Reconstruction Path and Practical Framework of AI Agent Empowered In-house Training in Mining Enterprises

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Abstract. In-house training in mining enterprises has long been constrained by the tension between work and learning, the disconnection between training content and operational scenarios, insufficient personalization, and the difficulty of quantitatively evaluating training outcomes. Drawing on educational theories, this study systematically examines the underlying deficiencies of mining training and proposes an "AI-agent-as-hub" training empowerment framework comprising four core modules: adaptive learning path generation, immersive scenario simulation, multi-agent collaborative coaching, and intelligent data-feedback loop. A 12-week quasi-experimental study was conducted across three coal mining enterprises using a pretest–posttest control group design, with 120 miners assessed across five competency dimensions. Results indicate that the experimental group significantly outperformed the control group across all five dimensions—safety regulation knowledge mastery, fault diagnosis accuracy, emergency decision-making soundness, equipment operation standardization, and safety behavior compliance ($p<0.01$)—with a composite competency improvement 3.0 times that of the control group. The findings confirm that AI agents restructure the training ecosystem through a human–AI collaboration paradigm, shifting mining training from "standardized inculcate" to "precision empowerment."

Keywords: Mining enterprises, In-house training, AI agent

1 Introduction

Safety production in the mining industry relies heavily on the continuous improvement of practitioners' professional skills. The 2026 revised Coal Mine Safety Regulations further tighten enterprise accountability for training, while the "Artificial Intelligence + Education" Action Plan jointly issued by five ministries, including the Ministry of Education[1], explicitly mandates the construction of immersive instructional spaces. These policy signals clearly indicate that mining training has entered a new phase of digital precision empowerment.

However, traditional training models—characterized by centralized lectures, video-based learning, and paper-based assessments—generally suffer from pronounced

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work–learning conflicts, disconnection between content and job requirements, low learner engagement, and difficulty in tracking outcomes. Meanwhile, AI agent technology has reached the stage of large-scale deployment. According to a PwC survey[2], 79% of organizations have adopted AI agent technology to varying degrees. Products such as Beisen CoolCollege[3] and Alibaba Cloud Qwen3-Learning demonstrate that agents are fundamentally restructuring the enterprise training paradigm.

Accordingly, this study draws on educational theories to examine the challenges of mining training, constructs an AI-agent-empowered training framework, and conducts a systematic empirical validation through a controlled experiment across multiple coal mining enterprises.

2 Theoretical Review of In-house Training in Mining Enterprises

2.1 Knowles' Adult Learning Theory

Knowles posits that adult learners are characterized by self-direction, rich experiential resources, problem-centered orientation, and intrinsic motivation. Mining trainees are working adults whose learning needs are highly problem-oriented—"how to handle gas exceedance" and "identifying roof collapse precursors"—necessitating content closely tied to job-related risk scenarios and the autonomy to choose learning time and pace. The traditional one-size-fits-all model violates these principles, reducing training to a perfunctory exercise[4].

2.2 Constructivism and Experiential Learning Theory

Vygotsky's Zone of Proximal Development (ZPD) theory holds that effective learning occurs in the region between current and potential development levels, requiring appropriate scaffolding[5]. Kolb's experiential learning cycle[6] describes learning as a spiral progression through concrete experience, reflective observation, abstract conceptualization, and active experimentation. In mining training, numerous operational skills constitute contextualized knowledge; for instance, operating hydraulic supports requires sensing roof pressure changes under specific geological conditions—knowledge that can only be effectively constructed in simulated or real contexts. AI agents can provide precise scaffolding at each stage of the experiential cycle: immersive scenario simulation, structured reflection guidance, pattern induction, and immediate corrective feedback.

2.3 Gagné's Instructional Events and Self-Regulated Learning Theory

Gagné emphasizes that different learning outcomes require distinct combinations of instructional events[4]. Mining training involves multiple outcome types: safety regulations (verbal information), fault diagnosis (intellectual skills, encompassing accuracy and speed), emergency decision-making (cognitive strategies, requiring rationality and timeliness), equipment operation (motor skills), and safety awareness (attitudes, including compliance and active reporting). Traditional training applies a uniform approach regardless of these differences. Zimmerman's three-phase self-regulated learning model[7,8] underscores the importance of learner agency; AI agents can serve as "learning partners," providing personalized guidance to enable "supported self-regulated learning."

