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Innovative teaching practice in vocational education using smart technology: A case study of cement production course

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Abstract
To address the shortcomings of traditional vocational education in terms of practical engagement and interactivity, this study focuses on the course raw material preparation and cement production. An innovative instructional model was designed and implemented, integrating virtual simulation, immersive virtual reality (VR) experiences, and a smart learning platform. Built around a four-stage process–train-learn-compete-evaluate–the model emphasizes task-driven learning and competency-based development. The platform records students' operational behavior in real time, enabling full-process, visualized, and data-driven teaching management and precise performance assessment. Teaching practices have shown that this model significantly improves students' hands-on skills, learning initiative, and professional competence, while enhancing instructors' ability to deliver targeted feedback in a timely manner. The results provide a replicable and scalable instructional framework for advancing curriculum reform in vocational education under the smart education paradigm.

Keywords: virtual simulation instruction, immersive VR learning, smart learning platform, vocational education teaching model

INTRODUCTION

Vocational education plays a pivotal role in supporting regional economic development and facilitating industrial transformation, particularly through the cultivation of highly skilled technical talent. As intelligent manufacturing continues to evolve, enterprises are placing greater demands on workers' hands-on abilities, adaptability to job roles, and capacity to handle complex working conditions. This trend necessitates a shift in vocational curricula toward stronger practice orientation, realistic scenario simulation, and alignment with actual job requirements, enabling students to gain work experience that closely mirrors real-world industrial environments during their studies (Zhang & Leong, 2024).

However, many vocational colleges are currently constrained by limited training resources and rely heavily on traditional, lecture-based teaching methods. These teacher-centered approaches, where students passively receive information, have proven insufficient in equipping learners with the practical skills and professional competencies required by modern industry. In cement production–related courses, for example, core procedures often involve high risk, strong technical complexity, and intricate workflow, factors that make it difficult for traditional instruction to effectively replicate authentic industrial contexts (Li et al., 2024). As a result, students often lack hands-on experience, and instructional outcomes are significantly hindered.

To address these challenges, this study focuses on the course raw material preparation and cement production and proposes an innovative instructional model that integrates virtual simulation, immersive virtual reality (VR) experiences, and a smart teaching platform. The model emphasizes three key elements: task-oriented learning, technological integration, and process-based assessment (Wang & Huang, 2019). Structured around a four-phase cycle, train-learn-compete-evaluate, it establishes a fully integrated, data-driven teaching management framework. This research aims to validate the model's practicality and scalability for high-risk

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Contribution to the literature

- This study introduces a structured four-phase instructional model that integrates virtual simulation, immersive VR, and smart teaching technologies for vocational engineering education.
- Empirical results demonstrate that the model significantly improves students' engagement, operational skills, and professional competence in high-risk, process-intensive learning environments.
- The study provides a scalable and replicable framework that supports data-driven instructional design and contributes to ongoing reform efforts in competency-based vocational education.

engineering courses, while exploring how smart learning environments (SLEs) can enhance students' operational skills, learning initiative, and professional development. The findings contribute a replicable and transferable instructional paradigm to ongoing vocational education reform efforts in engineering disciplines.

LITERATURE REVIEW

With the rapid advancement of technologies such as artificial intelligence (AI), VR, and big data, vocational education is undergoing a significant transformation, from knowledge transmission to competency development (Muñoz-García & Villena-Martínez, 2021). This shift is especially critical in high-risk, process-intensive, and operation-heavy engineering courses, where enhancing immersion, interactivity, and visualization through technological means has become a key research priority. Existing studies have explored various aspects of SLEs, virtual simulation systems, immersive VR instruction, and pedagogical reform, laying a theoretical and technical foundation for the construction of integrated teaching models.

Smart Learning Environments and Data-Driven Instructional Mechanisms

SLEs integrate technologies such as the Internet of things, AI, and learning analytics to create learner-centered ecosystems. By capturing learning data in real time and enabling dynamic modeling, SLEs support intelligent resource delivery, personalized learning path design, and precise instructional interventions. Studies have shown that SLEs can significantly enhance student motivation, learning efficiency, and engagement sustainability (Muñoz-García & Villena-Martínez, 2021). Benita et al. (2021) designed a smart learning ecosystem that incorporates data-driven thinking into STEM education by integrating real-time data visualization, adaptive feedback, and collaborative tools to strengthen students' analytical and decision-making abilities.

Application of Virtual Simulation in Engineering Instruction

Virtual simulation technology provides high-fidelity interactive environments that overcome limitations related to space, time, and safety in traditional teaching. It has been widely adopted across disciplines such as mechanical engineering, electrical engineering, civil engineering, and chemical engineering. Its benefits are especially pronounced in replicating complex industrial workflows. Sun and Yang (2022) reviewed VR-based health and safety training across high-risk engineering industries, concluding that immersive environments significantly enhance hazard recognition, risk perception, and learner engagement compared to traditional methods.

Immersive Virtual Reality Technology and Spatial Cognition Development

VR technology, with its high level of immersion, interactivity, and controllability, introduces a transformative experience in vocational education. It is particularly effective in courses involving complex structures, spatial reasoning, and safety risk identification. Zhao et al. (2020) demonstrated that immersive VR training in construction safety significantly improved learners' hazard perception and task coordination skills. Liu et al. (2020) highlighted that both augmented reality (AR) and VR technologies play a critical role in improving engagement, operational understanding, and hands-on performance in industrial maintenance training.

