine-tuned for different subjects and teaching-experience levels. A real-time feedback mechanism should be added: if a teacher's engagement with a recommended course or activity falls below expectations, the system would automatically trigger a follow-up survey or suggest alternative offerings, thereby avoiding wasted resources from one-off recommendations.

Moreover, training content must be closely linked to classroom practice by designing an "online-offline-school-based" closed loop. Smartly recommended micro-courses and thematic seminars should be seamlessly combined with mentor-led on-site observations and in-school research workshops, ensuring that teachers can practice and reflect on new methods in real contexts. The platform should also incorporate a collaborative community module to encourage teachers to share cases, peer-review one another, and support each

other. Incentives such as points or continuing-education credits can motivate sustained participation. Finally, at the institutional level, a quantitative evaluation-driven incentive and promotion pathway should be established. Training outcomes ought to feed into annual performance reviews and title-promotion criteria, linking professional development achievements to career advancement. By embedding "learning gains, practical application, and future prospects" into a coherent ecosystem, these optimized strategies will both consolidate the advantages demonstrated in our pilot study and lay a solid foundation for scaling AI-empowered precision training to a wider rural context.

6.2. Considerations for Scaling and Sustainable Development

When scaling and promoting this system, planning should adhere to three guiding principles: platform integration, local customization, and collaborative support. First, platform integration calls for deep interoperability with existing educational-technology systems through standardized interfaces to avoid redundant development and resource waste. Education authorities at provincial and municipal levels can coordinate procurement or licensing of the intelligent training platform, lowering technical and operational barriers for rural schools. Simultaneously, localized secondary development — tailoring content to regional curriculum standards and local cultural characteristics — will increase the relevance and impact of training materials. Second, promotion efforts must foster school-region collaboration by engaging educational research institutions, teacher-training colleges, and model schools as dual technical and pedagogical partners. Mechanisms such as intensive workshops, on-the-job mentoring, and tutor-apprentice pairings will create effective synergies between online recommendations and face-to-face guidance.

From a sustainability perspective, a "dual-engine" approach of technology and governance is essential. On the technical side, the platform's autonomy and extensibility must be strengthened: algorithmic models should be continually optimized to handle growing numbers of teachers and diverse deployment scenarios. Operationally, leveraging cloud services and container orchestration will enable elastic scaling and phased rollouts, ensuring stable performance. On the governance side, a multi-stakeholder management framework involving government, schools, and civil society should be established. Rural teacher training must be incorporated into annual education budgets and performance targets, and aligned with local economic-development and poverty-alleviation policies to secure dedicated funding. Partnerships with businesses and non-profits can introduce innovative service models and financial support, supplying diverse revenue streams for ongoing platform enhancements and content updates. Only by integrating these technical and institutional pathways can we both expand the system's reach and preserve its vitality and capacity for innovation, thereby delivering enduring benefits to rural teachers' professional growth and the broader revitalization of rural education.

7. Conclusion

This study's pre-test/post-test control-group experiment with 120 rural teachers confirmed that an AI-empowered precision-training system significantly enhances both professional competence and classroom practice transfer. First, the experimental group's subject-knowledge scores improved by an average of 21.7%, compared to 9.0% in the control group, demonstrating that multidimensional, personalized recommendations more effectively address teachers' knowledge gaps. Second, teaching-satisfaction ratings rose from 3.1 to 4.2 in the experimental group, versus 3.0 to 3.4 in the control group, indicating stronger engagement with AI-driven training content, resources, and user experience. Third, the rate at which teachers applied training content in their classrooms reached 80.5% in the experimental group, compared with 61.3% in the control group, validating the feasibility of a closed "learn-apply" loop under AI guidance. Finally, online participation and course-match accuracy — 96% participation and an average self-rated match score of 4.3

out of 5 — far exceeded the control group, underscoring the hybrid recommendation algorithm's ability to boost engagement and resource utilization. Overall, the AI-empowered precision-training mechanism not only delivers rapid, substantial improvements in rural teachers' learning outcomes but also establishes a data-driven, continuous foundation for their ongoing professional development.

To promote widespread adoption of AI-empowered precision training, we recommend focusing on three areas: platform integration, talent cultivation, and resource assurance. First, integrate the AI training platform into regional education-technology plans via standardized data interfaces, and deploy it at provincial and municipal levels with tiered authorization to ensure zero-barrier access for rural schools. Second, enhance rural teachers' data literacy and technical skills by provisioning necessary hardware and network infrastructure, and by introducing AI-education interdisciplinary courses in teacher-training colleges and research institutions to develop hybrid educators proficient in both pedagogy and data analysis. Third, establish incentive and evaluation mechanisms tied to training outcomes: include platform participation metrics, empirical results, and classroom-application evidence in annual performance evaluations and title-promotion criteria. Concurrently, secure dedicated funding — through government budgets, social capital, and philanthropy — to create a multi-stakeholder governance model involving government, schools, and industry partners. By aligning policy, resources, and talent cultivation, this integrated approach will ensure the sustainable development of precision training and support the overall enhancement of rural teachers' professional capabilities and rural education quality.

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