3 Practical Challenges of In-house Training in Mining Enterprises

(1) Pronounced work–learning conflict and fragmented training time. Mining operations follow a three-shift system, with miners working 8–10 hours underground daily. Centralized training sessions typically last only 30–60 minutes, making it difficult to form systematic learning loops; "training yielding to production" has become the norm.

(2) Disconnection between training content and operational scenarios. Traditional training focuses primarily on policy promulgation and general safety knowledge, lacking scenario-based training tailored to specific positions and operational procedures. The tacit knowledge involved in gas exceedance handling—reading monitoring equipment, adjusting ventilation systems, selecting evacuation routes—cannot be transmitted through text alone.

(3) Monotonous training methods and low learner engagement. Traditional e-Learning platforms report course completion rates below 30%[8], severely conflicting with adult learners' need for autonomy.

(4) Difficulty in quantitative evaluation of training effectiveness. Assessments emphasize knowledge retention rather than behavioral change, resulting in a prevalent phenomenon of high scores but low competence, without a "training–evaluation–improvement" data loop[9].

(5) Insufficient instructional capacity and scarce quality resources. Remote mining areas struggle to attract and retain qualified trainers. Frontline technical experts lack pedagogical skills, while external instructors lack understanding of mining operations.

4 Path Design of AI Agent-Empowered Mining Training

Based on the theoretical review and challenge analysis above, this study proposes an "AI-agent-as-hub" training empowerment framework[4,10] comprising four core modules. As shown in Figure 1.

4.1 Module 1: Generation of Adaptive Learning Paths

AI agents construct multi-dimensional learner profiles based on position information, historical training records, and learning behavior data, automatically generating personalized learning paths. The technical implementation relies on the semantic understanding of large language models and the structured reasoning of knowledge graphs:

mining enterprises vectorize and store safety regulations, operation manuals, and incident case databases; agents match learner needs through RAG-based semantic retrieval, then perform topological sorting based on prerequisite dependencies in the knowledge graph to ensure cognitively logical learning sequences[5]. The agent provides a dual mechanism of "recommended path + self-selection," continuously monitoring progress and adjusting recommendations accordingly.

4.2 Module 2: Immersive Scenario Simulation

VR/XR technology can reproduce the sensory experience of underground disaster scenarios, while AI agents inject "instructional intelligence" into immersive experiences[11]. The agent plays three roles: (1) scenario director—dynamically adjusts scenario difficulty based on the learner's proficiency level to ensure the learner remains in the ZPD[5]; (2) scaffolding provider—offers moderate clues rather than direct answers when learners encounter difficulties; (3) reflection guide—generates post-simulation review reports with decision timelines, critical node selections, and error attribution analyses. The XR smart safety training practice at Jiulishan Coal Mine demonstrated that employees' risk perception of irregular operations increased by approximately 60%, the time for mastering core vocational skills was shortened by 30–50%, and average emergency decision-making speed rose by 35%.

4.3 Module 3: Multi-Agent Collaborative Training

This module deploys three categories of agents working in coordination: a teaching agent responsible for content presentation and key point explanation; a coaching agent simulating real-scenario interactions to elicit performance and provide immediate feedback; and an evaluation agent conducting multi-dimensional scoring and diagnostic analysis of operational performance. Taking "gas inspector" training as an example, the coaching agent simulates an underground patrol scenario and poses questions; learner responses are assessed in real time, and structured feedback is provided. This cycle of "scenario questioning–performance elicitation–immediate feedback" represents a vivid application of Gagné's instructional events theory[4] in an AI-agent environment. The Beisen CoolCollege AI Learning platform[3], which integrates five collaborative agents, reported that a new energy vehicle enterprise's professional assessment pass rate increased from 65% to 99.5% after adopting AI collaborative training, providing compelling evidence for the efficacy of multi-agent coaching systems.