Evolution of Pedagogical Models: From Teacher-Centered to Learner-Centered

Modern vocational education is shifting from teacher-centered to learner-centered approaches. action-oriented learning and project-based learning emphasize competency development through authentic or simulated tasks, integrating learning, practice, and evaluation into a unified instructional process. Models such as the "learn-practice-evaluate" loop, the "train-learn-compete-evaluate" process, and competency-based feedback mechanisms have increasingly been adopted in vocational classrooms, demonstrating strong adaptability and future potential (Li & Leong, 2024; Or, 2024). These approaches encourage active participation, collaborative learning, and diversified assessment strategies aligned with industry expectations.

In summary, significant progress has been made in SLEs, virtual simulation systems, VR-based instructional practices and pedagogical model reforms are paving the way for more integrated and future-oriented vocational education systems. However, from a systems integration perspective, the coordinated fusion of SLEs, virtual simulation, and immersive VR into a structured, data-driven instructional process remains in the exploratory phase. This is especially true in high-risk, workflow-intensive engineering courses such as those related to cement production, where empirical studies and practical implementations remain limited (Kilroy et al., 2023). In response, this study takes the raw material preparation and cement production course as a case, proposing a new instructional model that integrates smart platforms, virtual simulation, and VR technologies, and evaluates its effectiveness in enhancing students' technical skills and professional competence through real-world teaching practice.

TEACHING MODEL DESIGN

This course is designed with a competency-based instructional philosophy, targeting students in material science and construction-related vocational programs. It closely aligns with the operational requirements of central control positions in the cement industry, establishing a comprehensive teaching system supported by smart technologies and centered on real-world tasks.

Instructional Objectives

The course objectives span three key dimensions: knowledge acquisition, skills development, and professional competence:

1. **Knowledge objectives:** Students are expected to understand the fundamental theories of raw material preparation, clinker production, and cement finishing processes, as well as become familiar with the structure of critical equipment and process flows.
2. **Skill objectives:** Learners will develop the ability to independently carry out raw material proportioning, operate key machinery, analyze production workflows, and identify and troubleshoot common faults.
3. **Professional competence objectives:** The course aims to instill a strong sense of operational safety, quality control awareness, and 6S workplace management principles, fostering students' adaptability to job roles and their capacity for problem-solving in industrial contexts.

Instructional Content and Task Design

Following the "**work process systematization**" approach, the course content is organized into task modules that reflect key stages of cement production. Examples include "cold start-up of the vertical mill," "diagnosis and recovery of kiln tail malfunctions," and "control of cement packaging process." These modules emphasize hands-on, task-based learning and promote the transformation of theoretical knowledge into practical competencies.

Task design follows a progressive learning structure: "**basic understanding → skills training → problem-solving → practical application**", which supports students in transitioning from conceptual learning to workplace proficiency (Middleton, 2020).

As shown in **Figure 1**, the task framework spans the entire production process, from raw material intake to finished product dispatch. The modular structure ensures that each task is embedded within a coherent industrial workflow, helping students build systematic knowledge and operational proficiency in authentic production contexts.

To ensure effective implementation of these instructional tasks, the course is supported by a comprehensive technological framework that includes a virtual simulation system, an immersive VR environment, and a smart teaching platform. These tools provide precise, stage-specific support through high-fidelity simulation, real-time behavioral tracking, and adaptive instructional feedback, creating an intelligent teaching ecosystem tailored to the needs of vocational learners (Benita et al., 2021).

Instructional Platform Architecture and Technical Support

The course is supported by a tri-integrated smart teaching platform, with each component serving distinct instructional functions in skills training, scenario simulation, and performance evaluation:

1. **Virtual simulation system:** This system covers the entire cement production process, enabling control of workflows, parameter adjustment, and fault simulation. It primarily supports the "train" phase by facilitating targeted skills training (Megía Cardeñoso, 2024).
2. **Immersive virtual reality system:** Designed to replicate the operational environment of an actual cement plant, this system enhances students' spatial awareness and job immersion during the "learn" and "compete" phases (Bühler et al., 2022).
3. **Smart teaching platform:** This component spans the full instructional cycle, including before, during, and after class, and supports the "evaluate" phase by enabling data tracking, performance analysis, and personalized feedback.

The three platforms operate in a coordinated manner, delivering comprehensive, full-process, and multi-dimensional technical support for the "train-learn-compete-evaluate" instructional model.

