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Reimagining Tradition: A Comparative Study of Artificial Intelligence and Virtual Reality in Sustainable Architecture Education

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Abstract: Artificial intelligence and virtual reality technologies have significant potential in traditional architectural education. Historically used separately, their educational impacts are not fully understood. To advance sustainable architecture education, this study incorporates language and illustration tools of artificial intelligence, along with immersive painting and simulation capabilities of virtual reality, into the curriculum of Jiangnan traditional architecture. Through a randomized controlled trial, 60 students were divided into AI, VR, and control groups. Based on the establishment of an adaptive course learning assessment system, this study empirically compares the effects of artificial intelligence methods, virtual reality methods, and traditional teaching methods across four dimensions: architectural knowledge, architectural design, architectural computation, and architectural learning. Independent sample *t*-tests and one-way analysis of variance are used to validate the differences in the effectiveness of these technological applications. Findings reveal that artificial intelligence notably enhances design and learning outcomes, whereas virtual reality shows pronounced effects in bolstering knowledge acquisition and computational tasks. Artificial intelligence proves particularly suited to conceptualization and narrative-based design tasks, while virtual reality aligns closely with model creation and post-design refinement activities. These findings provide new perspectives for hybridizing artificial intelligence and virtual reality in sustainable architecture education, contributing to sustainable outcomes.

Keywords: artificial intelligence; virtual reality; sustainable education; traditional architecture

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1. Introduction

1.1. The Application of Artificial Intelligence in Design Education

In 1956, John McCarthy introduced the concept of artificial intelligence, marking the official beginning of this transformative field. Artificial intelligence emerged from an interdisciplinary fusion, with computer science as its core, integrating research from linguistics, psychology, mathematics, and other disciplines, all aiming to explore how machines can emulate human intelligence and behavior. This marked the start of the journey of artificial intelligence into the educational realm, initially through the use of computers and related technologies, and later evolving into sophisticated, web-based intelligent education systems [1]. Artificial intelligence has since made significant strides in higher education, ushering in new opportunities for growth and transformation. In 2017, the State Council of China released the "New Generation Artificial Intelligence Development Plan", explicitly calling for the use of artificial intelligence to accelerate reforms in talent cultivation and teaching methodologies. By 2022, the Chinese Ministry of Education had launched the "Action Plan for Innovation in Artificial Intelligence in Higher Education", setting forth initiatives to leverage artificial intelligence in enhancing the development of teaching staff and redefining education in the modern era.

Artificial intelligence technology is experiencing rapid growth in the field of design education, with its benefits being widely recognized [2]. Artificial intelligence opens new doors for designing more effective learning activities and enriching the learning environment [3]. In design education, its key contributions lie in enhancing the creative process, accelerating prototype development, and offering personalized teaching approaches [4]. To keep pace, students must become proficient in a variety software and hardware of artificial intelligence, boosting their capacity for innovative practice. Artificial intelligence tailors learning experiences by providing personalized guidance and technical support, shaped by learning progress, preferences, or individual traits [5]. Artificial intelligence is also being integrated into specific design education curricula, as educators explore the most effective ways to harness its potential. For instance, art and media courses utilizes multimodal artificial intelligence technologies to generate landscape designs and simulate human activity scenarios. In product design courses, artificial intelligence supports students in refining their design thinking skills and boosting their creativity [6]. Moreover, quantitative models have been developed to gauge the receptiveness of students to artificial intelligence design courses, offering valuable insights for future course design [7]. Additionally, multimodal language models are employed to elevate the abilities of students to appreciate and critique design work [8].

