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Cultivating design creativity of vocational students: A model of project-based learning in AI-enabled immersive virtual environments

Shuaizhen Jin [1], Zheng Zhong [1,2] *, Xu Cao [1] and Wenzhuo Zhang [1]

*Correspondence:
zhongzheng@ccnu.edu.cn
National Engineering Research Center for E-learning, Central China Normal University, No. 152 Luoyu Road, Wuhan 430079, Hubei, China
Full list of author information is available at the end of the article

Abstract

This study integrates the advantages of an AI-enabled immersive virtual environment (AI-IVE), characterized by stereoscopic immersion, embodied engagement, intelligent interaction, and real-time feedback, with the features of project-based learning (PBL), including inquiry, collaboration, and active participation. We propose a PBL in AI-IVE (AI-IVE-PBL) model, structured around four key dimensions: teachers, students, agents, and teaching phases. The study pursued two objectives: (1) to conceptualize and articulate the AI-IVE-PBL model, and (2) to provide initial empirical evidence of its effectiveness through a two-group quasi-experimental evaluation. A quasi-experiment conducted in a vocational college in Fuzhou, China, implemented this model in the Public Space Interior Design course to examine its impact on students' design creativity, learning engagement, and learning experience. The results indicate that, relative to traditional PBL (T-PBL), the AI-IVE-PBL model significantly enhances learning outcomes by fostering sustained idea-developing discourse (SIDD), as demonstrated by: (1) a marked improvement in students' design ability and creative ability; (2) a substantial increase in both cognitive and behavioral engagement; (3) a pronounced elevation in learning motivation and satisfaction accompanied by a reduction in cognitive load. Findings from this study contribute to advancing design creativity among vocational students and provide valuable insights for the innovation of pedagogical strategies in vocational education.

Keywords: AI-enabled immersive virtual environment, project-based learning, vocational education, design creativity, sustained idea-developing discourse

Introduction

In today's digital economy, cultivating innovative talent is a key objective of higher vocational education (Luengo-Aravena et al., 2024). Design creativity, a core competency, enables vocational students to integrate theory with practice and gain professional advantage (Chang et al., 2022). However, traditional vocational education, characterized by monotonous instruction and repetitive methods, often limits students' cognitive capacity, reasoning, and knowledge transfer, reinforcing rigid cognitive patterns that hinder creativity (Cox & Prestridge, 2020; Kovalchuk et al., 2022).

Immersive Virtual Environments (IVEs) provide authentic contexts for inquiry, collaboration, and knowledge transfer (Makransky & Petersen, 2021; Zhong et al., 2022). Yet pre-scripted scenarios restrict adaptation to students' evolving needs, limit real-time feedback, and fragment learning, resulting in shallow interaction and poor knowledge construction (Herrera-Pavo, 2021; Zhao & Zhao, 2022). Recent advances in large language models have enabled AI teaching assistants to provide real-time guidance, feedback, and motivation (Gill et al., 2024; Song, 2024). When integrated into IVEs, they form AI-Enabled IVEs (AI-IVEs) that combine immersive contexts with adaptive knowledge generation and cognitive scaffolding. AI-IVEs dynamically create learning scenarios, support multilayered sustained idea-developing discourse (SIDD), which refers to the continuous and collaborative refinement of ideas, and enhance learner-content interaction. These affordances deepen students' conceptual understanding and stimulate innovative thinking (Bekteshi, 2025; Jin et al., 2024).

Project-based learning (PBL) engages students in authentic problem-solving and promotes creative and practical skills (Eswaran, 2024). However, traditional PBL (T-PBL) frequently encounters challenges such as limited resources, difficulties in replicating realistic scenarios, and delayed scaffolding (Mutanga, 2024). AI-IVEs address these challenges by providing blended virtual and physical contexts supported by AI-driven cognitive interaction. They offer intelligent assistance during needs analysis, solution design, and prototype validation, thereby supporting problem-solving, empirical inquiry, and creative design (Fleury et al., 2021; Khodabandeh, 2022). Despite these advantages, research on PBL in AI-IVE (AI-IVE-PBL) remains limited, and the mechanisms through which it enhances design creativity have not been sufficiently explored. Accordingly, this study positions the AI-IVE-PBL model as its primary contribution and adopts a two-phase research logic guided by a design-oriented rationale. First, we theoretically propose, conceptualize, and operationalize the AI-IVE-PBL instructional model by aligning AI-IVE affordances (e.g., stereoscopic immersion, embodied engagement, intelligent interaction, and real-time feedback) with PBL pedagogy to support SIDD. Second, we conduct an initial empirical evaluation through a two-group quasi-experiment to examine whether implementing AI-IVE-PBL yields measurable advantages over T-PBL in design creativity, learning engagement, and learning experience. By integrating model construction with evidence-based testing, this study aims to contribute a novel pedagogical framework for vocational design creativity and provide initial empirical insights into its efficacy in authentic classroom settings.

To avoid terminological ambiguity, this paper uses AI-IVE to denote the AI-enabled immersive virtual environment as a technological environment. In this study, it also refers to the AI-IVE teaching platform described in the Experimental environment subsection. By contrast, AI-IVE-PBL denotes the instructional model implemented within AI-IVE, specifying the orchestration of PBL phases and the role relations among teachers, students, and AI agents to support SIDD. The AI-IVE-PBL model was intentionally designed to align with the platform's affordances and was conceptualized and operationalized prior to the quasi-experimental evaluation; accordingly, the experiment evaluates the effectiveness of the AI-IVE-PBL implementation rather than the platform in isolation.

Literature review

Sustained idea-developing discourse in AI-IVEs

SIDD is a key indicator of deep learning and creative thinking. It emphasizes cohesive, in-depth, and collaborative engagement around core issues (Hong & Sullivan, 2009). Rooted in knowledge construction and collaborative innovation, SIDD promotes the continuous evolution of ideas and systematic knowledge building rather than superficial information exchange (Scardamalia & Bereiter, 2021). Traditional IVEs often rely on static, pre-configured scenarios with limited branching and insufficient event-based feedback, making it difficult to meet diverse cognitive needs (Khan, 2024). Consequently, SIDD remains superficial, with fragmented discussions and poor integration of knowledge.

Recent design-based research shows that generative AI can transform superficial dialogues into deeper cognitive collaboration (Hong et al., 2025). AI-IVEs integrate GenAI-powered assistants with IVEs to provide intelligent situational responses, dynamic guidance, and collaborative meaning construction (Jin & Zhong, 2026). Cognitively, AI teaching assistants use layered questioning strategies aligned with Bloom's taxonomy, guiding students from factual recall to creative exploration (Baxter & Hainey, 2024). For instance, they may start with functional decomposition questions, then use defect-reversal prompts for critical reflection, and finally introduce cross-domain questions to inspire breakthroughs. This scaffolding sustains productive discourse and gradually builds a structured knowledge framework (Sikström et al., 2024). Technologically, AI-IVEs enhance SIDD continuity through real-time knowledge integration and team coordination. Using natural language processing and knowledge graphs, AI assistants identify conceptual links, recommend relevant knowledge modules, and foster divergent thinking (Qin & Zhang, 2025). Dynamic grouping algorithms and shared virtual workspaces facilitate collaborative modeling and annotation, reducing coordination conflicts and enabling collective intelligence to converge into innovative outcomes.

Cultivating design creativity of vocational students in AI-IVEs

Creativity was first defined by Guilford (1950) as rooted in divergent thinking. In creative industries, vocational students must demonstrate strong design creativity across areas such as product fabrication and artistic design (Bilan et al., 2019). Design creativity is typically defined as the ability to synthesize knowledge, transcend conventions, and generate innovative solutions that are both novel and practical (Chang et al., 2022).

Vocational students often face weak foundational knowledge and low confidence, making art and design courses appear challenging (Xue, 2023). Traditional instruction, characterized by one-way transmission and insufficient feedback, exacerbates difficulties in integrating disciplines and developing creativity (Jiang et al., 2024). AI-IVEs provide a promising solution by combining high-fidelity virtual contexts with intelligent cognitive support. Embodied learning mechanisms in IVEs allow students to gain experiential knowledge, such as simulating furniture assembly to develop spatial awareness and attention to detail (Tilhou et al., 2020). AI teaching assistants analyze sketches and proposals in real time, generate interdisciplinary knowledge maps, and support the integration of aesthetic and technical considerations (Gill et al., 2024). Teachers can use AI-IVE to design progressive tasks that mirror real-world projects, track students' interactions, and provide timely Socratic questioning to guide conceptual development (Kennedy, 2021). Multimodal interaction, including voice commands, gesture recognition, and haptic feedback, encourages full sensory participation, stimulating creativity across artistic, functional, and technological dimensions. Developing design creativity therefore requires not only new learning environments but also a shift from efficiency-oriented instruction toward innovation-driven pedagogy (Pusic et al., 2018). Well-designed strategies in AI-IVE, such as PBL, can strengthen SIDD, support iterative knowledge construction, and enhance students' creative output (Cacciamani et al., 2021).

PBL in AI-IVEs

PBL is a widely applied constructivist pedagogy that uses authentic and complex driving questions to provoke cognitive conflict and promote active knowledge construction (Jumaat et al., 2017). It positions students as protagonists, teachers as facilitators, and emphasizes the coherence and systematicity of knowledge. Through the reorganization of disciplinary content into interconnected project tasks, PBL encourages independent inquiry, collaborative teamwork, and situated engagement, ultimately supporting the development of higher-order thinking skills (Jabli, 2024; Žerovnik & Nančovska Šerbec, 2021). Despite these advantages, T-PBL faces practical challenges, particularly for vocational students who often have weaker self-regulation and lower motivation. Limited access to equipment, difficulties in replicating real-world scenarios, and time-consuming teacher guidance can lead to low collaboration efficiency and superficial project outputs (Reynolds et al., 2013).