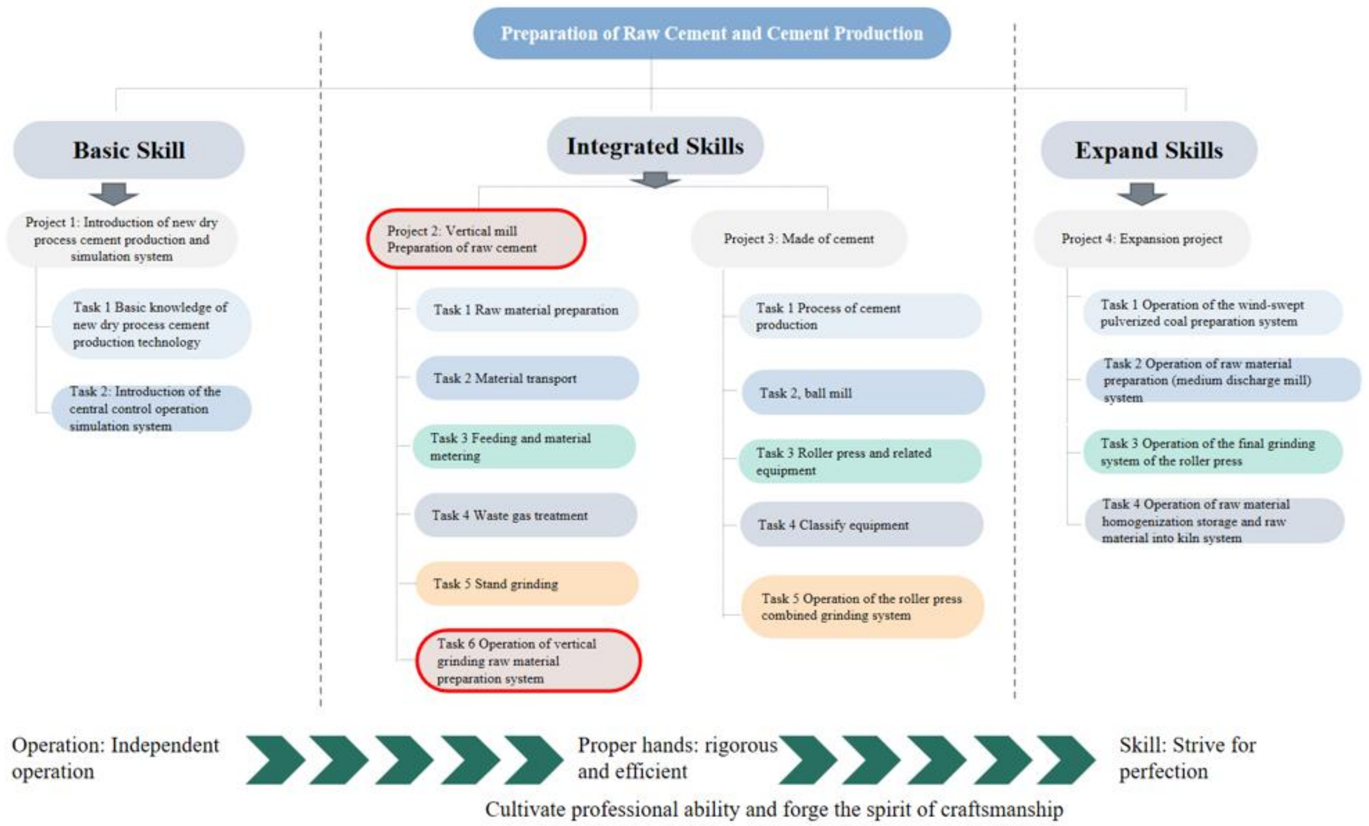


Figure 1. Modular design of representative operational tasks in the course (Source: Authors' own elaboration)

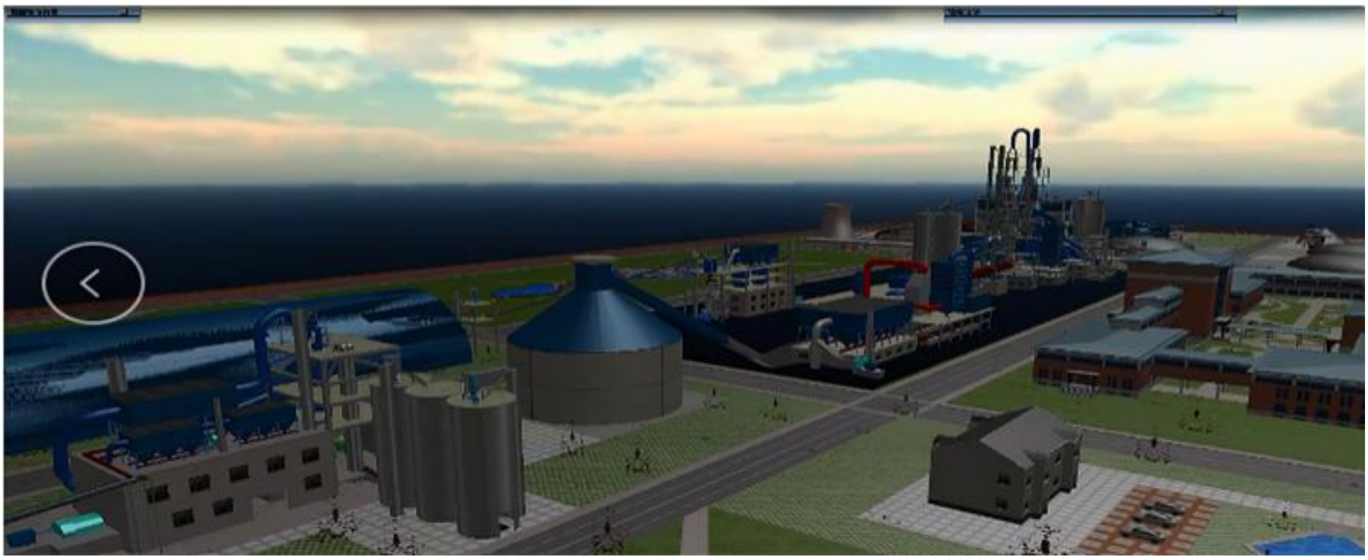


Figure 2. Virtual simulation system interface 1–Cement plant overview (Source: Authors' own elaboration)

Virtual simulation teaching system: Supporting skills training in the "train" phase

Developed using the Unity3D engine, the virtual simulation system covers the entire cement production process, including raw material intake, grinding, preheating, calcination, cooling, and packaging. It enables process control, parameter adjustment, fault simulation, and multi-role interaction, creating a high-fidelity, low-risk, and high-frequency training environment. Students can repeatedly practice critical operations without safety risks, enhancing their understanding of equipment structures and process flows.