1.2. The Application of Virtual Reality Technology in Design Education

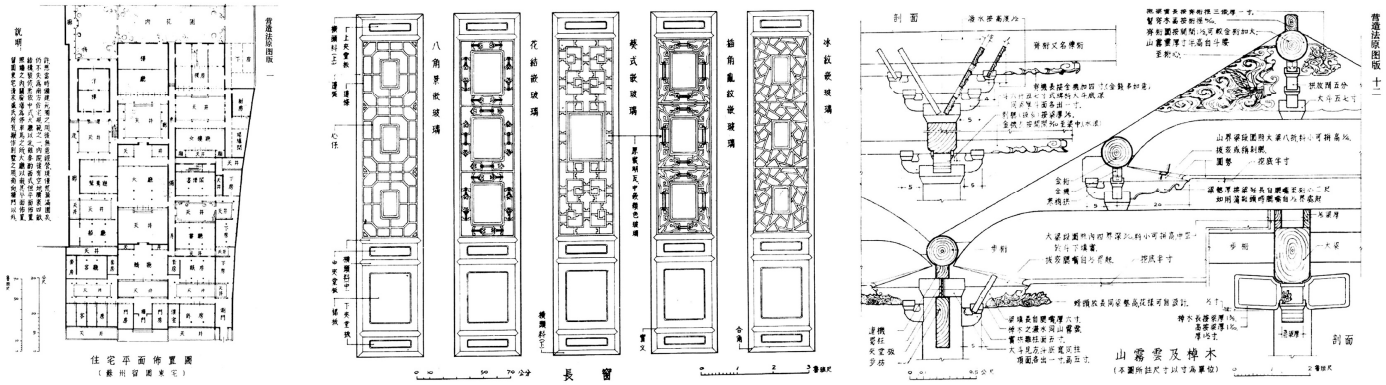
Virtual reality technology offers users a deeply interactive experience by simulating virtual environments. Since the 1980s, virtual reality has been utilized in education, initially for industry training and vocational programs. By the 1990s, it found its way into higher and basic education [9]. Virtual reality can be divided into immersive and non-immersive systems, with immersive virtual reality requiring head-mounted displays, while non-immersive versions rely on screens or computers for simulation [10]. Today, virtual reality technology is extensively applied in higher education. In 2020, the Chinese Ministry of Education launched the national virtual simulation experimental teaching project, advancing virtual reality applications in the reform of university-level experimental teaching.

Compared to artificial intelligence, research into the role of virtual reality in design education began earlier, leading to more stable technology and significantly enhanced learning outcomes. The immersive, interactive, and conceptual qualities of virtual reality foster effective immersive, interactive, and high-efficiency learning experiences [11]. Virtual reality technology is primarily used in design courses that emphasize spatial experience, enabling students to grasp concepts like spatial types, scales, and perceptual experiences [12]. Virtual software is incorporated into spatial composition courses, allowing students to explore virtual environments in the visualized, abstract spaces they create [13]. Studies on scale perception have shown that teaching with virtual reality significantly improves understanding of spatial scale [14]. In architectural aesthetics courses, students utilize Mars software and VR hardware to engage with architectural aesthetics through immersive experiences [15]. Tests on immersive education systems for construction site planning, which is based on virtual reality, showed that such systems notably enhanced learning outcomes [16].

1.3. The Integration of Artificial Intelligence and Virtual Reality into Traditional Architectural Education

Traditional architecture, shaped by historical heritage and natural environments, serves as a cultural and architectural hallmark, reflecting the distinctive construction styles and techniques of historical structures. It carries profound regional characteristics and holds immense cultural and educational value, particularly in understanding the evolution of regional architecture. In architectural education, traditional architecture holds an essential place. Early traditional architectural education combined theoretical learning with fieldwork, where students conducted on-site measurements of architectures. These measurements were then translated into hand-drawn plans, elevations, and sectional

diagrams. For example, Figure 1 depicts the plan of the east residence in Lingering Garden, the elevation of its long windows, and a sectional view of mountain mist cloud and zhuo wood [17]. These drawings, along with historical records, were used to construct physical models, replicating the traditional structures. As the field evolved, AutoCAD software began to be employed, marking the intermediate phase of traditional architectural education. It allowed for the creation of more sophisticated diagrams, such as Figure 2, which shows the sectional view of the Deng family residence in Mingyue Bay village. Software tools were also used to build virtual models of traditional architecture [18], with video outputs enhancing the learning experience. In recent years, virtual reality and artificial intelligence have been integrated into traditional architectural education [19]. Virtual reality technology provides a deeper understanding of timber-frame structures by offering immersive, panoramic tours of traditional architectures [20]. At the same time, artificial intelligence technologies have been employed to generate architectural designs, renderings, and videos. Figure 3 show cases of Ge Garden in Yangzhou, created using drawing software of artificial intelligence and virtual reality tools.