Students may resort to rote execution, resulting in designs that lack creativity or cultural depth. Beyond creativity-related outcomes, vocational learning also critically depends on students' learning engagement and learning experience, including sustained motivation, learning satisfaction, and manageable cognitive demands, which may be challenging to maintain throughout extended project work (Niittylahti et al., 2023; Nouwen et al., 2022). This suggests that evaluating AI-IVE-PBL should consider not only design creativity but also whether it supports vocational students' ongoing engagement and positive learning experiences over time. At the same time, it is important to recognize that collaboration quality is also shaped by group-process and knowledge-related conditions that technology cannot inherently guarantee. Socio-motivational issues such as social loafing, unequal participation, and limited accountability may persist even when immersive environments facilitate communication, and differences in prior knowledge and emerging misconceptions may still constrain shared understanding and design decision-making. Therefore, effective AI-IVE-PBL implementation requires not only immersive technological affordances but also deliberate instructional orchestration and process scaffolding to sustain meaningful discourse and timely feedback throughout design work.

Integrating PBL with AI-IVEs offers a way to overcome these constraints. AI-IVE-PBL creates blended virtual–physical contexts where students explore open-ended scenarios while completing structured project tasks. Immersive environments allow them to freely manipulate spatial elements and access a rich repository of materials and tools, which expands opportunities for experimentation and imagination (Adera, 2025). Crucially, AI teaching assistants provide multimodal data collection and analysis to generate detailed cognitive profiles, detect learning obstacles, and deliver immediate scaffolding and information resources. This ensures that guidance is precise and timely, enabling students to sustain SIDD, engage in iterative design refinement, and challenge existing cognitive frameworks (Meng et al., 2023). Through these processes, AI-IVE-PBL supports deep collaboration, persistent idea development, and creative transformation of knowledge. Students learn to navigate real and complex problems, acquire practical skills, and enhance their ability to generate innovative design solutions. The integration of AI-IVE with PBL thus represents not only a technological enhancement but also a paradigm shift in vocational pedagogy, offering a scalable approach for cultivating creativity in resource-constrained teaching environments.

Research objectives and questions

Building upon the existing theoretical and empirical research, this study centers on the cognitive attributes of vocational students and the requirements for the development of design creativity. It harnesses the dynamic cognitive guidance aspect of SIDD within the AI-IVE to construct the AI-IVE-PBL model. Accordingly, this study specifies two objectives. The primary objective is to conceptualize and articulate the AI-IVE-PBL model and its operational workflow for cultivating vocational students' design creativity. The secondary objective is to provide initial empirical evidence by evaluating the model through a two-group quasi-experimental comparison (AI-IVE-PBL vs. T-PBL). Based on these objectives, the research questions are:

RQ1: Compared with T-PBL, what is the impact of AI-IVE-PBL on the design creativity (innovative thinking, design ability, creative ability) of vocational students?

RQ2: Compared with T-PBL, how does AI-IVE-PBL affect the learning engagement (cognitive engagement, behavioral engagement, affective engagement) of vocational students?

RQ3: Compared with T-PBL, how does AI-IVE-PBL affect the learning experience (learning motivation, learning satisfaction, cognitive load) of vocational students?

Construction and application of the AI-IVE-PBL model

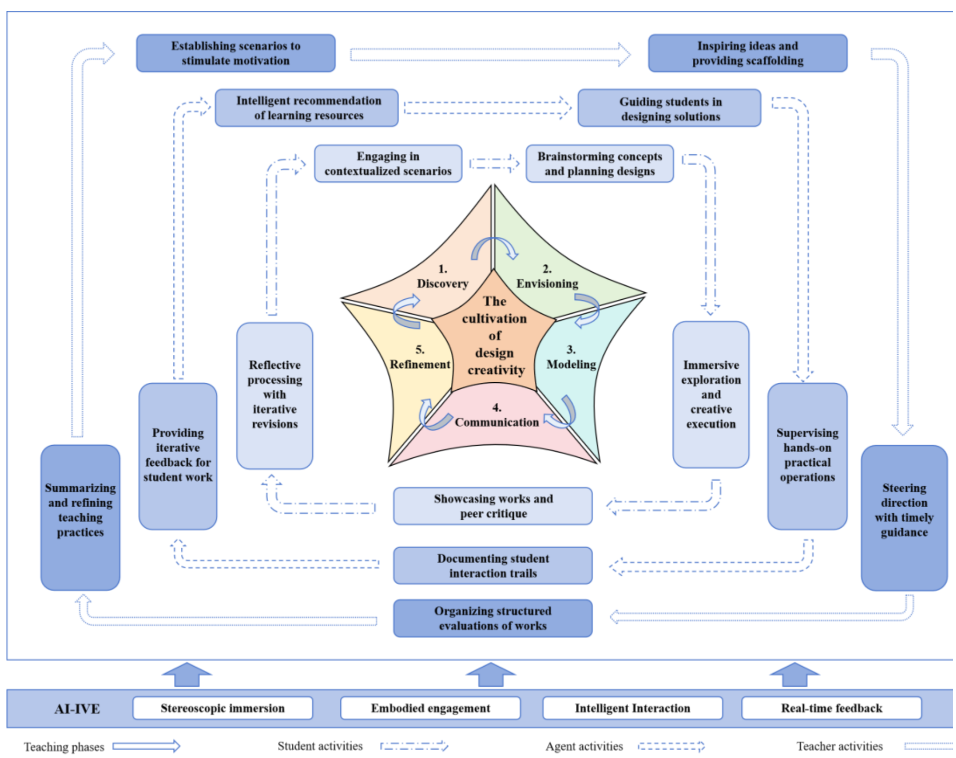
Construction of the AI-IVE-PBL model

In the age of intelligence, teaching involves the deep integration of intelligent technology, educational objectives, pedagogical philosophies, and instructional models (Yadav & Shrawankar, 2025). This research primarily endeavors to foster design creativity among vocational students. Rooted in the pedagogical principles of learning by doing and learning through design associated with PBL, it deeply integrates the situated cognition principle that knowledge is grounded in real-world contexts from Situated Cognition Theory (Kirshner & Whitson, 2021) with the core constructivist tenet that learners actively construct knowledge (Zajda, 2021). Inspired by the IDEO design thinking model (Auernhammer & Roth, 2021) and the Design-based learning (DBL) model (Barak, 2020), the study employs SIDD as the cognitive impetus, seamlessly incorporating the technical attributes of AI-IVE such as stereoscopic immersion, embodied engagement, intelligent interaction, and real-time feedback, as well as the characteristics of PBL including inquiry, collaboration, and active participation. The AI-IVE-PBL model is constructed from four dimensions: teachers, students, agents, and teaching phases, as depicted in Figure 1, offering a sequential, iterative process to advance the cultivation of design creativity in vocational students.

The model, grounded in the needs of students and the realities of teaching, interconnects the varied environments, diverse multimodal resources, and multi-agent interactions within the AI-IVE to craft authentic and engaging problem scenarios that catalyze the learning process (Nazlidou et al., 2024). It offers robust learning scaffolds to vocational students, orchestrating group-based collaborative inquiry sessions, guiding them through creative tasks, and thereby facilitating immersive, deeply engaged, and embodied learning experiences (Al-Kamzari & Alias, 2025). In summary, AI-IVE-PBL harnesses the technological affordances of AI-IVE to provide intelligent support throughout PBL, establishing a closed-loop teaching process comprising five phases: discovery, envisioning, modeling, communication, and refinement. This process aids vocational students in effectively navigating creative challenges, achieving a structured evolution of design thinking from divergence to convergence, and ultimately realizing the sustained enhancement of design creativity and the substantial enhancement of innovation competencies.

Figure 1

The AI-IVE-PBL model



Detailed introduction to the five phases of the AI-IVE-PBL workflow:

1. Discovery: Task definition and motivation activation

In the discovery phase, clarifying tasks guides students to focus on key problems and plan creative projects. Teachers use AI-IVE to create realistic project scenarios that stimulate interest, evoke empathy, and generate positive emotions (Zhong et al., 2024). The AI teaching assistant leverages students' prior learning data to recommend resources, assist in task decomposition, and provide personalized guidance. Immersive, multisensory experiences help students internalize task requirements, link current learning with future applications, and actively search for information. They break projects into manageable subtasks and initiate hands-on exploration, thereby improving problem-solving and creative thinking capacity.

2. Envisioning: Embodied experience and solution conceptualization

This phase focuses on generating and refining design ideas. Teachers use AI-IVE's modular content generation to provide scaffolds that connect prior knowledge to project tasks. The AI assistant analyzes students' brainstorming logs and behaviors, offering targeted suggestions to broaden solution space. Students adopt multiple perspectives, explore exemplars, and generate creative insights. Through collaborative SIDD, groups converge ideas into coherent proposals, which fosters aesthetic awareness and strengthens design creativity.

3. Modeling: Immersive exploration and unconstrained creation

Modeling transforms ideas into prototypes. AI-IVE dynamically configures spatial layouts to create authentic scenarios where students use VR tools to explore, test, and refine spatial arrangements. Guided by plans and collaborative dialogue, students co-construct models while AI assistants provide real-time feedback, detect design flaws, and recommend appropriate tools or resources. Teachers support teamwork, resolve operational or aesthetic challenges, and ensure smooth implementation. This stage consolidates interdisciplinary knowledge and enhances students' adaptive design skills.

4. Communication: Project presentation and peer interaction

Communication acts as the feedback loop of AI-IVE-PBL. Students present their work through verbal, visual, and performative modes, enhancing critical thinking and interaction (Hu & Shu, 2025). AI-IVE supports multi-level exchanges, from individual feedback to group discussions, and AI assistants log interactions, suggest references, and trigger new insights. Teachers guide students to explain their design concepts, functions, and innovations clearly. Frequent and meaningful SIDD during this stage helps identify key problems, extract successful strategies, and develop communication and collaboration skills.

5. Refinement: Critical reflection and iterative revision

In the refinement phase, students critically evaluate their design process and outcomes, applying metacognitive strategies to refine their work. Teachers use AI-IVE to visualize group progress and provide professional feedback. Students revise prototypes based on feedback, iteratively improving their designs. AI assistants track improvement trajectories and provide continuous cognitive and technical support. This cycle of identifying, analyzing, and solving problems strengthens design creativity, critical thinking, and self-reflection skills.