As shown in **Figure 2**, the system presents a 3D virtual plant with key components such as raw material silos, rotary kilns, and control rooms–helping students build a holistic view of the production workflow. **Figure 3** illustrates the interactive interface of the vertical mill system, offering an immersive experience for cold start-up procedures and process adjustments.

Figure 3. Virtual simulation system interface 2–Raw material preparation subsystem (Source: Authors' own elaboration)

Figure 4. VR-enhanced learning scenario in a virtual cement production environment (Source: Authors' own elaboration)

This platform serves as the foundational environment for skills acquisition and operational proficiency during the "train" phase, marking the essential starting point for task-based instruction.

Immersive virtual reality system: Enhancing perception and task practice in the "learn-compete" phases

The VR system is built upon a digital twin model of the cement plant, reconstructing a highly realistic 3D production environment. It addresses the limitations of traditional instruction in spatial cognition, job role immersion, and high-risk scenario training. Using standalone VR headsets, students can engage in guided activities such as inspection, equipment checks, process navigation, and interactive operations (Sepasgozar et al., 2024).

As illustrated in **Figure 4**, students are immersed in first-person, dynamic simulations of cement production, reinforcing their understanding of complex processes and operational details. The system is particularly effective for concept clarification in the "learn" phase and task simulation in the "compete" phase, enhancing learners' sense of job immersion, problem identification skills, and emergency response coordination.

This platform is designed to solve three key challenges of traditional instruction:

1. **Access denied:** Due to plant safety restrictions.
2. **Cannot see:** Internal equipment structures are difficult to visualize.
3. **Cannot touch:** High-risk operations cannot be practiced physically.

Smart teaching platform: Driving data-driven evaluation in the "evaluate" phase

The smart teaching platform spans the entire teaching process, before, during, and after class, and integrates features such as micro-lesson delivery, learning behavior tracking, stage-based assessments, peer/instructor evaluation, and AI-based feedback. It supports a combination of formative and diagnostic assessment mechanisms.

The platform captures students' operational behaviors across all learning phases in real time, generating learning archives, competency profiles, and process analytics. As shown in **Figure 5**, the system architecture aligns with the four instructional stages–train-learn-compete-evaluate–creating a closed-loop data feedback system. This provides teachers with accurate instructional insights and enables students to receive personalized learning suggestions and progress tracking.

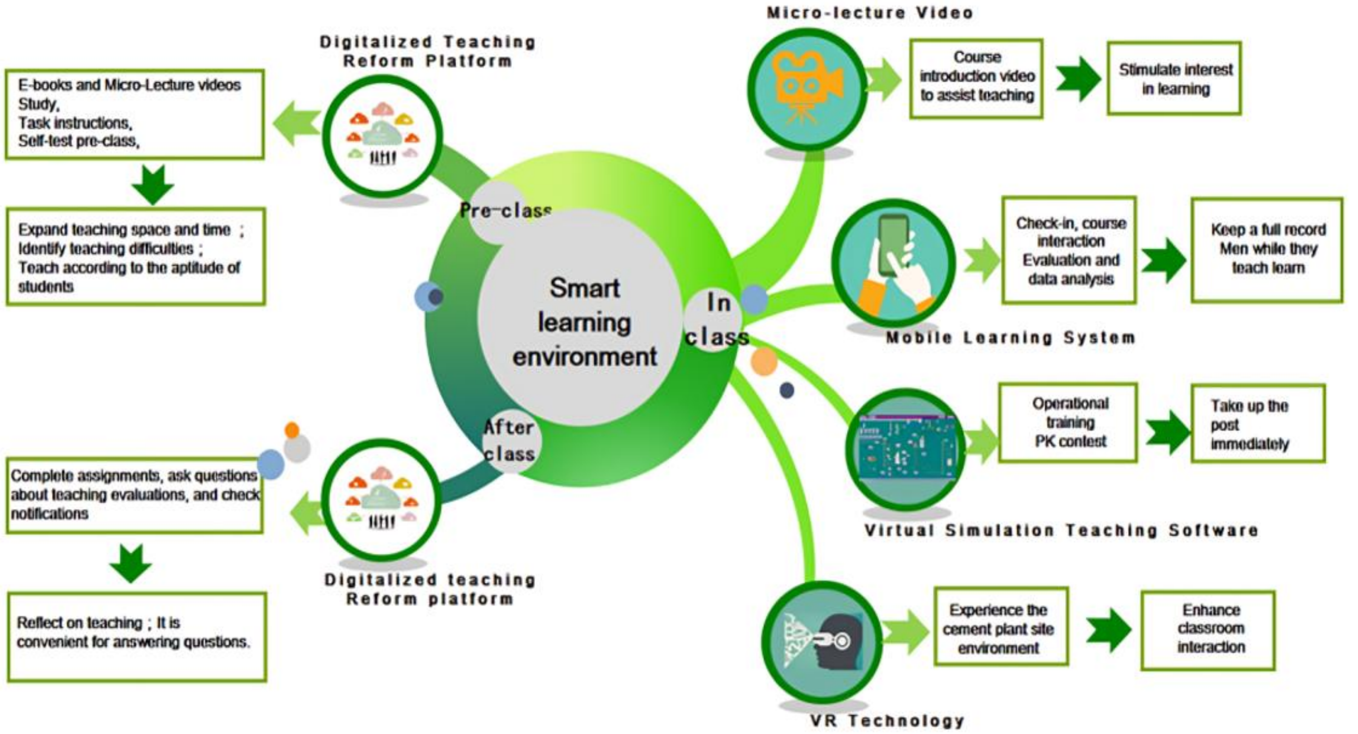


Figure 5. Smart teaching platform structure aligned with the "train-learn-compete-evaluate" cycle (Source: Authors' own elaboration)

The smart teaching platform serves as the core support tool during the "evaluate" phase, providing essential technological infrastructure for full-process visualized instruction and learning outcome optimization (Yazdi, 2024).

