Region-Educational Research and Reviews, 2025,Volume 7, Issue 8
DOI:10.32629/rerr.v7i8.4466
ISSN Online:2661-4634
ISSN Print:2661-4626

Integration of Smart Teaching Technologies in Catalyst Skills Instruction for Vocational Education an Empirical Study

Zhiqiang Xu*, Hongmei Yin, Zhengyong Yu

Jiangsu Vocational College of Electronics and Information, Huaian, jiangsu, 223003, China

Abstract: Vocational education cultivates catalyst-skill chemical talents, but traditional instruction faces three issues: abstract microscale concepts (e.g., catalytic active sites), high equipment costs (XRD: 50k–200k), and limited hands-on training (8–10 students/share device, <5 min individual operation). This study proposes an integrated smart framework (VR/AR + virtual simulation + big data) and validates it via a quasi-experiment with 98 vocational chemical students (experimental: 50; control: 48). Results: (1) Experimental group's theoretical score (82.5 ± 6.3) > control (75.3 ± 7.1, $p < 0.01$), 20% higher catalytic mechanism accuracy; (2) 25% faster Ni/Al_2O_3 preparation (45 ± 5 min vs. 60 ± 8 min), 30% higher parameter precision (pH: ±0.2 vs. ±0.5), 21.7% higher BET (185 ± 12 m^2/g vs. 152 ± 15 m^2/g, meeting Sinopec's ≥180 m^2/g); (3) 85% experimental group reported high interest vs. 52% control ($p < 0.001$). This framework bridges theory-practice gaps, offering a replicable model for vocational chemical education.

Keywords: Vocational Education, Catalyst Instruction, VR/AR, Virtual Simulation, Big Data Analytics

1. Introduction

1.1 Background and Industry Demand

Driven by the EU Green Deal and China's "Dual Carbon" goals, the global chemical industry's low-carbon transition boosts demand for catalyst-skill talents (catalysts core to hydrogenation, oxidation, environmental catalysis) (ICCA, 2023)[1]. OECD (2023)[2] notes over 40% of chemical enterprises cite insufficient catalyst operation skills as a bottleneck, especially in emerging economies with limited vocational resources.

Traditional catalyst instruction has three limitations: (1) Microscale concepts (e.g., ZSM-5 pores, Pt/Al_2O_3 distribution) are hard to visualize—only 45% of vocational students explain pore size-reactant diffusion vs. 72% university students with tools (Bodde et al., 2022)[3]; (2) High equipment costs (XRD: 50k–200k, fixed-bed reactors: 10k–30k) force demonstration-only experiments; (3) "One-size-fits-all" teaching fails to address heterogeneous student needs.

Smart technologies (VR/AR, virtual simulation, big data) offer solutions, but existing studies focus on general disciplines (mechanical maintenance, nursing), lacking exploration in catalyst instruction (unique intersection of chemical principles, equipment operation, industrial scenarios). This study fills this gap.

1.2 Literature Review and Research Gaps

UNESCO (2024)[4] reports VR/AR reduces cognitive load for abstract concepts by 30–40%, virtual simulation improves skill retention by 25–35% (Smetana & Bell, 2023)[5], and big data identifies learning bottlenecks with >85% accuracy, boosting efficiency by 25% (Romero & Ventura, 2010; Zhang et al., 2024)[6,7].

Three gaps: (1) No integrated frameworks—most use single tools (e.g., VR for structure teaching) instead of "theory-practice-application"; (2) Insufficient objective validation—few use lab-verified data (BET, XRD) vs. self-reports; (3) Limited industry collaboration—resources rarely align with enterprise standards (e.g., Sinopec's catalyst regeneration).

1.3 Research Objectives and Significance

Objectives: (1) Develop an integrated smart framework for catalyst instruction; (2) Validate via quasi-experiment (theoretical, practical, motivation metrics); (3) Propose industry-academia collaboration strategies.

Significance: Theoretically, extends constructivist/situated learning theories to catalyst instruction; practically, provides a replicable model to improve teaching quality and address talent shortages.

2. Theoretical Framework and Research Methods

2.1 Theoretical Foundations

Framework grounded in three theories: (1) Constructivist Theory (Piaget, 1970)[8]: Knowledge built via interaction—VR/AR/simulation create "cognitive scaffolds" (e.g., 3D Pt/Al_2O_3 models); (2) Situated Learning Theory (Lave & Wenger, 1991)[9]: Emphasizes authentic contexts—virtual simulations replicate industrial scenarios (e.g., reactor troubleshooting per Sinopec's Q/SH 3035-2024); (3) Personalized Learning Theory (Bloom, 1984)[10]: Tailored instruction—big data identifies deficits (e.g., poor XRD interpretation) to address the "2 sigma problem".