Model-based course design and implementation

Course objectives

Guided by the student-centered philosophy underpinning AI-IVE-PBL and by principles of design thinking, the overarching objectives for the first-year Interior Art Design program's Public Space Interior Design course are as follows: Students shall be competent to utilize the extensive resources and tools available within the AI-IVE to investigate solutions to design challenges and engage in structured design processes. By means of in-depth inquiry, SIDD, hands-on design work, presentation, and iterative improvement, they should accomplish the design and creation of open and innovative projects. Furthermore, they should gain theoretical knowledge and practical skills in both two-dimensional and three-dimensional design, dynamically enhancing their design creativity and innovative capacities.

Course implementation

The course is primarily dedicated to the exploration of classification methods, constituent elements, and design considerations of indoor spaces as presented in the textbook *Public Space Interior Design*. Utilizing the AI-IVE-PBL model, the course comprised three thematic projects: Aviation Exhibition Hall Design, Memorial Hall Design, and Construction Drawing Deepening Design. Each project is decomposed into several sub-projects tailored to the students' requirements and the specific teaching context. Below is a detailed description of the teaching process for the Interior Space Organization and Layout in Public Buildings subproject within the Aviation Exhibition Hall Design project:

(1) Discovery: Authentic problem scenarios stimulating exploratory curiosity

Teachers use AI-IVE to generate diverse interior spatial configurations and provide project background materials and resources. The AI teaching assistant monitors students' learning in real time, adapting materials and guiding questions to individual progress and interests, which quickly engages students in the task. In this immersive environment, students apply prior knowledge to identify requirements for spatial organization, layout, and scale. Through self-directed exploration, they form initial design concepts such as spatial form composition, color distribution, and deconstructivist techniques. Students upload outcomes and unresolved questions, which the AI assistant aggregates into reports for teachers. Teachers review these reports to diagnose common issues and plan targeted instruction for the next phase.

(2) Envisioning: Rich interactive experiences fostering multi-perspective thinking

Using AI analytics, teachers analyze students' characteristics and learning profiles, then form diverse groups to promote collaboration and role-based task solving. Equipped with VR headsets, students explore a virtual aviation exhibition hall, freely adjusting their perspective to experience spatial scale, textures, and lighting, as depicted in Figure 2. This embodied exploration helps them analyze color schemes, spatial organization, and functional layouts, stimulating new design thinking. The AI teaching assistant provides real-time scene information and design prompts to guide perception of key spatial elements. Group discussions identify major challenges such as thematic positioning, visitor routing, and exhibit arrangement. Brainstorming sessions, supported by SIDD, converge ideas into preliminary design proposals, refining and enhancing creativity.

Figure 2

Students explore and experience freely in the AI-IVE

(3) Modeling: Open-ended environments activating creative engagement

The modeling phase combines individual sketching with group collaboration in an iterative workflow. Students apply design knowledge to create preliminary sketches for the aviation exhibition hall, integrating functional zones such as the history exhibit, model display, and digital experience areas in modular or grid layouts. Following principles of ergonomics and circulation design, they allocate spatial dimensions for audience movement and balance functional and aesthetic requirements. Using SketchUp, students develop initial spatial layouts, as shown in Figure 3. The AI teaching assistant provides real-time feedback and creative suggestions to refine proposals. Teachers facilitate group critique sessions, where members evaluate elevation drawings and select the most promising scheme for further development through SIDD. This process blends individual creativity with collective insight, producing more sophisticated and innovative designs.

Figure 3

Design of the spacecraft experience area

(4) Communication: Virtual-physical interactions training expressive competence

After completing their group layouts, students upload proposals to AI-IVE. A representative conducts a virtual walkthrough of the exhibition hall, explaining the rationale and solutions for design challenges, as depicted in Figure 4. Peers listen, raise questions, and provide constructive feedback, forming a collaborative dialogue. The AI assistant transcribes and analyzes the discussion in real time, offering teachers insights into communication quality and suggestions for improvement. Teachers highlight original ideas, guide students to apply principles of layout, composition, and focus, and synthesize key design points into shared course resources. Through continuous SIDD, teachers and students refine proposals, deepen critical thinking, and advance project development.

Figure 4

Student presentations and communication

(5) Refinement: Multidimensional evaluations inspiring reflective cognition

Teachers provide a design and presentation rubric outlining criteria for aesthetics, layout, functionality, and collaboration. After reviewing all proposals, students conduct self-, peer-, and teacher evaluations, with results shared online for transparency. Guided by these evaluations, students reflect on strengths and weaknesses and use AI-IVE tools to iteratively refine their models. The AI assistant monitors progress, adapts scaffolding based on real-time data, and supports students in gradually perfecting their designs, thereby strengthening creativity, critical thinking, and metacognitive skills.

Research design

Participants

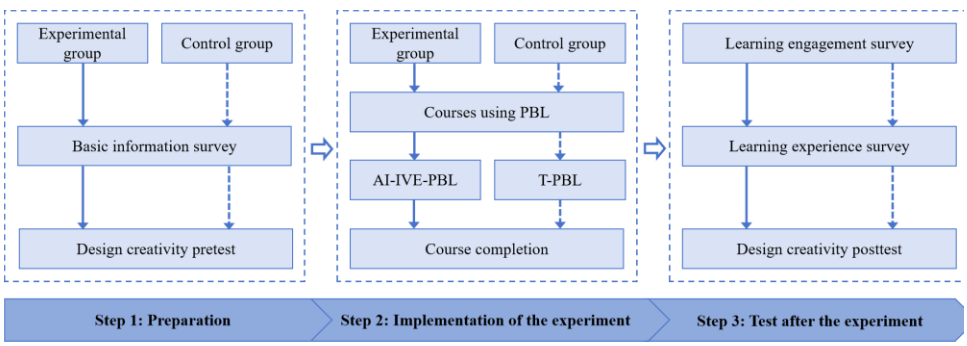
This study employs a random sampling strategy, selecting two parallel classes of first-year students from the Interior Art Design major at Fuzhou Software Technology Vocational College in China, ensuring that the subjects possess similar initial abilities. The college has two smart classrooms equipped to support AI-IVE, and since the first-year students had no prior experience with AI-IVE, this design avoids any potential interference from pre-existing usage on the experimental outcomes. In the sampling process, classes were initially chosen based on entrance examination scores and students' self-reported design-related learning experiences, to ensure a homogeneity in terms of professional foundation and learning experience. The two selected classes were then randomly assigned to a control group (33 students) and an experimental group (31 students) to reduce the likelihood of systematic baseline differences between the groups. The educational background of all participants includes graduation from general or vocational technical high schools, with a primary focus on the field of interior design. Culturally, the student body encompasses students from multiple cities within Fujian Province and neighboring regions, predominantly influenced by the culture and digital creativity industry of the southeastern coastal region, with minimal cultural background variations. All students provided written informed consent prior to the experiment, and were given the freedom to withdraw at any time. The study adheres to the ethical principles of the Declaration of Helsinki and has obtained formal approval from the Ethical Review Committee of Fuzhou Software Technology Vocational College, ensuring data anonymization and industry-standard privacy protection.

Experimental design

Following the model construction and course operationalization described in the Construction and application of the AI-IVE-PBL model section, this study employs a quasi-experimental design to examine the effects of AI-IVE-PBL versus T-PBL on students' design creativity, engagement, and overall learning experience. The experimental phase extends over 12 weeks, with a single instructor, who is proficient in both AI-IVE and interior design pedagogy, delivering the courses to both groups, thereby ensuring uniformity in the teaching content, pace, and evaluation criteria. Two researchers oversaw the implementation of the courses. Prior to the commencement of the experiment, researchers conducted an operational training session for the experimental group to familiarize them with the AI-IVE platform. The specific experimental process is illustrated in Figure 5. Before the first week of classes, researchers organized the participants to complete a basic information survey and a design creativity pretest. During the PBL course phase, the control group employed traditional design tools, including electronic drawing tablets and AutoCAD, supplemented by multimedia resources such as images and videos, to execute T-PBL. The teacher primarily functioned as a facilitator, advancing the teaching through the explanation of design cases, distribution of task lists, and organization of group discussions. For example, in the Aviation Exhibition Hall Design project, the teacher provided design specification documents and a reference case library, guiding students to draft floor plans using AutoCAD, and completing the project through offline group presentations and teacher feedback. Researchers conducted non-interventional observations in the classroom, documenting the progression of teaching activities.

Figure 5

Experimental process (The solid line represents the procedure of the experimental group; the dotted line represents the procedure of the control group.)



The experimental group utilizes the AI-IVE platform, incorporating PICO 4 VR devices, SketchUp modeling software, and the AI teaching assistant to execute AI-IVE-PBL. The teacher, in the role of designer and coordinator of learning activities, is tasked with pre-creating virtual scenarios for the aviation exhibition hall design within the AI-IVE, including unadorned open spaces and basic architectural structure models, and setting task parameters such as budgetary constraints and functional requirements. The AI teaching assistant serves as real-time learning support, for example, during the discovery phase, it proactively suggests relevant materials based on student behavior data and employs natural language processing technology to analyze student questions, offering targeted guidance; in the envisioning phase, it employs a layered questioning strategy to provoke deep thinking and generates interdisciplinary knowledge maps in real time to assist in conceptualizing the scheme; in the modeling phase, it utilizes 3D visualization technology to simulate design effects, providing immediate feedback and optimization suggestions. Researchers, functioning as technical coordinators, ensure the stable operation of the AI-IVE platform and document the progression of teaching activities. After the conclusion of all course learning activities, researchers distribute questionnaires on design creativity posttest, learning engagement, and learning experience to the participants, and subsequently collect and analyze the responses.