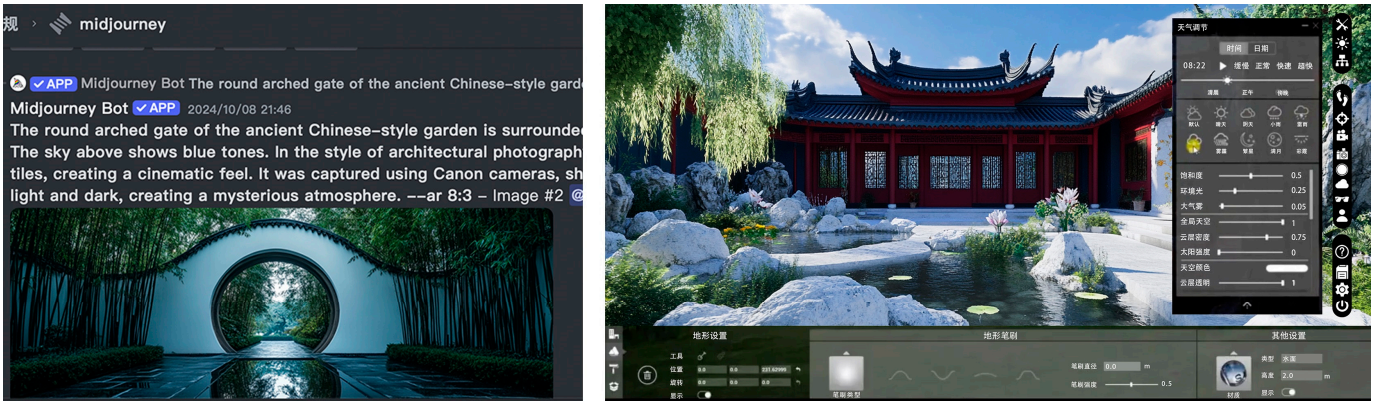


(**a**) (**b**) (**c**)

Figure 1. Hand-drawn diagram for early traditional architecture education (Yao,1986) [17]: (**a**) plan atlas of the east residence in the Lingering Garden; (**b**) elevation atlas of a long window; (**c**) section atlas of mountain mist cloud and zhuo wood (a type of woodwork construction in Jiangnan traditional architecture).



Figure 2. Computer-aided sectional drawing for mid-stage traditional architecture education.



(**a**) (**b**)

Figure 3. Jiangnan traditional architecture generated by artificial intelligence and virtual reality: (**a**) Ge Garden landscape generated using AI drawing software Midjourney (Ge Garden is a renowned classical Chinese garden.); (**b**) Ge Garden architecture generated by VR simulation software.

1.4. Sustainable Architecture Education

The concept of sustainable architecture first gained prominence in the 1990s. It embodies sustainable development principles through a balance of functionality, economic viability, cultural preservation, and ecological responsibility. Its objectives include reducing energy consumption, curbing pollution, optimizing efficiency, and safeguarding ecosystems. This study delves into sustainable architecture education, an innovative field that merges artificial intelligence and virtual reality technologies with traditional architectural curricula. This fusion seeks to preserve and enrich the cultural legacy of regional architecture while simultaneously enhancing learning efficiency and achieving sustainable educational outcomes. The approach aligns with foundational principles of sustainable architecture education, particularly the emphasis on understanding regional cultural identity and fostering public familiarity with advanced technologies. By promoting lifelong learning and ensuring educational equity, it contributes to the long-term benefits of sustainable architecture education, supporting broader societal goals across economic, cultural, and environmental dimensions. With technological advancements accelerating, scholarly attention to sustainable education increasingly highlights the role of artificial intelligence and virtual reality technologies. For example, Ajda (2024) examines how university students perceive artificial intelligence tools and integrate them into sustainable education practices [21]. Zhou (2024) investigates key factors shaping sustainable learning behaviors in virtual simulation environments [22]. Michael (2024) evaluates the inclusiveness and efficacy of artificial intelligence technologies in fostering sustainable learning environments [23].