In summary, the three platforms work in synergy within the "train-learn-compete-evaluate" instructional framework, each fulfilling distinct roles: the virtual simulation system enhances skills training, the VR system reconstructs authentic industrial scenarios, and the smart platform enables closed-loop data analysis. Together, they ensure the structured execution of the entire teaching process, forming an intelligent instructional system characterized by rational structure, technological integration, and transparent procedures.

Building upon this system design, the next section will provide a detailed explanation of the implementation of each instructional phase and the corresponding technological support mechanisms.

RESEARCH METHODOLOGY

To ensure research transparency, this study adopted a mixed-methods design combining quantitative and qualitative approaches.

Participants

A total of 72 students participated in the raw material preparation and cement production course across two cohorts (2023 and 2024). The 2023 cohort primarily received traditional instruction, while the 2024 cohort was taught using the smart instructional model. Both cohorts were comparable in entry GPA, demographic background, and program structure, ensuring sample homogeneity.

Data Collection

Three main data sources were used:

(1) operational logs automatically recorded by the simulation platform (task completion rates, error frequencies, and operation time),

(2) expert evaluations of task performance using rubrics developed by three cement-engineering instructors with over ten years of experience, and

(3) post-class satisfaction and perceived-improvement questionnaires.

Data Analysis

Descriptive statistics summarized student engagement and task performance. Inferential statistics, including independent-samples t-tests and one-way ANOVA, were applied both to compare the 2023 and 2024 cohorts (longitudinal analysis) and to contrast the smart instructional model with traditional instruction (cross-sectional analysis). Effect sizes (Cohen's d, η^2) were calculated to quantify the magnitude of improvements. Questionnaire reliability was verified (Cronbach's alpha = 0.89), and inter-rater reliability of expert scoring was assessed (Cohen's $\kappa = 0.82$).

Table 1. Instructional workflow and support matrix

Instructional phase	Teaching focus	Core activities	Supporting technology
Train	Skill acquisition through simulation	Equipment operation drills, parameter adjustment, fault handling	Virtual simulation system
Learn	Cognitive development and scenario analysis	Process flow interpretation, spatial structure recognition	Immersive VR system
Compete	Task execution and problem solving	Simulated job tasks, troubleshooting, peer competition	VR system + smart teaching platform
Evaluate	Feedback and personalized improvement	Behavior tracking, learning analytics, competency profiling	Smart teaching platform (data analytics)

Figure 6. Training phase: Operational simulation scenario (Source: Field study)

Figure 7. Learning phase: Interactive instructional session (Source: Field study)

Theoretical Basis

The use of real-time behavioral data aligns with the learning analytics paradigm, while the competency assessment framework is consistent with competency-based education widely adopted in vocational training.

TEACHING IMPLEMENTATION

This course adopts a four-phase, task-driven instructional strategy based on the "train-learn-compete-evaluate" model. It establishes a closed-loop pathway that spans process cognition, collaborative problem-solving, task-based practice, and data-driven feedback, reflecting the core pedagogical logic of task orientation, data support, and competency development (Li & Leong, 2024).

Instructional Workflow and Support Matrix

Table 1 shows the instructional workflow and support matrix.

Key Implementation Strategies for Each Instructional Phase

Train: Process cognition and operational practice

In the initial phase, students complete representative operational tasks–such as the cold start-up of the vertical mill and kiln head temperature adjustments–using the virtual simulation system. The system automatically records their operation paths and error frequencies. Based on this data, instructors provide targeted explanations and reinforce key operational points (**Figure 6**).

Learn: Problem-guided inquiry and deep learning

Using data from the "train" phase, instructors analyze common issues and explain equipment linkages and fault mechanisms via interactive interfaces. Students engage in group discussions and explore related digital learning resources to deepen their understanding of critical process concepts (**Figure 7**).

Compete: Practical drills and competency activation

Building on prior knowledge, students work in teams to complete task competitions involving injected fault scenarios that require emergency handling and process recovery. The platform scores team performance based on task completion efficiency, response time, and operational accuracy, enhancing both collaborative skills and adaptive capabilities (**Figure 8**).

Evaluate: Multi-dimensional diagnostics and precision feedback

The smart teaching platform automatically generates individual competency profiles and radar charts reflecting students' operational patterns, performance growth curves, and weak points. This enables instructors to adjust teaching strategies while supporting student

Figure 8. Competition phase: Group-based operational drill (Source: Field study)

self-regulation. A peer and instructor evaluation mechanism is also incorporated to promote reflective thinking and enhance the granularity of feedback (**Figure 9** and **Figure 10**).

This model not only increases student engagement but also encourages instructors to continuously refine their strategies, enabling more effective alignment between teaching resources and student capabilities.