Instruments

Experimental environment

This study employed the AI-IVE teaching platform, which was developed by the National Engineering Research Center for E-learning at Central China Normal University. The platform allows learners to interact via VR headsets and controllers, providing an immersive and interactive educational experience. Additionally, it incorporates a fully operational AI teaching assistant that integrates the API of the Xinghuo cognitive large model, a technology developed by iFLYTEK Co., Ltd. (https://www.iflytek.com). This assistant facilitates language comprehension, knowledge querying, and logical reasoning throughout the learning process. The AI teaching assistant's visual design is realized through digital human technology, involving the creation of a three-dimensional mesh body model and the simulation of real instructor facial expressions and movements using video capture technology. Furthermore, the assistant can tailor its voice and visual characteristics to different teaching scenarios or learner preferences, enhancing interactivity and adaptability to the learning environment. During the AI-IVE-PBL implementation on the AI-IVE platform, the AI assistant serves as both a pedagogical assistant to human instructors and a collaborative partner for students. It can access the Xinghuo general large model's functions and computational resources in real time, utilizing its strong language comprehension and generation capabilities to respond to student inquiries. Through the application of natural language processing technologies, the assistant synthesizes knowledge content and delivers it orally to learners, effectively addressing the challenge of catering to personalized learning needs with prompt and accurate responses.

Translation and cultural adaptation of survey instruments

All survey instruments were administered in Chinese to ensure that participants could accurately understand and respond to the items. For scales originally developed in English, we followed a forward–back translation procedure. Specifically, two bilingual researchers independently translated the items into Chinese and reconciled discrepancies through discussion to form a preliminary Chinese version. An independent bilingual translator, who was not involved in the initial translation, then back-translated the Chinese version into English. The back-translated items were compared with the original items to identify and resolve semantic inconsistencies, and wording was refined to enhance conceptual equivalence and readability for vocational students. In addition, we conducted a smallscale pilot check for clarity and cultural appropriateness with 15 students who had a similar background to the target participants, and minor wording adjustments were made based on their feedback.

Design creativity survey

The Design creativity survey is designed to evaluate participants' capacity to produce solutions that are characterized by novelty, practicality, and innovative breakthroughs. The survey consists of three subscales: innovative thinking, design ability, and creative ability, and encompasses a total of 12 items (details are provided in Appendix 1). All items are rated on a 5-point Likert scale, ranging from 1 (completely inconsistent) to 5 (completely consistent). Innovative thinking refers to a student's ability, within the context of PBL, to transcend traditional thought patterns and approach problems or tasks with novel perspectives. This construct is measured by four items adapted from Runco et al. (2001) (e.g., "I excel at proposing novel ideas to solve problems"), with a Cronbach's alpha of .883. Design ability signifies a student's skill in translating innovative ideas into tangible design proposals, evaluated through four items from Oluwatayo et al. (2017) (e.g., "I am adept at ingeniously integrating or utilizing virtual technologies within interior design schemes"), with a Cronbach's alpha of .804. Creative ability encompasses a student's practical skills in transforming design proposals into physical works or products, measured by four items from Runco et al. (2001) (e.g., "I generate design ideas for interior spaces and bring them to fruition"), showing a Cronbach's alpha of .875. A factor analysis using principal component analysis was conducted on the entire scale. The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy was .85, and Bartlett's test of sphericity was statistically significant, $p < .001$. When varimax rotation was applied, three distinct factors were extracted, collectively accounting for 66.53% of the variance. The factor loadings of the items on their respective factors all exceeded .70, indicating the strong construct validity of the scale.

Learning engagement survey

The learning engagement survey is formulated to gauge participants' level of engagement in PBL activities. It includes three subscales: cognitive engagement, behavioral engagement, and affective engagement, and consists of a total of 12 items (details are found in Appendix 2). All items are evaluated using a 5-point Likert scale, ranging from 1 (completely inconsistent) to 5 (completely consistent). Cognitive engagement measures the degree to which students actively engage their thoughts and perspectives during PBL activities. This dimension is assessed by four items adapted from Greene (2015) (e.g., "I am able to fully immerse myself in the AI-IVE during the PBL activities"), with a Cronbach's alpha of .825. Behavioral engagement reflects the extent to which students proactively allocate time and effort to PBL tasks, evaluated through four items from Reeve and Tseng (2011) (e.g., "I am able to complete all the learning tasks in the AI-IVE–supported PBL activities"), with a Cronbach's alpha of .809. Affective engagement pertains to the enjoyment and satisfaction students derive from PBL activities, measured by four items from Gunuc and Kuzu (2015) (e.g., "I am satisfied with my learning experience during the AI-IVE–supported PBL activities"), showing a Cronbach's alpha of .828. A factor analysis using principal component analysis was performed on the entire scale. The KMO measure of sampling adequacy was .86, and Bartlett's test of sphericity was statistically significant, $p < .001$. When varimax rotation was applied, three distinct factors were extracted, collectively explaining 70.42% of the variance. All items displayed factor loadings above 0.70 on their respective constructs, validating the robust validity of the scale.

Learning experience survey

The learning experience survey aimed to measure the participants' emotional experiences throughout the PBL process. The survey consisted of three subscales: learning motivation, learning satisfaction, and cognitive load, comprising a total of 12 items (details are found in Appendix 3). The items in the learning motivation and learning satisfaction subscales were evaluated using a 5-point Likert scale. Learning motivation refers to the internal psychological state that stimulates students to actively participate in and persist with PBL activities, directing their behavior towards achieving specific learning objectives. It was measured by four items adapted from Gagné et al. (2015) (e.g., "I am very interested in the novel learning activities organized by the teacher"). The Cronbach's alpha for this subscale was .937. Learning satisfaction indicates the level of enjoyment, visual comfort, and ease of interaction that students experience during PBL activities. It was measured by four items adapted from Richardson and Swan (2003) (e.g., "I am satisfied with the rich interactive methods in the AI-IVE"). The Cronbach's alpha for this subscale was .888. Cognitive load was measured as the extent to which students consumed cognitive resources and exerted mental effort while processing PBL tasks. It was measured using a 9-point Likert scale and by four items adapted from Hwang et al. (2013) (e.g., "I need a relatively long time to contemplate the problems encountered in the learning activities"). The Cronbach's alpha for this subscale was .788. Factor analysis of the entire scale was conducted using principal component analysis, yielding a KMO value of .89; Bartlett's test of sphericity was statistically significant, $p < .001$. Varimax rotation extracted three distinct dimensions, accounting for a cumulative variance contribution of 75.05%. All items showed factor loadings exceeding .70 on their respective factors, suggesting robust construct validity for the instrument.

Data collection and analysis

Prior to and following the PBL activities, questionnaires were distributed to two groups of students to collect basic demographic information, design creativity assessments, learning engagement measures, and experiential feedback. A total of 64 questionnaires were collected, with 33 from the control group and 31 from the experimental group. After excluding any invalid responses, 63 valid questionnaires were retained, resulting in a validity rate of 98.44%. The research team's data analysts coded and entered the questionnaire responses into IBM SPSS Statistics 27 for further statistical analysis. The results were then synthesized and evaluated comprehensively by an independent results assessor. To minimize the risk of biasing the assessments of the participants, the data analysts and outcome evaluators were blinded until the entire analysis was completed (Karanicolas et al., 2010). Neither the analysts nor the evaluators were involved in the initial randomization, supervision of the PBL activities, or any other experimental processes. Their work was conducted based solely on anonymized group labels (e.g., Group A and Group B), ensuring the integrity of the blind assessment methodology.

Research results

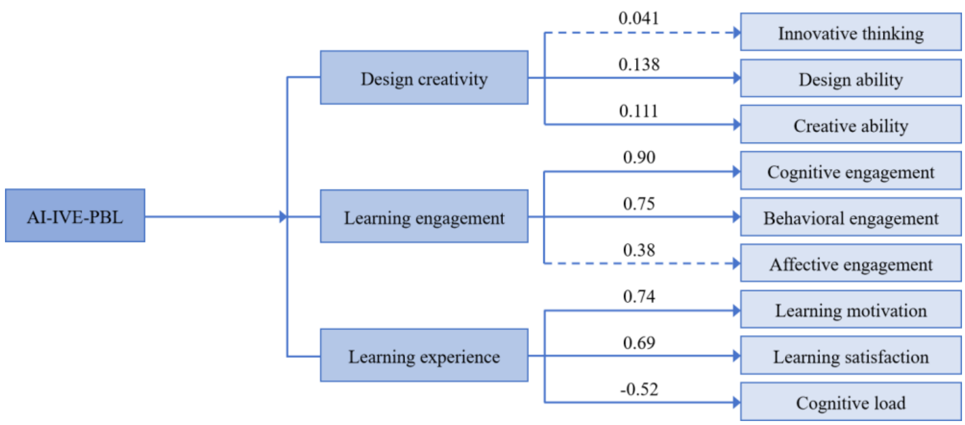
Overview of the AI-IVE-PBL model

The AI-IVE-PBL model (see Figure 1), central to this study, is designed to enhance students' design creativity in vocational education through the integration of AI-IVE and PBL. Centered on SIDD as the cognitive core, the model brings together the technical characteristics of AI-IVE, such as stereoscopic immersion, embodied engagement, intelligent interaction, and real-time feedback, and the pedagogical characteristics of PBL, including inquiry, collaboration, and active participation. The synergy between these features is realized through a four-dimensional structure, consisting of teachers, students, agents, and teaching phases, and a five-phase closed-loop workflow: discovery, envisioning, modeling, communication, refinement. In this model, teachers are responsible for scenario construction and guidance, students engage in collaborative creation through multimodal interaction, agents provide personalized cognitive support, and teaching phases ensure the continuity and iteration of learning. Together, these elements support the sustained development of design creativity by fostering an immersive, interactive, and iterative learning experience.

Furthermore, before reporting the statistical results, this paper provides an evidence-linked overview visualized in Figure 6. This figure conceptually links the AI-IVE-PBL model to the three empirically examined outcome domains (design creativity, learning engagement, and learning experience), thereby highlighting the model as the central integrative framework of the study. Detailed statistics are reported in Tables 2–4.

Figure 6

Evidence-linked overview of the AI-IVE-PBL model and tested outcomes (Solid lines denote outcome pathways supported by the quasi-experimental evidence (p < .05), whereas dashed lines denote positive but nonsignificant trends ($p \geqslant .05$). Effect sizes are reported as partial eta squared ($\eta^2 p$) for ANCOVA and Cohen's d for independent-samples t-tests to summarize the magnitude of group differences.)