4.4 Module 4: Intelligent Closed-Loop Training Data System

AI agents construct a "training–execution–evaluation–improvement" closed-loop system, recording multi-dimensional learning behavior data, generating learner competency radar charts and knowledge weakness heat maps, and feeding diagnostic results back to the learning path and scenario simulation modules for dynamic iteration. Based on Gagné's taxonomy of learning outcomes[4], a five-dimensional evaluation framework is established: verbal information (safety regulation knowledge mastery), intellectual skills (fault diagnosis accuracy and speed), cognitive strategies (emergency decision-making rationality and timeliness), motor skills (equipment operation standardization), and attitudes (safety behavior compliance and active reporting rate).

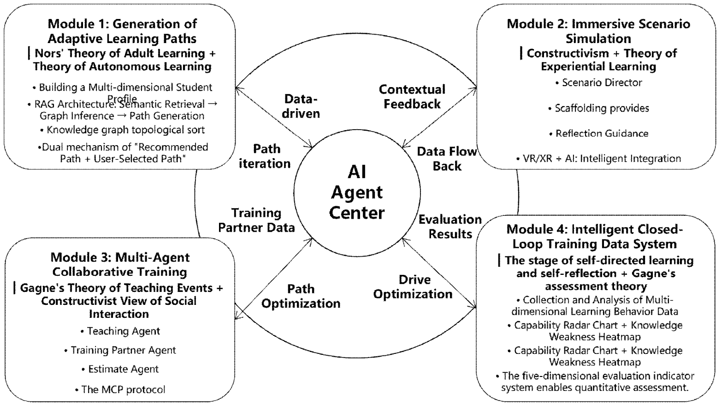

Fig. 1. Path Design Framework Diagram (Written by the author)

5 Controlled Experiment Design and Empirical Validation

To validate the effectiveness of the proposed framework, a 12-week quasi-experimental study was conducted across three coal mining enterprises using a pretest–post test control group design.

5.1 Experimental Design

Participants. Three coal mining enterprises were selected from northwestern and southwestern China, encompassing both state-owned and private mines. Approximately 40 miners were randomly sampled from each mine across three core positions—excavation, electromechanical, and ventilation—yielding a total of 120 participants. After stratification by mine, miners within the same position were randomly assigned to the experimental group (n=122) and the control group (n=118). The two groups showed no significant differences in age, years of service, educational attainment, or position distribution (p>0.05).

Experimental treatment. The experimental group received the complete AI-agent-empowered training framework, including: adaptive learning path delivery (2–3 times per week, 15–30 minutes per session); VR + AI-agent immersive emergency drills (once every two weeks, 45 minutes per session); AI coaching agent dialogue-based skill training (available for self-paced use daily); and intelligent data-feedback loop (real-time personalized reinforcement task delivery). The control group continued with the enterprises' existing training model, including centralized classroom lectures, video-based learning, paper-based examinations, and master-apprentice on-site instruction.

Measurement instruments and indicators. Based on the five-dimensional evaluation framework proposed in Section IV, a Mining Training Competency Assessment Scale was developed (Cronbach's α=0.87), comprising 5 dimensions and 16 secondary indicators. Unified assessments were administered before training (Week 0) and after training (Week 12). Additionally, safety behavior records and position skill assessment scores were tracked during the training period.

5.2 Experimental Results

Comparison of pre- and post-test scores across five dimensions. The experimental group showed significant improvement across all five dimensions after training, whereas the control group exhibited only marginal improvement in safety regulation knowledge. The detailed results are presented in Table 1.

Table 1. Comparison of Pre- and Post-Test Scores Across Five Dimensions (M±SD)

Dimension	Exp. Pre-test	Exp. Post-test	Ctrl. Pre-test	Ctrl. Post-test
Safety regulation knowledge	62.3±8.1	86.7±6.3	61.8±7.9	68.2±8.4
Fault diagnosis accuracy	45.2±10.3	78.6±8.7	44.9±9.8	52.1±10.2
Emergency decision-making soundness	38.7±9.5	74.3±7.9	39.2±9.1	47.6±9.4
Equipment operation standardization	52.1±11.2	81.4±7.2	51.6±10.8	58.3±10.6
Safety behavior compliance	58.6±9.7	85.2±5.8	57.9±10.1	63.8±9.2