2.2 Framework Design

Three interconnected modules

2.2.1 VR/AR Concept Visualization

VR: Unity3D-developed (Pico 4 Pro, 3664×1920) for catalyst structures (ZSM-5, $Cu/ZnO/Al_2O_3$) and mechanisms (Langmuir-Hinshelwood). Students zoom/rotate 3D models, simulate molecular adsorption, with real-time annotations.

AR: Superstar AR (0.1mm accuracy) overlays virtual info—scanning XRD images triggers animations, precipitation flowcharts provide feedback (e.g., "pH >9 reduces surface area").

2.2.2 Virtual Simulation Training

Co-developed with a university in Nanjing (WebGL-based): Catalyst Preparation: Adjust pH (4–10) and calcination temperature (300–800°C) with real-time performance prediction;

Reactor Operation: Simulate 1L fixed-bed benzene hydrogenation with 5 faults (coking, flow fluctuation) and troubleshooting;

Data Analysis: Interpret simulated XRD/SEM/BET data with instant feedback.

2.2.3 Big Data Personalized Support

Data Collection: 12 metrics from Superstar LMS (VR usage, simulation accuracy, quiz scores);

Analytics: Python models (deficit classification: 89.2% accuracy; recommendation: precision@5=0.78);

Intervention: Tailored resources and weekly 30-minute tutoring for high-risk students.

2.3 Research Design

2.3.1 Participants

98 second-year vocational students (Jiangsu, China): Experimental ($n=50$, smart teaching); Control ($n=48$, traditional: 48h lectures + 16h shared lab). Pre-study prerequisite scores showed no difference (Physical Chemistry: 76.2±5.8 vs. 75.8±6.1, $p=0.78$; Chemical Engineering Principles: 74.5±6.3 vs. 73.9±5.9, $p=0.65$).

2.3.2 Intervention and Evaluation

16-week intervention (64h total). Experimental group time: VR/AR (12h), simulation (24h), lectures (20h), tutoring (8h).

Metrics:

Theoretical Exam: 100-point ($\alpha=0.87$) covering concepts (40pt), XRD (30pt), design (30pt);

Practical Test: 300-point (inter-rater reliability=0.92) covering preparation, fault handling, operation;

Motivation Survey: 20-item Likert ($\alpha=0.89$) measuring interest, relevance, confidence.

2.3.3 Statistical Analysis

SPSS 26.0/R 4.3.1: Independent t-tests, Cohen's d ($d>0.8$=large effect), $p<0.05$.

3. Results

3.1 Theoretical Knowledge

Experimental group outperformed control ($p<0.01$). Total score (82.5±6.3) was 7.2 points higher (d=1.14). Largest gap: catalytic mechanism accuracy (70.0±8.5% vs. 50.0±10.2%, d=2.13). XRD interpretation: 22.1±2.8 vs. 16.5±3.1 (30pt, d=1.87), 82% vs. 56% correct zeolite phase identification.

3.2 Practical Skills

3.2.1 Catalyst Preparation

Experimental group: 45±5 min (25% faster than control's 60±8 min, t=9.82, $p<0.001$, d=2.01). 30% higher precision (pH: ±0.2 vs. ±0.5; temperature: ±5℃ vs. ±10℃). BET: 185±12 m^2/g (21.7% higher than control's 152±15 m^2/g, t=9.12, $p<0.001$), meeting Sinopec's Q/SH 3165-2024 (≥180 m^2/g)[11, 12].

3.2.2 Reactor Fault Handling

Response time: 5.0±0.8 min (37.5% faster than control's 8.0±1.2 min, t=13.54, $p<0.001$, d=2.83). Diagnosis accuracy: 92.0±5.3% vs. 68.0±7.8% (t=16.21, $p<0.001$); coking faults: 95.0±4.1% vs. 62.0±8.3% (d=4.68).

3.2.3 Instrument Operation

XRD time: 8±1.5 min (46.7% shorter than control's 15±2.3 min, t=16.87, $p<0.001$, d=3.52). Overall instrument score: 85.2±6.7 vs. 68.5±7.4 (t=11.03, $p<0.001$, d=2.30).

3.3 Learning Motivation

Experimental group scored higher ($p<0.001$). 85% high interest (≥4/5) vs. 52% control. Job relevance: 4.3±0.5 vs. 3.0±0.7 (d=2.06); operational confidence: 4.1±0.7 vs. 2.8±0.9 (d=1.68); 82% vs. 43% agreed smart tools reduced equipment anxiety.

4. Discussion

4.1 Key Findings and Mechanisms

VR/AR resolves abstract barriers: 20% higher mechanism accuracy aligns with UNESCO's (2024) cognitive load reduction—3D visualization makes intangible concepts interactive.

Simulation optimizes skills: 25% faster preparation and 34% higher fault accuracy from "deliberate practice" (Ericsson et al., 1993)[13]—virtual training enables repeated adjustment, leading to industrial-standard performance.