Integrated Instructional Environment and Classroom Transformation

Through the seamless connection of the "train-learn-compete-evaluate" phases, students experience a complete transformation from knowledge acquisition to skills training and contextual decision-making within virtual simulation and immersive VR environments. This approach shifts classroom instruction away from traditional lectures toward a data-driven, scenario-based, feedback-rich participatory learning model, significantly improving students' spatial cognition, operational autonomy, and professional competency.

EVALUATION AND RESULTS

Analysis of Student Engagement

The instructional experiment involved 72 students, with the platform automatically recording individual learning behaviors and generating digital learner

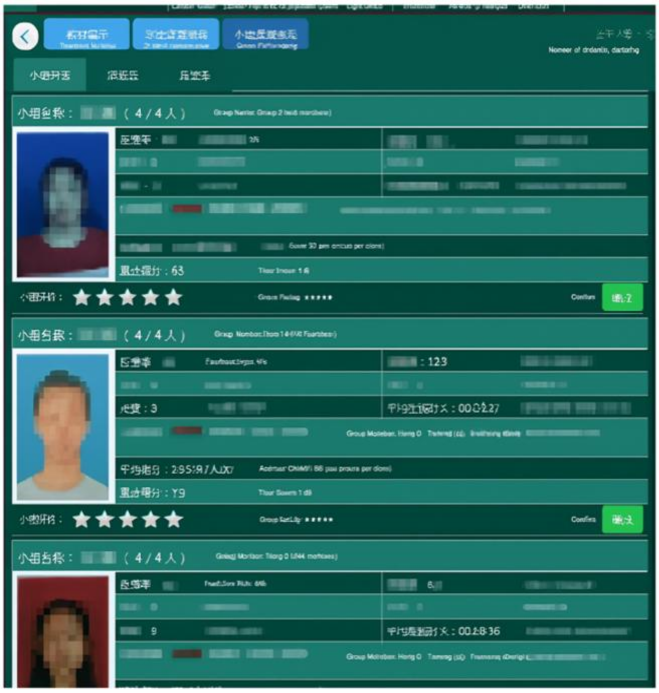
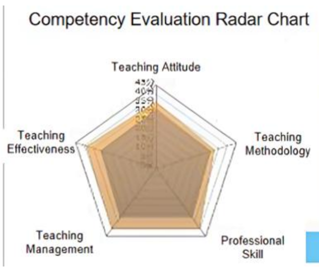


Figure 9. Evaluation phase: Group reporting and peer assessment interface (Source: Authors' own elaboration)

profiles. Analysis of engagement revealed several key findings:

1. Over 95% of students completed pre-class simulation training, with an average of more than 18 operations per student.
2. More than 80% actively participated in class discussions and group collaboration, demonstrating enhanced learning initiative.
3. The VR-based activities received highly positive feedback, significantly improving spatial cognition and job-role understanding.
4. The "compete" and "evaluate" phases effectively stimulated students' sense of challenge and self-reflection.

These findings are further supported by visualized learning data generated by the platform, as shown in **Figure 11** and **Figure 12**. The reports illustrate task completion rates, operation time logs, and performance distribution, providing instructors with real-time, data-driven insights to inform instructional decisions.



Item	Score	Overall Avg	Rank
Teaching Attitude	36.00	32.00	2
Teaching Methodology	33.00	30.33	2
Professional Skill	40.00	32.67	1
Teaching Management	40.00	32.67	1
Teaching Effectiveness	39.00	39.001	1

Figure 10. Multi-dimensional instructor evaluation dashboard based on student feedback (Source: Authors' own elaboration)

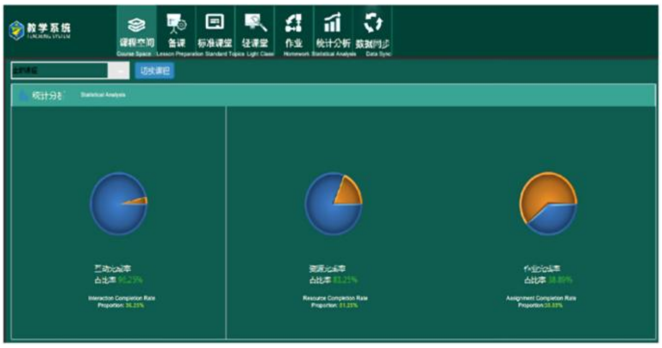


Figure 11. Student engagement and task completion in pre-class activities (Source: Authors' own elaboration)

Competency Development Outcomes

Inferential statistical analyses were conducted to evaluate the differences between the 2023 and 2024 cohorts. As summarized in **Table 2**, the 2024 cohort (using the smart instructional model) achieved significantly higher task completion rates and longer self-study times, while error rates were substantially lower. Independent-samples t-tests and one-way ANOVA confirmed these differences as statistically significant ($p < 0.01$), with large effect sizes for task achievement and moderate effect sizes for error reduction.

Challenges Identified and Suggested Improvements

Some students demonstrated insufficient preparation for pre-class tasks; therefore, a push-notification reminder mechanism is recommended.

The instructional flow required finer coordination, as dynamic group strategies were underutilized.

The platform's data visualization capabilities should be more effectively leveraged through teacher usage guides to maximize the impact of data-driven teaching.