Despite the growing interest in artificial intelligence and virtual reality technologies, their potential in traditional architectural education remains largely untapped. The exact impact of these technologies on learning outcomes is still unclear, which has hindered their wider adoption. Furthermore, artificial intelligence and virtual reality are typically used independently in architectural education, with few examples of both being combined, leaving the question of their relative effectiveness unanswered.

To address this gap, this study integrates drawing and language tools of artificial intelligence with drawing and simulation technologies of virtual reality into sustainable architectural education. A pilot randomized controlled trial was conducted, involving 60 students who were divided into three groups: an AI group, a VR group, and a control group. Using an adaptive course assessment system, the study empirically compared the effects of artificial intelligence, virtual reality, and traditional teaching across four key dimensions: architectural knowledge, architectural design, architectural computation, and architectural learning. This research seeks to offer new theoretical insights and practical strategies for enhancing the use of artificial intelligence and virtual reality in sustainable

architectural education. It helps achieve multiple sustainable development goals by optimizing design education, promoting sustainable educational practices, and fostering a healthy environment.

2. Research Foundation

2.1. Experimental Fundamentals of Artificial Intelligence and Virtual Reality

2.1.1. Artificial Intelligence Language Processing Technology

Artificial intelligence language processing technology harnesses the power of algorithms and models to transform human natural language into machine-readable formats, enabling seamless human–machine interaction, efficient information extraction, semantic analysis, and fluent text generation. Chat generative pre-trained transformer (ChatGPT), developed by OpenAI, represents a breakthrough in this field. By incorporating reinforcement learning with human feedback, ChatGPT continuously refines its language generation capabilities through real-time interactions with humans, producing content that aligns closely with user preferences [24]. The versatility of ChatGPT spans conversations, language translation, image creation, video output, and content writing [25]. In the realm of traditional architectural education, ChatGPT offers significant advantages, from quickly generating design suggestions based on textual input to broadening the scope of knowledge available to students. Its ability to assist in conceptualizing ideas and enhancing design efficiency is invaluable. The typical workflow involves defining the design challenge, interacting to gather feedback, refining design concepts, and producing the final design outcomes.

2.1.2. Artificial Intelligence Drawing Technology

Artificial intelligence drawing technology leverages deep learning to interpret textual descriptions through computer models, automatically producing images and videos. This cutting-edge technique enhances image data training with feedback from human interaction, generating images that cater to a wide array of styles and user needs [26]. Midjourney, a drawing tool of artificial intelligence, utilizes generative adversarial network technology, enabling users to create images of various design styles by simply inputting keywords. In the context of traditional architectural education, the strengths of Midjourney lie in its ability to swiftly generate design concepts, empowering students to explore a variety of design options and visual expressions while significantly reducing the time required for manual drawing. This leads to more efficient design iterations. The process typically involves crafting descriptive prompts, submitting them, and selecting or iterating the generated images. Students can fine-tune their prompts to steer the image generation process toward results that better match their design intentions.

2.1.3. Immersive Virtual Reality Technology

Immersive virtual reality technology merges head-mounted displays, hand controllers, and voice recognition systems to integrate rich media resources, creating a multi-sensory virtual environment that offers users visual, auditory, and tactile stimulation, resulting in an intensely immersive experience [27]. Mars, a software platform developed by Sheen city, serves as an architectural extended reality design tool. Within traditional architectural education, Mars allows for real-time rendering based on three-dimensional virtual models, offering a realistic simulation of environments that enhances spatial understanding of traditional architectural designs while increasing the motivation and active participation of students. The workflow of Mars includes importing design models, creating in virtual environments, real-time rendering, and experiencing virtual spaces. The system works in conjunction with computer hardware, virtual reality headsets, hand controllers, and tracking devices.