Big data enables personalization: Targeted resources reduced XRD deficits (73.7% vs. 55% accuracy), validating Bloom's (1984) theory—data identifies gaps traditional assessments miss.

4.2 Advantages Over Prior Studies

Holistic integration: VR/AR (concepts) → simulation (practice) → big data (personalization), unlike single-tool studies;

Industrial alignment: Incorporates Sinopec's standards, bridging "school-industry" gaps;

Objective metrics: Uses lab-verified data (BET, XRD time) vs. self-reports, enhancing credibility.

4.3 Limitations and Future Work

Single-college sample: Multi-center studies (n>200) needed for generalizability;

Short-term focus: 6–12-month internship tracking for skill retention;

Cost barriers: Test low-cost VR (Google Cardboard) for scalability;

AI integration: Add generative AI chatbots for real-time troubleshooting (Zawacki-Richter et al., 2019)[14].

4.4 Practical Implications

Institutions: Adopt modular components and share resources to cut costs by 40–50%;

Industry: Contribute production data (deactivation curves) to update simulations;

Policymakers: Prioritize funding (align with China's 2024–2027 Vocational Education Digital Plan).

Conclusions

This study validates an integrated smart framework for vocational catalyst instruction. It improves theoretical mastery (7.2-point increase), practical proficiency (25% faster operation), and motivation (33% higher interest). The framework extends constructivist/situated learning theories to chemical education and provides an industry-aligned model. Future work will scale via multi-center studies and integrate generative AI.

Funding:

The authors are grateful for the supports provided by the Youth Fund Project of Jiangsu Vocational College of Electronics and Information (grant number JSEIZYB202403), the General Project of Philosophy and Social Science Research in Jiangsu Universities in 2025 (grant number 2025SJYB1436), the Second Batch of High-Level Professional Group Sub-Projects in Jiangsu Province - Mold Design and Manufacturing Professional Group (grant numbers XGQ-460113-JG-202503 and XGQ-460113-ZK-202516), the 2025 School-Level Teaching Construction and Reform Project of Jiangsu Vocational College of Electronics and Information (grant number JX-JG-202514), the 2025 Annual Jiangsu Provincial Educational Science Planning Project (Project title: Research on the Reconstruction and Practice Path of Intelligent Teaching Paradigm in Vocational Education Empowered by AI), and the "Qinglan Project" Excellent Teaching Team Funding Project of Jiangsu Province.

References

[1] ICCA. Innovation for a Sustainable Future: The Role of Chemicals [R]. Brussels: International Council of Chemical Associations, 2023.

[2] OECD. OECD Skills Outlook 2023: Skills for a Resilient Green and Digital Transition [R]. Paris: OECD Publishing, 2023.Bodde, S., et al.

[3] Virtual reality in chemistry education: A review of the application and research landscape[J]. Journal of Chemical Education, 2022, 99(9), 3160-3170.

[4] UNESCO. Global Education Monitoring Report 2023: Technology in education [R]. Paris: UNESCO, 2023.

[5] Smetana, L. K., Bell, R. L. Using virtual labs in science education: A systematic review[J]. Journal of Science Education and Technology, 2023, 32(2), 195-214.

[6] Romero, C., Ventura, S. Educational data mining: a review of the state of the art[J]. IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), 2010, 40(6): 601-618.

[7] Zhang, Q., et al. Learning analytics and educational data mining: An overview[J]. Computers and Education: Artificial Intelligence, 2024, 6, 100200.

[8] Piaget, J. Genetic Epistemology [M]. New York: Columbia University Press, 1970.

[9] Lave J., Wenger E. Situated Learning: Legitimate Peripheral Participation [M]. Cambridge: Cambridge University Press, 1991.

[10] Bloom, B. S. The 2 Sigma Problem: The Search for Methods of Group Instruction as Effective as One-to-One Tutoring[J]. Educational Researcher, 1984, 13(6), 4–16.

[11] Xu Z ,Liu W ,Yu Z , et al.Advances and Challenges in Catalyst Dense-Phase Packing Technology: A Review[J].Catalysts,2025,15(3):222-222.

[12] Sinopec Group. *Technical Specification for Hydrogenation Catalysts (Q/SH 3165-2024)* [S]. Beijing: Sinopec Publ House, 2024.

[13] Ericsson, K. A., Krampe, R. T., & Tesch-Römer, C. The role of deliberate practice in the acquisition of expert performance[J]. Psychological Review, 1993, 100(3), 363–406.

[14] Zawacki-Richter, O., et al. Systematic review of research on artificial intelligence applications in higher education – where are the educators?[J]. International Journal of Educational Technology in Higher Education, 2019, 16(1), 39.

Corresponding Author Bio:

Zhiqiang Xu (1999 -), male, Han nationality, Huai'an, Jiangsu Province, Master's degree, teaching assistant, research interests: vocational education, mechanical engineering