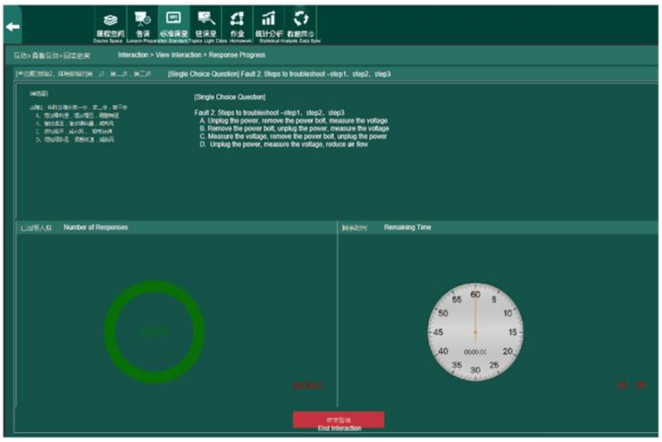


Figure 12. Post-class testing statistics interface (Source: Authors' own elaboration)

Comparative Analysis with Traditional Instruction

To complement the cohort comparison, a cross-sectional analysis was conducted between smart instruction and traditional instruction. As shown in **Table 3** and **Figure 13**, the smart instructional model consistently outperformed traditional teaching across five indicators. Task achievement rates and satisfaction scores were markedly higher, while error rates were lower. Students also reported longer self-study times and significantly higher simulation participation.

In summary, the dual-perspective evaluation provides consistent evidence: **Table 2** validates longitudinal improvements across cohorts, while **Table 3** confirms the superiority of the smart instructional model in a cross-sectional comparison. Together, these findings demonstrate the robustness and replicability of the proposed teaching approach.

Table 2. Comparative statistics of competency outcomes between the 2023 and 2024 cohorts

Indicator	Cohort (M ± SD) (2023)	Cohort (M ± SD) (2024)	t/F value	p-value	Effect size
Task achievement rate (%)	68.4 ± 6.2	90.6 ± 4.7	$t(70) = 14.22$	< 0.001	$d = 1.92$
Error rate (%)	12.5 ± 3.1	5.3 ± 2.4	$F(1, 70) = 11.35$	< 0.010	$\eta^2 = 0.14$
Self-study time (h/week)	4.8 ± 1.0	6.8 ± 0.9	$t(70) = 3.47$	< 0.010	$d = 0.81$

Note. Values are presented as mean ± standard deviation (M ± SD); Effect sizes are reported as Cohen's d for t-tests and η^2 for ANOVA; & A larger effect size indicates a stronger practical impact

Table 3. Comparative statistics of competency outcomes between the smart instructional model and traditional instruction

Indicator	Smart instruction (M ± SD)	Traditional instruction (M ± SD)	t/F value	p-value	Effect size
Task achievement rate (%)	90.6 ± 4.7	68.4 ± 6.2	$t(70) = 12.45$	< 0.001	$d = 1.75$
Error rate (%)	5.3 ± 2.4	12.5 ± 3.1	$F(1, 70) = 10.68$	< 0.010	$\eta^2 = 0.13$
Self-study time (h/week)	6.8 ± 0.9	4.8 ± 1.0	$t(70) = 3.92$	< 0.010	$d = 0.82$
Satisfaction score (%)	94.6 ± 3.8	78.3 ± 5.2	$t(70) = 8.21$	< 0.001	$d = 1.45$
Simulation participation (%)	98.6 ± 2.1	85.0 ± 4.6	$t(70) = 6.77$	< 0.001	$d = 1.20$

Note. Values are presented as mean ± standard deviation (M ± SD); Effect sizes are reported as Cohen's d for t-tests and η^2 for ANOVA; & Statistically significant differences ($p < 0.010$) were observed across all indicators, consistently favoring the smart instructional model

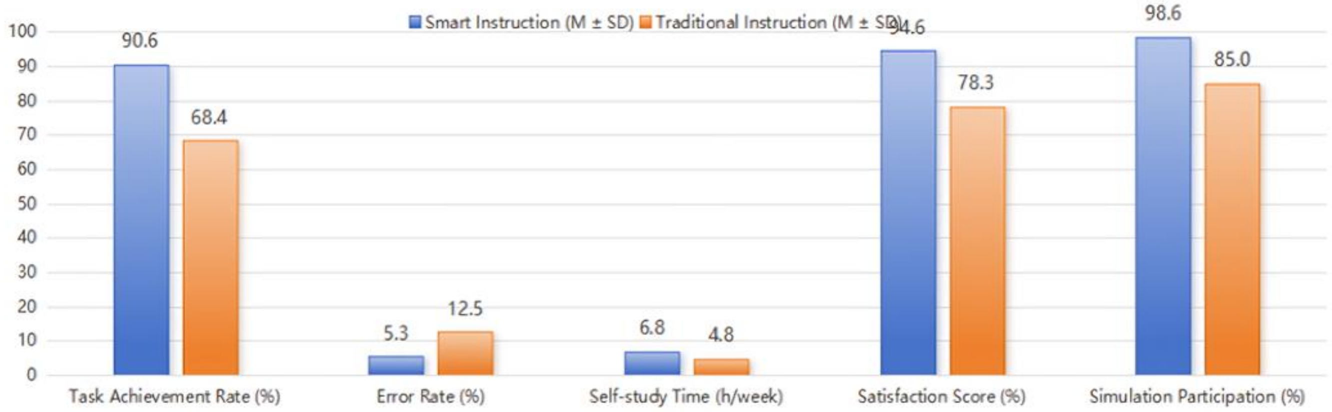


Figure 13. Comparative analysis of competency outcomes under smart instructional model and traditional instruction (Source: Authors' own elaboration)

DISCUSSION

The proposed "train-learn-compete-evaluate" model, integrating virtual simulation, immersive VR, and a smart teaching platform, effectively addresses shortcomings of traditional vocational education, particularly the lack of practice, weak interactivity, and delayed feedback. The model significantly improves student engagement and competency achievement.