A 2 (group: experimental/control) × 2 (time: pretest/post test) repeated-measures ANOVA revealed that the group × time interaction effects were significant across all five dimensions (F range: 18.7–47.3, $p<0.001$, η^2 range: 0.06–0.15), indicating that the experimental group's improvement was significantly greater than that of the control group. The interaction effect was strongest for emergency decision-making soundness ($F=47.3$, $\eta^2=0.15$), suggesting that AI-agent scenario simulation is most effective in enhancing emergency decision-making competency.

Comparison of composite competency improvement. After standardizing and summing the five-dimensional scores, the experimental group's composite improvement was 24.6 points, compared with 8.2 points for the control group—a 3.0-fold difference ($t=12.4$, $p<0.001$, Cohen's $d=1.32$, indicating a large effect size).

Safety behavior tracking data. During the training period (Weeks 1–12), the experimental group accumulated 7 safety violation incidents, versus 23 for the control group. The monthly violation rate was 0.36 per 100 persons for the experimental group versus 1.17 for the control group, a statistically significant difference ($\chi^2=8.93$, $p<0.01$). The experimental group's average position skill assessment pass rate was 91.4%, compared with 72.6% for the control group ($p<0.01$).

Position-specific effect differences. Further stratified analysis revealed that AI-agent training was most effective for ventilation position miners (composite improvement: 29.8 points), followed by excavation (23.7 points) and electromechanical (20.4 points).

Interviews indicated that ventilation training content has a higher proportion of emergency decision-making and regulatory execution tasks, which aligns closely with the core advantages of AI-agent scenario simulation and coaching.

5.3 Discussion of Results

The experimental results validate the effectiveness of the AI-agent empowerment framework at three levels. First, the comprehensive improvement across five dimensions confirms the theoretical coherence of the framework—adaptive paths address the fragmented learning needs under work–learning conflicts, scenario simulation compensates for the absence of operational practice contexts, AI coaching achieves scalable one-on-one feedback, and the data feedback loop ensures continuous iterative optimization. Second, the largest gain in the emergency decision-making dimension corresponds precisely to the weakest aspect of traditional training—the inability to conduct live drills for underground disaster scenarios—where AI-agent scenario simulation plays an irreplaceable role. Third, the safety behavior tracking data demonstrate that training effects have migrated from "test scores" to "behavioral changes," achieving a substantive transformation from knowledge retention to competency Internalization[10].

It should be noted that this study has certain limitations. First, although this study moves beyond the prior conceptual framework by incorporating a quasi-experimental design[12] across three mining enterprises, the number of participating enterprises remains limited, and more systematic empirical validation across a larger number of mining enterprises with rigorously controlled experimental designs is needed to strengthen the generalizability of the findings. Second, the experimental period was 12 weeks, and long-term effects require further tracking; the participating mines were all voluntary, which may introduce selection bias. Third, differences in technical infrastructure across mining areas may have affected the consistency of experimental treatment. Future research could extend the tracking period, enlarge the sample size, and incorporate process data (e.g., learning duration, interaction frequency) for mediation analysis.

6 Implementation Framework for AI Agent-Empowered Mining Training

(1) Technical architecture. The architecture comprises three layers: an infrastructure layer including large language model backbones (supporting localized deployment), vector databases, mining knowledge graphs, and learner data warehouses; an intelligent service layer deploying various functional agents coordinated via MCP protocol; and an application interaction layer supporting PC, mobile, and VR device access.

(2) Phased implementation pathway. Phase I (3–6 months): pilot validation, starting with AI knowledge retrieval Q&A and VR safety training modules deployed at 1–2 mining areas for the first 50–100 employees. Phase II (6–12 months): deepening expansion, developing position-specific agent training modules and constructing knowledge graphs and learner profiles. Phase III (1–2 years): full integration, deeply

connecting the agent training system with safety management and HR systems to build a comprehensive intelligent training ecosystem.