Analysis of students' situation

The sample consisted of 63 participants, comprising 29 males and 34 females (see Table 1). A chi-square analysis indicated no significant difference in gender distribution between the AI-IVE-PBL and T-PBL groups ($\chi^2(1, N = 63) = 0.019$, $p = .891$). Additionally, the majority of participants (96.83%) were aged between 19 and 20 years. An independent samples t-test demonstrated no significant difference in age between the two groups ($t(61) = 0.147$, $p = .884$, 95% CI [−0.27, 0.31]).

Table 1

Baseline information

Group	Gender		
	Male	Female	Total
AI-IVE-PBL	14 (22.2%)	17 (27.0%)	31 (49.2%)
T-PBL	15 (23.8%)	17 (27.0%)	32 (50.8%)

Analysis of the interventions

Results for RQ1: Influence of models on design creativity

To mitigate the potential confounding effect of students' pretest design creativity scores on posttest outcomes, this study employed analysis of covariance (ANCOVA) to assess the impact of AI-IVE-PBL compared to T-PBL on the vocational students. The pretest scores of design creativity were used as the covariate, group membership (AI-IVE-PBL vs. T-PBL) as the fixed factor, and the posttest scores of design creativity as the dependent variable. The results are presented in Table 2. Overall, the AI-IVE-PBL group showed higher posttest scores across innovative thinking, design ability, and creative ability. For innovative thinking, the group difference was not statistically significant ($F(1, 60) = 2.570$, $p = .114$, $\eta^2p = .041$), suggesting that students' entrenched thinking patterns may be less amenable to short-term change, even within a technology-enriched ideation environment. In contrast, AI-IVE-PBL produced significantly higher design ability ($F(1, 60) = 9.630$, $p = .003$, $\eta^2p = .138$), indicating that embodied interaction and real-time cognitive support facilitated practical competencies in spatial planning, functional design, and technological application. Similarly, the AI-IVE-PBL group demonstrated significantly higher creative ability ($F(1, 60) = 7.465$, $p = .008$, $\eta^2p = .111$), consistent with the view that SIDD-driven collaboration and ongoing AI teaching-assistant scaffolding help students translate conceptual ideas into actionable outcomes.

Table 2

Results of the ANCOVA for design creativity

Dimension	*M* (*SD*)		*F*	*p*	η^2p
	AI-IVE-PBL (*n* = 31)	T-PBL (*n* = 32)			
Innovative thinking	4.05 (0.53)	3.85 (0.65)	2.570	.114	.041
Design ability	3.98 (0.51)	3.62 (0.62)	9.630	**.003**	.138
Creative ability	4.00 (0.44)	3.73 (0.61)	7.465	**.008**	.111

Note: Statistically significant results are bolded.

Results for RQ2: Influence of models on learning engagement

Independent-samples t-tests were conducted to examine group differences in learning engagement (see Table 3). Results showed that AI-IVE-PBL significantly enhanced cognitive engagement ($t(61) = 3.882$, $p < .001$, Cohen's $d = 0.90$) and behavioral engagement ($t(61) = 3.227$, $p = .002$, Cohen's $d = 0.75$) compared with T-PBL. These findings suggest that AI-supported cognitive scaffolding (e.g., hierarchical questioning and knowledge-map generation) and immersive multimodal interaction can promote deeper thinking, knowledge integration, and active task enactment. For affective engagement, the difference was not statistically significant ($t(61) = 1.662$, $p = .102$, Cohen's $d = 0.38$), although a positive trend was observed. This implies that, while high-fidelity scenarios and intelligent feedback may foster a more engaging learning atmosphere, additional affect-oriented interaction design may be needed to yield a robust emotional advantage.

Table 3

Independent samples t-test results on learning engagement between the two groups

Dimension	*M* (*SD*)		*t*	*df*	*p*	*d*
	AI-IVE-PBL (*n* = 31)	T-PBL (*n* = 32)				
Cognitive engagement	4.66 (0.35)	4.29 (0.41)	3.882	61	**< .001**	0.90
Behavioral engagement	4.60 (0.41)	4.22 (0.51)	3.227	61	**.002**	0.75
Affective engagement	4.58 (0.47)	4.34 (0.64)	1.662	61	.102	0.38

Note: Statistically significant results are bolded.

Results for RQ3: Influence of models on learning experience

Independent-samples t-tests were conducted to compare learning experience between AI-IVE-PBL and T-PBL in terms of learning motivation, learning satisfaction, and cognitive load (see Table 4). The AI-IVE-PBL group reported significantly higher learning motivation ($t(61) = 3.071$, $p = .003$, Cohen's $d = 0.74$) and learning satisfaction ($t(61) = 2.900$, $p = .005$, Cohen's $d = 0.69$), indicating that intelligent context building and sustained support may strengthen students' perceived value and achievement during project work. Moreover, AI-IVE-PBL significantly reduced cognitive load ($t(61) = -2.127$, $p = .038$, Cohen's $d = -0.52$), suggesting that intelligent scaffolding can reduce inefficient searching and psychological burden in the design process. Taken together, these results indicate that AI-IVE-PBL can optimize learning experience by enhancing motivation and satisfaction while alleviating cognitive burden.

Table 4

Independent samples t-test results on learning experience between the two groups

Dimension	*M* (*SD*)		*t*	*df*	*p*	*d*
	AI-IVE-PBL (*n* = 31)	T-PBL (*n* = 32)				
Learning motivation	4.30 (0.58)	3.84 (0.62)	3.071	61	**.003**	0.74
Learning satisfaction	4.27 (0.47)	3.89 (0.55)	2.900	61	**.005**	0.69
Cognitive load	3.83 (1.49)	4.66 (1.59)	−2.127	61	**.038**	−0.52

Note: Statistically significant results are bolded.

Discussion and conclusions

This study addresses the challenge of the arduous development of design creativity among vocational students. It synthesizes the technological benefits of AI-IVE with the pedagogical framework of PBL to construct the AI-IVE-PBL model. Aligned with the stated objectives, we first conceptualized and operationalized the AI-IVE-PBL model to support SIDD, and then evaluated it via a two-group quasi-experimental comparison in the Public Space Interior Design course. Regarding RQ1, AI-IVE-PBL significantly improved students' design ability and creative ability, whereas the advantage in innovative thinking did not reach statistical significance. Regarding RQ2, AI-IVE-PBL significantly increased cognitive and behavioral engagement, while affective engagement showed a positive but nonsignificant trend. Regarding RQ3, AI-IVE-PBL significantly enhanced learning motivation and satisfaction and reduced cognitive load. Taken together, these findings indicate that the proposed model can foster vocational students' design creativity and related learning processes, while highlighting specific outcomes that may require longer-term or affect-oriented optimization.

In contrast to T-PBL, AI-IVE-PBL significantly enhances vocational students' design and creative abilities. In terms of design ability, the dynamic and real-time interactions enabled by AI-IVE-PBL provide students with expanded avenues for communication and expression, along with increased design freedom (Chen, 2024). This environment equips students with the knowledge and skills necessary to proficiently use design modeling tools, thereby enhancing their design expertise. Moreover, the immersive learning-by-doing scenarios and immediate cognitive support offered by AI-IVE-PBL effectively alleviate the constraints of T-PBL, such as limited practical settings, restricted physical resources, and inadequate personalized guidance, enabling students to gain design experience through risk-free experimentation. For creative ability, AI-IVE-PBL empowers instructors to holistically and immediately observe and pinpoint students' challenges during the creative process, enabling precise interventions that help students iteratively improve their work in a hybrid virtual–physical environment. This reinforces the systematic integration and innovative application of design elements. Additionally, the deep collaborative discussions spurred by the SIDD mechanism and the dynamic creative interventions by AI teaching assistants, including interdisciplinary knowledge graph recommendations and feasibility assessments, substantially enhance students' control over the entire process from ideation to prototype realization, fostering continuous improvement of their creative abilities through persistent cognitive conflict and collaborative development.

However, this study indicates that while the AI-IVE-PBL cohort demonstrated greater innovative thinking than the T-PBL group, the difference was not statistically significant. This could be due to AI-IVE-PBL's focus on generating open and authentic project contexts that stimulate flexibility and divergence in innovative thought. Yet, as innovative thinking is a higher-order cognitive skill, its development necessitates extended cross-contextual transfer training and metacognitive strategy guidance (Sunday et al., 2021). Despite the enhancement of creative stimulation through multimodal interaction and intelligent feedback, AI-IVE-PBL may struggle to significantly alter deeply rooted cognitive patterns in the short term, requiring further substantiation through prolonged, targeted development. In addition to these pedagogical considerations, the nonsignificant result may also reflect measurement sensitivity and learner-related constraints. Innovative thinking was measured with a brief self-report subscale and a limited response range, which may be less sensitive to subtle, task-specific shifts in ideation and may attenuate detectable group differences, particularly when score variability is limited. Furthermore, many first-year vocational students have limited prior exposure to open-ended problem solving and explicit ideation routines. As a result, even when AI-IVE affords rich exploration and AI prompts, some learners may default to execution-oriented strategies, such as imitating reference examples or prioritizing task completion, which constrains the depth of conceptual reframing needed for measurable gains in innovative thinking. Accordingly, future implementations may benefit from more explicit ideation and metacognitive scaffolding, including deliberate divergence and convergence cycles, justification prompts, and reflective critique, as well as longer-term iterative practice to help students progressively appropriate the affordances of AI-IVE for creative reframing.