Recent studies further validate the effectiveness of immersive VR and smart learning platforms in vocational education. For instance, Yazdi (2024) demonstrated that AR/VR-based maintenance training improved learners' fault detection accuracy and reduced error rates, while Zhao et al. (2020) confirmed that immersive VR environments significantly enhanced learners' safety awareness in construction tasks (Kumbo et al., 2024). In parallel, Gligorea et al. (2023) reviewed AI-driven adaptive learning systems and highlighted their role in improving personalized learning behaviors, and Younas et al. (2025) further emphasized that AI-powered smart platforms can foster adaptive and self-regulated learning in vocational contexts. The present findings align with these studies but extend them to the domain of cement production. By embedding VR and simulation into a structured four-phase instructional cycle, this study contributes to theories of situated learning and cognitive load reduction, while offering practical guidance for task-driven vocational curricula.

Innovation and Value for Replication

This study represents the first successful integration of the four-phase instructional model with a tri-platform smart teaching ecosystem in cement-related vocational courses. Key contributions include:

1. Establishing a complete instructional loop spanning pre-class, in-class, and post-class activities, enabling gradual skill accumulation and application.
2. Enhancing task orientation and scenario immersion through VR experiences to deepen process understanding and systems thinking.
3. Introducing data-driven strategies for process visualization, real-time adjustment, and controlled assessment.
4. Empowering instructors to dynamically adapt instructional content, pacing, and feedback delivery based on performance analytics.

Challenges and Limitations

1. **Technical:** High hardware requirements for VR; platform stability issues under multi-user operation.
2. **Instructor readiness:** Some faculty lack full mastery of system functions, presenting a usability barrier.
3. **Institutional:** Long development cycles for simulation content; limited mechanisms for cross-institutional resource sharing.

Several indicators, such as student satisfaction and perceived improvement, were based on self-reported questionnaires. While useful, such data are prone to response bias and social desirability effects. To mitigate this limitation, surveys were conducted anonymously, independently of grading procedures, and triangulated with behavioral logs recorded by the platform.

Strategies for Future Optimization

To enhance the system and support broader adoption, the following strategies are proposed:

1. Integrate AI-based behavior analytics to support learning path prediction and personalized task recommendations.
2. Develop a shared regional simulation resource bank to encourage institutional collaboration and reuse.

3. Establish a dual-capacity model to enhance both teacher digital fluency and platform utilization skills.
4. Construct a 3D evaluation framework encompassing skills, cognition, and innovation, transitioning from behavioral assessment to capability modeling.

Overall, this model shows broad potential for replication in high-risk, process-intensive engineering courses, providing a scalable solution for vocational education's intelligent transformation.

Another limitation is the short-term scope of this study. While immediate improvements were observed, it remains uncertain whether these gains can be sustained (Leong, 2025). Future research will include longitudinal follow-ups, such as 3-6 month re-assessments, to evaluate knowledge retention, skill transfer, and long-term professional competency.

CONCLUSION

This study addresses the urgent need to cultivate compound technical talent in vocational education by implementing a novel "train-learn-compete-evaluate" instructional framework. By integrating a self-developed virtual simulation system, an immersive VR environment, a smart teaching platform, a data-driven, controllable, and practice-oriented smart teaching ecosystem was established.

Experimental results show substantial improvements in student engagement, operational skills, and professional competence. Moreover, a comparative analysis with the previous cohort reveals marked gains: the task achievement rate increased by 22.2%, the average operational error rate dropped by over 7 percentage points, and participation in simulation and discussion activities significantly improved. These quantitative results confirm the replicability and effectiveness of the model.

The model successfully overcomes long-standing challenges in traditional teaching, such as lack of visibility, restricted access, and weak interactivity. It marks a shift from teacher-centered to learner-centered instruction and enables dynamic instructional refinement through real-time data feedback.

Despite these advancements, challenges remain in terms of equipment cost, teacher training, and resource sharing. Future research will explore AI-assisted personalized learning, 3D assessment frameworks, and cross-institutional simulation resource platforms to further expand application scenarios and promote scalable implementation across disciplines.

Author contributions: YL: conceptualization, data curation, formal analysis, investigation, methodology, project administration, software, validation, visualization, writing – original draft; **WYL:** conceptualization, resources, supervision, writing – review & editing; **HZ:** data curation, investigation, methodology, software, visualization. Both authors agreed with the results and conclusions.

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Ethical statement: The authors stated that the study involved regular instructional activities, anonymized learning logs, and standard educational surveys. No medical procedures, sensitive personal data, or vulnerable populations were involved. According to the institutional guidelines of Heilongjiang Institute of Construction Technology and INTI International University, such educational research is exempt from formal ethics committee approval. All participants were informed of the study purpose, participation was voluntary, and all data were anonymized prior to analysis.

AI statement: The authors stated that generative AI tools (e.g., ChatGPT) were not used to generate or analyze research data. They were employed only for language polishing and minor grammatical editing during manuscript preparation. All interpretations, analyses, and conclusions were produced entirely by the authors.

Declaration of interest: No conflict of interest is declared by the authors.

Data sharing statement: Data supporting the findings and conclusions are available upon request from the corresponding author.

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