(3) Key safeguards. These include: data security and privacy protection, supporting localized deployment and data desensitization; content quality control through a three-tier "AI generation–expert review–knowledge base ingestion" mechanism; change management through top-down promotion combined with bottom-up experiential engagement; and continuous iteration with regular technology stack updates aligned with the latest model capabilities and industry standards.

7 Conclusion

Drawing on educational theories, this study has systematically demonstrated the theoretical legitimacy and practical feasibility of AI-agent-empowered mining training, constructed a training empowerment framework comprising four core modules, and validated it through a quasi-experimental study involving 120 miners across three coal mining enterprises. The experimental results show that AI-agent training significantly outperforms traditional training across five dimensions—safety regulation knowledge, fault diagnosis, emergency decision-making, equipment operation, and safety behavior—with a composite competency improvement 3.0 times that of the control group and a 69% reduction in safety violation rates. AI agents do not simply replace traditional training; rather, they restructure the training ecosystem through a human–AI collaboration paradigm—enabling agents to handle standardized, data-intensive tasks while human trainers focus on creative, affective, and complex activities—shifting mining training from "standardized inculcate" to "precision empowerment," from "knowledge retention assessment" to "behavioral competency evaluation," and from "one-time events" to "sustained growth."

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References

1. Ministry of Education et al. "Artificial Intelligence + Education" Action Plan[Z]. 2026. http://www.moe.gov.cn/srcsite/A16/s3342/202604/t20260410_1433240.html
2. PwC. 2026 AI Business Predictions[R]. Price water house Coopers, 2026.
3. Beisen CoolCollege. Next-generation AI Learning platform launch: Enterprise learning enters the Agents era[EB/OL]. 36Kr, 2026-05-21. https://www.coolcollege.com/original-news/2284.html

4. Abuhassna H, Alnawajha S. Instructional design made easy! Instructional design models, categories, frameworks, educational context, and recommendations for future work[J]. European Journal of Investigation in Health, Psychology and Education, 2023, 13(4): 715-735. DOI: 10.3390/ejihpe13040054.
5. Sweller J. Cognitive load theory and the curriculum[M]//Research Handbook on Curriculum and Education. Cheltenham: Edward Elgar, 2024: 155-166. DOI: 10.4337/9781802208542.00017.
6. Dinç Uyaroğlu İ, Caner Yüksel Ç. Experiential learning in basic design studio: Body, space and the design process[J]. International Journal of Art & Design Education, 2021, 40(3): 508-525. DOI: 10.1111/jade.12364.
7. Broadbent J, Sharman S, Panadero E, et al. How does self-regulated learning influence formative assessment and summative grade? Comparing online and blended learners[J]. The Internet and Higher Education, 2021, 50: 100805. DOI: 10.1016/j.iheduc.2021.100805.
8. Guntur M I S, Budiarto B. A meta-analysis of the efficacy of self-regulated learning interventions on academic achievement in online and blended environments in K-12 and higher education[J]. Behaviour & Information Technology, 2023, 42(8): 741-758. DOI: 10.1080/0144929X.2022.2151935.
9. Anvari F, Kievit R, Lakens D, et al. Not all effects are indispensable: Psychological science requires verifiable lines of reasoning for whether an effect matters[J]. Perspectives on Psychological Science, 2022, 17(6): 1723-1738. DOI: 10.1177/17456916221091565.
10. Hu W, Hu Y, Lyu Y, et al. Research on integrated innovation design education for cultivating the innovative and entrepreneurial ability of industrial design professionals[J]. Frontiers in Psychology, 2021, 12: 693216. DOI: 10.3389/fpsyg.2021.693216.
11. Saris B, Doyle S, Loveridge J. Analysing creative design process: A set of tools to understand activity in its socio-cultural and historic context[J]. International Journal of Art & Design Education, 2023, 42(3): 439-453. DOI: 10.1111/jade.12467.
12. Nianogo R A, Benmarhnia T, O'Neill S. A comparison of quasi-experimental methods with data before and after an intervention: An introduction for epidemiologists and a simulation study[J]. International Journal of Epidemiology, 2023, 52(5): 1522-1534. DOI: 10.1093/ije/dyad032.