This study demonstrates significant disparities between the AI-IVE-PBL group and the T-PBL group in both cognitive and behavioral engagement. In terms of cognitive engagement, students engaged in AI-IVE-PBL activities, through unrestricted exploration and interactive manipulation, showcased an improved ability to ponder, comprehend, and internalize knowledge and skills. They experienced a more interactive and rich learning environment, which in turn heightened their cognitive engagement. Grounded in Social Constructivism, which posits that learning is fundamentally achieved through social interaction and collaborative knowledge construction (Saleem et al., 2021), AI-IVE-PBL offers an ideal setting for SIDD. The AI teaching assistant dynamically analyzes students' discussion content, promptly identifies cognitive conflicts, and seamlessly integrates interdisciplinary knowledge modules (Ding et al., 2023). This facilitates a shift from superficial creative exchanges to profound cognitive collaboration, significantly extending the duration of meaningful discourse. This deep SIDD likely underpins the observed enhancement in cognitive engagement, as students engage in ongoing debates and articulations of viewpoints, transcending preconceived cognitive frameworks, and displaying heightened levels of deep intellectual engagement as they resolve contradictions and synthesize diverse information (Al Mamun & Lawrie, 2024). In line with Cognitive Behavioral Theory, which posits cognition as the primary driver of behavior (Singh et al., 2008), when students achieve enriched cognitive experiences through SIDD in AI-IVE-PBL, their behavioral engagement intensifies accordingly, a phenomenon supported by this research. Following extensive discussion and ideation, students display increased initiative in designing and iteratively refining within the virtual environment, thereby significantly enhancing the proactivity and persistence of their behavioral participation through the validation of creative solutions. However, no significant differences were observed between the AI-IVE-PBL and T-PBL groups in terms of affective engagement. This may be due to the implicit nature of emotional involvement (Newmann, 1996), which is shaped by complex factors such as individual personality traits, technology acceptance, and interpersonal interaction preferences, rendering it resistant to rapid alteration through technological interventions in the short term. Future research could explore optimizing human–computer emotional interactions to enhance affective resonance within AI-IVE.

Furthermore, this study also shows that AI-IVE-PBL significantly enhances vocational students' learning motivation and satisfaction while reducing cognitive load. Consistent with previous research linking learning interaction to motivation (El-Seoud et al., 2016), AI-IVE-PBL fosters deeper SIDD and richer learner-content interaction, allowing students to gain a sense of achievement through ongoing intellectual exchange and iterative creation, which strengthens motivation and supports flow experiences. Aligned with Self-Determination Theory, the immersive setting, adaptive tasks, and real-time AI feedback meet students' needs for autonomy, competence, and relatedness (Fung et al., 2024; Osei & Bjorklund, 2024), increasing their willingness to learn. Regarding learning satisfaction, AI-IVE-PBL offers personalized design scenarios and tiered project tasks that help students set clear goals, receive timely support, and experience efficient, immersive learning. In the blended virtual-physical environment, immediate feedback, intelligent suggestions, and collaborative discussions allow students to quickly translate ideas into solutions within the five-phase discovery–envisioning–modeling–communication–refinement cycle, deepening their recognition of both process and outcomes. In line with Cognitive Load Theory, which holds that exceeding working memory capacity hinders learning (Anmarkrud et al., 2019), AI-IVE-PBL reduces extraneous load by providing continuous guidance and helping students allocate cognitive resources effectively. Features such as the preset furniture model library and one-click material switching streamline technical tasks, allowing students to focus on creative generation. Moreover, real-time semantic analysis and knowledge graph recommendations reduce the cognitive effort required for information retrieval and cross-disciplinary integration, further lightening the cognitive burden.

Limitations and future research

This study employs a quasi-experiment to explore the effects of AI-IVE-PBL on the design creativity, learning engagement, and learning experience of vocational students. The research initially relies exclusively on self-report questionnaires for data collection, a method susceptible to subjective bias. In addition, the innovative thinking measure, as a brief self-report subscale with a limited response range, may have limited sensitivity for detecting subtle, task-specific changes over a short intervention period. Secondly, to minimize disruption to the participants' regular teaching schedule, the study confines its focus to the content of the vocational course Public Space Interior Design. This limits the generalizability of the findings, and it is essential to expand the scope of the sample in subsequent research. Finally, the presence of multiple research questions in this article introduces the risk of conflating primary and secondary issues. Additionally, the discussion section does not adequately address the limitations and potential biases that arise from the absence of blinding in the study design.

For future investigations, it is recommended to broaden the research sample by including participants from diverse geographical regions and institutional backgrounds. This could involve combining survey questionnaires with interviews, observations, and other approaches to leverage the strengths of both quantitative and qualitative methods, thereby enhancing the validity of the research conclusions. To better capture nuanced changes in innovative thinking, future studies should triangulate self-report data with product- and process-based indicators, such as expert ratings of design artifacts and learning analytics from AI-IVE logs.

Secondly, diversifying the sample by implementing teaching interventions across various courses and academic levels is advised. Given that students at different stages of their academic progression exhibit distinct cognitive capacities and learning requirements, evaluating and refining the AI-IVE-PBL model in heterogeneous educational contexts will facilitate continuous improvement in its generalizability and scalability.

Thirdly, extending the duration of the experimental period is recommended, such as conducting a quasi-experimental study spanning an entire academic year or longer. This approach would enable a comprehensive assessment of the long-term effects of the AI-IVE-PBL model on the creative design abilities of vocational students, thereby enriching both the depth and scope of the research outcomes. Longitudinal analyses can elucidate the developmental trajectory of students' competencies across multiple project cycles and reveal enduring impacts of the intervention.

Fourthly, the implementation of blinding procedures, to the greatest extent feasible, is suggested for participants and instructors involved in the study. Careful consideration of potential biases introduced by the absence of blinding should be incorporated into the evaluation and interpretation of results. Such methodological rigor will minimize assessment bias and enhance the reliability and credibility of the study's conclusions.

Future research should comprehensively address the ethical implications associated with the deployment of AI-IVE within educational contexts. As AI-IVE technologies become increasingly integrated into pedagogical frameworks, salient ethical challenges, including data privacy concerns, algorithmic bias, and dependence on technology, must be rigorously examined. Establishing stringent ethical guidelines is imperative to ensure the protection and confidentiality of student data, enable the identification and mitigation of biases within algorithms to uphold educational equity, and promote responsible technology usage among students to prevent over-reliance while cultivating independent and critical thinking skills. Moreover, advancing technological empowerment through the enhancement of AI teaching assistants' affective interaction capabilities is essential to reinforce the psychological rapport between learners and technology, thereby elevating the educational experience towards an integrated cognitive–behavioral–affective paradigm. Concurrently, deeper exploration into the convergence of AI-IVE with neuroscience methodologies, such as functional near-infrared spectroscopy and eye-tracking, offers the potential to monitor neural activation patterns and attentional dynamics in real time during design and creative tasks. This neuroscientific insight can underpin the development of personalized learning support strategies, facilitating a paradigm shift from experience-driven to data-driven and precision-oriented instructional interventions and assessments. Through multidisciplinary research and iterative optimization, these efforts aim to establish a robust theoretical and practical foundation for vocational teaching approaches, thereby fostering innovation-driven advancement in educational practices and pedagogical effectiveness.

Appendix 1

Items of the design creativity survey

Dimensions	Items
Innovative thinking	
IT_1	I excel at proposing novel ideas to solve problems.
IT_2	I frequently shift perspectives to explore alternative solutions.
IT_3	I have learned to ask critical questions and explore multiple solution paths during the Public Space Interior Design course.
IT_4	I critically reflect on course content from multiple viewpoints.
Design ability	
DA_1	I demonstrate proficiency with modeling tools.
DA_2	I consciously analyze socio-cultural contexts relevant to interior design.
DA_3	I am adept at ingeniously integrating or utilizing virtual technologies within interior design schemes.
DA_4	I can integrate functional, aesthetic, and technical considerations into a coherent interior design solution.
Creative ability	
CA_1	I generate design ideas for interior spaces and bring them to fruition.
CA_2	My design works exhibit significant differentiation from reference prototypes.
CA_3	I can produce multiple design variants for the same interior space based on different user needs or contexts.
CA_4	I am able to express my creative thoughts and ideas through my interior design work.

Appendix 2

Items of the learning engagement survey

Dimensions	Items
Cognitive engagement	
CE_1	I am able to fully immerse myself in the AI-IVE learning environment during the PBL activities.
CE_2	I can accurately identify the tasks required at each stage of the project workflow.
CE_3	I can clearly grasp key concepts and challenging aspects of learning content.
CE_4	Upon design completion, I critically review and reflect on potential issues in my work.
Behavioral engagement	
BE_1	I can carefully observe and analyze the design scenarios in the AI-IVE.
BE_2	I am able to listen carefully to my classmates' opinions and express my own views in the communication sessions.

BE_3	I am able to complete all the learning tasks in the AI-IVE–supported PBL activities.
BE_4	When I have difficulty understanding the learning content, I repeat the operation and seek clarification until I master the design knowledge.
Affective engagement	
AE_1	I am happy with the clarity of the images in the AI-IVE teaching resources.
AE_2	I am satisfied with my learning experience during the AI-IVE–supported PBL activities.
AE_3	I enjoy the interactive features of the AI-IVE platform, which allow me to explore ideas flexibly.
AE_4	I feel relaxed and comfortable while completing the learning tasks.

Appendix 3

Items of the learning experience survey

Dimensions	Items
Learning motivation	
LM_1	I found the AI-IVE–supported PBL activities interesting.
LM_2	I am very interested in the novel learning activities organized by the teacher.
LM_3	The AI-IVE–supported PBL activities can arouse my interest in learning.
LM_4	I would like to participate in similar AI-IVE–supported PBL activities in the future.
Learning satisfaction	
LS_1	I am satisfied with my learning experience in the AI-IVE–supported PBL activities.
LS_2	I can complete the interior design tasks smoothly during the AI-IVE–supported PBL activities.
LS_3	I am satisfied with the rich interactive methods in the AI-IVE.
LS_4	I am satisfied with my overall learning outcomes in this course.
Cognitive load	
CL_1	The learning tasks in AI-IVE-PBL are difficult for me.
CL_2	Participating in AI-IVE-PBL activities requires a lot of effort on my part.
CL_3	I need a relatively long time to contemplate the problems encountered in the learning activities.
CL_4	The learning activities required a high level of mental effort.

Abbreviations

AI-IVE: AI-enabled immersive virtual environment; PBL: Project-based learning; AI-IVE-PBL: PBL in AI-IVE; T-PBL: traditional PBL; SIDD: sustained idea-developing discourse; GenAI: generative artificial intelligence; DBL: Design-based learning; ANCOVA: Analysis of covariance

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Author's contributions

Shuaizhen Jin: Conceptualization, data collection, data analysis, and manuscript draft. Zheng Zhong: Conceptualization, supervision, project administration, and manuscript revision. Xu Cao: Conceptualization, data collection, and manuscript revision. Wenzhuo Zhang: Data analysis, interpretation of data, and manuscript revision. All authors read and approved the final manuscript.

Author's information

SJ is a doctoral student at Central China Normal University. Her research focuses on educational applications of virtual reality. ZZ is a professor at Central China Normal University and a distinguished research fellow at the Institute for Lifelong Education, Hubei Open University. His research focuses on educational applications of virtual reality. XC is a doctoral student at Central China Normal University. His research focuses on educational applications of artificial intelligence. WZ is pursuing a master's degree at Central China Normal University. Her research focuses on educational applications of artificial intelligence.

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Availability of data and materials
The data that support the findings of this study are available from the corresponding author upon reasonable request.

Declarations

Competing interests
The authors declare that they have no competing interests.

Author details
[1] National Engineering Research Center for E-learning, Central China Normal University, Wuhan, China
[2] Institute for Lifelong Education, Hubei Open University, Wuhan, China

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References

Adera, N. (2025). Innovative learning spaces and blended learning: Quest for 21st-century competency teaching and learning approaches. In G. N. Areba, B. N. Gisore, & E. W. Njurai (Eds.), *Creating dynamic space in higher education: Modern shifts in policy, competencies, and governance* (pp. 139–174). IGI Global. https://doi.org/10.4018/979-8-3693-6930-2.ch006

Al-Kamzari, F., & Alias, N. (2025). A systematic literature review of project-based learning in secondary school physics: Theoretical foundations, design principles, and implementation strategies. *Humanities and Social Sciences Communications*, *12*, Article 286. https://doi.org/10.1057/s41599-025-04579-4

Al Mamun, M. A., & Lawrie, G. (2024). Cognitive presence in learner–content interaction process: The role of scaffolding in online self-regulated learning environments. *Journal of Computers in Education*, *11*(3), 791–821. https://doi.org/10.1007/s40692-023-00279-7

Anmarkrud, Ø., Andresen, A., & Bråten, I. (2019). Cognitive load and working memory in multimedia learning: Conceptual and measurement issues. *Educational Psychologist*, *54*(2), 61–83. https://doi.org/10.1080/00461520.2018.1554484

Auernhammer, J., & Roth, B. (2021). The origin and evolution of Stanford University's design thinking: From product design to design thinking in innovation management. *Journal of Product Innovation Management*, *38*(6), 623–644. https://doi.org/10.1111/jpim.12594

Barak, M. (2020). Problem-, project- and design-based learning: Their relationship to teaching science, technology and engineering in school. *Journal of Problem-Based Learning*, *7*(2), 94–97. https://doi.org/10.24313/jpbl.2020.00227

Baxter, G., & Hainey, T. (2024). Using immersive technologies to enhance the student learning experience. *Interactive Technology and Smart Education*, *21*(3), 403–425. https://doi.org/10.1108/ITSE-05-2023-0078

Bekteshi, L. (2025). Education in the era of AI and immersive technologies: A systematic review. *Journal of Research in Engineering and Computer Sciences*, *3*(1), 1–14. https://doi.org/10.63002/jrecs.31.779

Bilan, Y., Vasilyeva, T., Kryklii, O., & Shilimbetova, G. (2019). The creative industry as a factor in the development of the economy: Dissemination of European experience in the countries with economies in transition. *Creativity Studies*, *12*(1), 75–101. https://doi.org/10.3846/cs.2019.7453

Cacciamani, S., Perrucci, V., & Fujita, N. (2021). Promoting students' collective cognitive responsibility through concurrent, embedded and transformative assessment in blended higher education courses. *Technology, Knowledge and Learning*, *26*(4), 1169–1194. https://doi.org/10.1007/s10758-021-09535-0

Chang, Y. S., Kao, J. Y., & Wang, Y. Y. (2022). Influences of virtual reality on design creativity and design thinking. *Thinking Skills and Creativity*, *46*, Article 101127. https://doi.org/10.1016/j.tsc.2022.101127

Chen, Z. (2024). Exploring the application scenarios and issues facing metaverse technology in education. *Interactive Learning Environments*, *32*(5), 1975–1987. https://doi.org/10.1080/10494820.2022.2133148

Cox, D., & Prestridge, S. (2020). Understanding fully online teaching in vocational education. *Research and Practice in Technology Enhanced Learning*, *15*, Article 16. https://doi.org/10.1186/s41039-020-00138-4

Ding, L., Li, T., Jiang, S., & Gapud, A. (2023). Students' perceptions of using ChatGPT in a physics class as a virtual tutor. *International Journal of Educational Technology in Higher Education*, *20*, Article 63. https://doi.org/10.1186/s41239-023-00434-1

El-Seoud, S. A., El-Khouly, M. M., & Taj-Eddin, I. A. T. F. (2016). Motivation in e-learning: How do we keep learners motivated in an e-learning environment? *International Journal of Learning and Teaching*, *2*(1), 63–66. https://doi.org/10.18178/ijlt.2.1.63-66

Eswaran, U. (2024). Project-based learning: Fostering collaboration, creativity, and critical thinking. In M. Bhatia & M. T. Mushtaq (Eds.), *Enhancing education with intelligent systems and data-driven instruction* (pp. 23–43). IGI Global. https://doi.org/10.4018/979-8-3693-2169-0.ch002

Fleury, S., Blanchard, P., & Richir, S. (2021). A study of the effects of a natural virtual environment on creativity during a product design activity. *Thinking Skills and Creativity*, *40*, Article 100828. https://doi.org/10.1016/j.tsc.2021.100828

Fung, K. Y., Lee, L. H., Sin, K. F., Song, S., & Qu, H. (2024). Humanoid robot-empowered language learning based on self-determination theory. *Education and Information Technologies*, *29*(14), 18927–18957. https://doi.org/10.1007/s10639-024-12570-w

Gagné, M., Forest, J., Vansteenkiste, M., Crevier-Braud, L., Van den Broeck, A., Aspeli, A. K., Bellerose, J., Benabou, C., Chemolli, E., Güntert, S. T., Halvari, H., Indiyastuti, D. L., Johnson, P. A., Molstad, M. H., Naudin, M., Ndao, A., Olafsen, A. H., Roussel, P., Wang, Z., & Westbye, C. (2015). The Multidimensional Work Motivation Scale: Validation evidence in seven languages and nine countries. *European Journal of Work and Organizational Psychology*, *24*(2), 178–196. https://doi.org/10.1080/1359432X.2013.877892

Gill, S. S., Xu, M., Patros, P., Wu, H., Kaur, R., Kaur, K., Fuller, S., Singh, M., Arora, P., Parlikad, A. K., Stankovski, V., Abraham, A., Ghosh, S. K., Lutfiyya, H., Kanhere, S. S., Bahsoon, R., Rana, O., Dustdar, S., Sakellariou, R., . . . Buyya, R. (2024). Transformative effects of ChatGPT on modern education: Emerging era of AI chatbots. *Internet of Things and Cyber-Physical Systems*, *4*, 19–23. https://doi.org/10.1016/j.iotcps.2023.06.002

Greene, B. A. (2015). Measuring cognitive engagement with self-report scales: Reflections from over 20 years of research. *Educational Psychologist*, *50*(1), 14–30. https://doi.org/10.1080/00461520.2014.989230

Guilford, J. P. (1950). Creativity. *American Psychologist*, *5*(9), 444–454. https://doi.org/10.1037/h0063487

Gunuc, S., & Kuzu, A. (2015). Student engagement scale: Development, reliability and validity. *Assessment & Evaluation in Higher Education*, *40*(4), 587–610. https://doi.org/10.1080/02602938.2014.938019

Herrera-Pavo, M. Á. (2021). Collaborative learning for virtual higher education. *Learning, Culture and Social Interaction*, *28*, Article 100437. https://doi.org/10.1016/j.lcsi.2020.100437

Hong, H. Y., Chen, M. J., Chang, C. H., Tseng, L. T., & Chai, C. S. (2025). AI-supported idea-developing discourse to foster professional agency within teacher communities for STEAM lesson design in knowledge building environment. *Computers & Education*, *229*, Article 105241. https://doi.org/10.1016/j.compedu.2025.105241

Hong, H. Y., & Sullivan, F. R. (2009). Towards an idea-centered, principle-based design approach to support learning as knowledge creation. *Educational Technology Research and Development*, *57*(5), 613–627. https://doi.org/10.1007/s11423-009-9122-0

Hu, Y., & Shu, J. (2025). The effect of drama education on enhancing critical thinking through collaboration and communication. *Education Sciences*, *15*(5), Article 565. https://doi.org/10.3390/educsci15050565

Hwang, G. J., Yang, L. H., & Wang, S. Y. (2013). A concept map-embedded educational computer game for improving students' learning performance in natural science courses. *Computers & Education*, *69*, 121–130. https://doi.org/10.1016/j.compedu.2013.07.008

Jabli, N. (2024). Innovative learning strategies for digital transformation in higher education. In M. D. Lytras, A. C. Şerban, A. Alkhaldi, T. Aldosemani, & S. Malik (Eds.), *Digital transformation in higher education, Part A: Best practices and challenges* (pp. 115–153). Emerald Publishing Limited. https://doi.org/10.1108/978-1-83549-480-620241007

Jiang, W., Zhan, Y., Sun, D., & Looi, C.-K. (2024). Development and validation of a blended learning perception scale for higher vocational students. *Research and Practice in Technology Enhanced Learning*, *19*, Article 032. https://doi.org/10.58459/rptel.2024.19032

Jin, S., & Zhong, Z. (2026). Effects of collaborative generative learning on learners with different motivation levels in AI-enabled immersive virtual environments. *Journal of Educational Computing Research*, *64*(2), 344–370. https://doi.org/10.1177/07356331251396412

Jin, S., Zhong, Z., Li, K., & Kang, C. (2024). Investigating the effect of guided inquiry on learners with different prior knowledge in immersive virtual environments. *Education and Information Technologies*, *29*(17), 22447–22473. https://doi.org/10.1007/s10639-024-12719-7

Jumaat, N. F., Tasir, Z., Halim, N. D. A., & Ashari, Z. M. (2017). Project-based learning from constructivism point of view. *Advanced Science Letters*, *23*(8), 7904–7906. https://doi.org/10.1166/asl.2017.9605

Karanicolas, P. J., Farrokhyar, F., & Bhandari, M. (2010). Blinding: Who, what, when, why, how? *Canadian Journal of Surgery*, *53*(5), 345–348. https://pmc.ncbi.nlm.nih.gov/articles/PMC2947122/

Kennedy, D. (2021). Schooling the new sensibility: Communal philosophical dialogue, play, and social democracy. In A. Koubová, P. Urban, W. Russell, & M. MacLean (Eds.), *Play and democracy: Philosophical perspectives* (pp. 191–206). Routledge. https://doi.org/10.4324/9781003122289-16

Khan, K. (2024). Advancements and challenges in 360° augmented reality video streaming: A comprehensive review. *International Journal of Computing, Communications and Networking*, *13*(1), 1–20. https://doi.org/10.30534/IJCCN/2024/011312024

Khodabandeh, F. (2022). Exploring the applicability of virtual reality-enhanced education on extrovert and introvert EFL learners' paragraph writing. *International Journal of Educational Technology in Higher Education*, *19*, Article 27. https://doi.org/10.1186/s41239-022-00334-w

Kirshner, D., & Whitson, J. A. (Eds.). (2021). *Situated cognition: Social, semiotic, and psychological perspectives*. Routledge. https://doi.org/10.4324/9781003064121

Kovalchuk, V., Maslich, S. V., Tkachenko, N., Shevchuk, S. S., & Shchypska, T. P. (2022). Vocational education in the context of modern problems and challenges. *Journal of Curriculum and Teaching*, *11*(8), 329–338. https://doi.org/10.5430/jct.v11n8p329

Luengo-Aravena, D., Cabello, P., & Bachino, B. R. M. (2024). Online collaborative problem-solving as a tangible outcome of digital skills in technical and vocational higher education. *Computers & Education*, *218*, Article 105079. https://doi.org/10.1016/j.compedu.2024.105079

Makransky, G., & Petersen, G. B. (2021). The cognitive affective model of immersive learning (CAMIL): A theoretical research-based model of learning in immersive virtual reality. *Educational Psychology Review*, *33*(3), 937–958. https://doi.org/10.1007/s10648-020-09586-2

Meng, N., Dong, Y., Roehrs, D., & Luan, L. (2023). Tackle implementation challenges in project-based learning: A survey study of PBL e-learning platforms. *Educational Technology Research and Development*, *71*(3), 1179–1207. https://doi.org/10.1007/s11423-023-10202-7

Mutanga, M. B. (2024). Students' perspectives and experiences in project-based learning: A qualitative study. *Trends in Higher Education*, *3*(4), 903–911. https://doi.org/10.3390/higheredu3040052

Nazlidou, I., Efkolidis, N., Kakoulis, K., & Kyratsis, P. (2024). Innovative and interactive technologies in creative product design education: A review. *Multimodal Technologies and Interaction*, *8*(12), Article 107. https://doi.org/10.3390/mti8120107

Newmann, F. M. (1996). Authentic assessment in social studies: Standards and examples. In G. D. Phye (Ed.), *Handbook of classroom assessment: Learning, achievement, and adjustment* (pp. 359–380). Academic Press. https://doi.org/10.1016/B978-012554155-8/50014-4

Niittylahti, S., Annala, J., & Mäkinen, M. (2023). Student engagement profiles in vocational education and training: A longitudinal study. *Journal of Vocational Education & Training*, *75*(2), 372–390. https://doi.org/10.1080/13636820.2021.1879902

Nouwen, W., Clycq, N., Struyf, A., & Donche, V. (2022). The role of work-based learning for student engagement in vocational education and training. *European Journal of Psychology of Education*, *37*(3), 877–902. https://doi.org/10.1007/s10212-021-00561-1

Oluwatayo, A. A., Ezema, I., & Opoko, A. (2017). Development of design expertise by architecture students. *Journal of Learning Design*, *10*(2), 35–56. https://doi.org/10.5204/jld.v10i2.268

Osei, P. C., & Bjorklund, D. F. (2024). Motivating the learning process: Integrating self-determination theory into a dynamical systems framework. *Educational Psychology Review*, *36*(3), Article 89. https://doi.org/10.1007/s10648-024-09934-6

Pusic, M. V., Santen, S. A., Dekhtyar, M., Poncelet, A. N., Roberts, N. K., Wilson-Delfosse, A. L., & Cutrer, W. B. (2018). Learning to balance efficiency and innovation for optimal adaptive expertise. *Medical Teacher*, *40*(8), 820–827. https://doi.org/10.1080/0142159X.2018.1485887

Qin, Q., & Zhang, S. (2025). Visualizing the knowledge mapping of artificial intelligence in education: A systematic review. *Education and Information Technologies*, *30*(1), 449–483. https://doi.org/10.1007/s10639-024-13076-1

Reeve, J., & Tseng, C. M. (2011). Agency as a fourth aspect of students' engagement during learning activities. *Contemporary Educational Psychology*, *36*(4), 257–267. https://doi.org/10.1016/j.cedpsych.2011.05.002

Reynolds, C., Stevens, D. D., & West, E. (2013). I'm in a professional school! Why are you making me do this? A cross-disciplinary study of the use of creative classroom projects on student learning. *College Teaching*, *61*(2), 51–59. https://doi.org/10.1080/87567555.2012.731660

Richardson, J. C., & Swan, K. (2003). Examining social presence in online courses in relation to students' perceived learning and satisfaction. *Journal of Asynchronous Learning Networks*, *7*(1), 68–88. https://doi.org/10.24059/olj.v7i1.1864

Runco, M. A., Plucker, J. A., & Lim, W. (2001). Development and psychometric integrity of a measure of ideational behavior. *Creativity Research Journal*, *13*(3–4), 393–400. https://doi.org/10.1207/S15326934CRJ1334_16

Saleem, A., Kausar, H., & Deeba, F. (2021). Social constructivism: A new paradigm in teaching and learning environment. *Perennial Journal of History*, *2*(2), 403–421. https://doi.org/10.52700/pjh.v2i2.86

Scardamalia, M., & Bereiter, C. (2021). Knowledge building: Advancing the state of community knowledge. In U. Cress, C. Rosé, A. F. Wise, & J. Oshima (Eds.), *International handbook of computer-supported collaborative learning* (pp. 261–279). Springer. https://doi.org/10.1007/978-3-030-65291-3_14

Sikström, P., Valentini, C., Sivunen, A., & Kärkkäinen, T. (2024). Pedagogical agents communicating and scaffolding students' learning: High school teachers' and students' perspectives. *Computers & Education*, *222*, Article 105140. https://doi.org/10.1016/j.compedu.2024.105140

Singh, N. N., Lancioni, G. E., Wahler, R. G., Winton, A. S., & Singh, J. (2008). Mindfulness approaches in cognitive behavior therapy. *Behavioural and Cognitive Psychotherapy*, *36*(6), 659–666. https://doi.org/10.1017/S1352465808004827

Song, X. (2024). Physical education teaching mode assisted by artificial intelligence assistant under the guidance of high-order complex network. *Scientific Reports*, *14*, Article 4104. https://doi.org/10.1038/s41598-024-53964-7

Sunday, M. O., Obogo, G. O., & Adie, R. U. (2021). Scaling up self-regulatory ability in childhood education as correlate of creative mindset. *Global Journal of Educational Research*, *20*(1), 63–71. https://doi.org/10.4314/gjedr.v20i1.7

Tilhou, R., Taylor, V., & Crompton, H. (2020). 3D virtual reality in K-12 education: A thematic systematic review. In S. Yu, M. Ally, & A. Tsinakos (Eds.), *Emerging technologies and pedagogies in the curriculum* (pp. 169–184). Springer. https://doi.org/10.1007/978-981-15-0618-5_10

Xue, X. (2023). Research on the self confidence training of higher vocational students based on group motivation. *International Journal of Education and Humanities*, *6*(2), 99–103. https://doi.org/10.54097/ijeh.v6i2.3646

Yadav, U., & Shrawankar, U. (2025). Artificial intelligence across industries: A comprehensive review with a focus on education. In K. L. Keeley (Ed.), *AI applications and strategies in teacher education* (pp. 275–320). IGI Global. https://doi.org/10.4018/979-8-3693-5443-8.ch010

Zajda, J. (2021). *Globalisation and education reforms: Creating effective learning environments*. Springer. https://doi.org/10.1007/978-3-030-71575-5

Žerovnik, A., & Nančovska Šerbec, I. (2021). Project-based learning in higher education. In C. Vaz de Carvalho & M. Bauters (Eds.), *Technology supported active learning: Student-centered approaches* (pp. 31–57). Springer. https://doi.org/10.1007/978-981-16-2082-9_3

Zhao, J., & Zhao, X. (2022). Computer-aided graphic design for virtual reality-oriented 3D animation scenes. *Computer-Aided Design and Applications*, *19*(S5), 65–76. https://doi.org/10.14733/cadaps.2022.S5.65-76

Zhong, Z., Feng, S., & Jin, S. (2024). Investigating the influencing factors of teaching anxiety in virtual reality environments. *Education and Information Technologies*, *29*(7), 8369–8391. https://doi.org/10.1007/s10639-023-12152-2

Zhong, Z., Zhang, G., Jin, S., Wang, J., Ma, N., & Feng, S. (2022). Investigating the effect of peer instruction on learners with different cognitive styles in VR-based learning environment. *Education and Information Technologies*, *27*(8), 11875–11899. https://doi.org/10.1007/s10639-022-11115-3

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