2.1.4. Virtual Reality Painting Technology

Virtual reality painting technology enables users to create three-dimensional artwork within a virtual environment by using virtual drawing tools and interacting with the

virtual canvas through hand gestures, applying various brushes and effects [28]. Tilt Brush, a virtual reality drawing application, provides a groundbreaking artistic experience, allowing users to freely create within a three-dimension virtual space. In the context of traditional architectural education, Tilt Brush enables students to quickly construct and modify architectural designs, create complex visual representations, and present their design ideas in an intuitive and vivid manner. The workflow involves selecting drawing tools and materials, creating within the virtual space, previewing and editing in real time, and exporting the final architectural designs.

2.1.5. The Application of Artificial Intelligence and Virtual Reality in Traditional Architecture Education Practices

Artificial intelligence and virtual reality technologies have primarily been applied separately in traditional architecture education. AI-assisted design leverages pattern analysis to deliver intelligent recommendations, thereby streamlining decision-making and enhancing design accuracy. Min (2023) harnessed the capabilities of generative artificial intelligence in content creation and interactive language applications to pioneer innovative generative imaging courses tailored to the artificial intelligence era [29]. Conversely, virtual reality technology enriches students' grasp of spatial configurations and architectural proportions through immersive, hands-on experiences. This reduces the need for revisions during the design phase and significantly elevates design quality. Guo (2024) compared the educational impacts of 360-degree panoramic virtual reality, immersive virtual reality, and desktop virtual reality technologies, presenting new VR-driven strategies for advancing traditional architecture education [30]. This study proposes an innovative teaching model by integrating artificial intelligence and virtual reality technologies. Through analyzing the compatibility between learning tasks and technological applications across various stages and evaluating their impact on learning outcomes in different architectural dimensions, the study offers theoretical insights and practical methodologies for the comprehensive application of artificial intelligence and virtual reality in traditional architecture education practices.

2.2. Experimental Questionnaire Design

2.2.1. Basic Information Questionnaire

To analyze the demographic profile of participants in the Jiangnan traditional architecture course, a basic information questionnaire was designed. The questionnaire includes five main aspects: age, gender, academic background, education level, and proficiency with artificial intelligence or virtual reality software. Comprising six questions, this survey aims to capture the diversity in academic background, education level, and technical readiness among students. The collected data will be analyzed separately for the AI, VR, and control groups and as a whole. An independent samples *t*-test will be conducted to confirm that there are no statistically significant differences in demographic variables between the three groups, ensuring the results of the experiment are unaffected.

2.2.2. Jiangnan Traditional Architecture Cognition Scale

The Jiangnan traditional architecture cognition scale was developed to assess the knowledge acquisition of students regarding Jiangnan traditional architecture. The scale is divided into three parts: architectural spatial design, major wooden structures, and minor wooden decorations, covering six areas: individual spaces, space combinations, column and beam construction, typical structures, typical styles, and craftsmanship. It consists of 12 questions, with a focus on comparing learning outcomes in space combinations, column and beam construction, and craftsmanship between the AI, VR, and control groups. The scale uses a Likert scoring system from 1 to 5, where a higher score reflects a greater level of mastery.

2.2.3. Design Thinking Scale

This study uses the design thinking scale to evaluate the design thinking skills improvement in students during the Jiangnan traditional architecture course. The scale is based on the five stages of design thinking, which were proposed by Stanford University, and it focuses on four key components: empathize, define, ideate, and prototype, consisting of 19 questions in total. The main goal is to compare how the AI group, VR group, and control group perform in the define and ideate aspects. The scale follows a 1 (strongly disagree) to 5 (strongly agree) rating system, where higher scores reflect stronger design thinking skills.

2.2.4. Computational Thinking Scale

This study assesses the improvement in students in computational thinking through the computational thinking scale. Developed by Korkmaz and Bai in 2019, the scale evaluates five key dimensions: creativity, algorithmic thinking, collaboration, critical thinking, and problem-solving, comprising 20 questions. The primary comparison focuses on differences between the AI group, VR group, and control group in algorithmic thinking, collaboration, and problem-solving. The scale uses a 1 to 5 scoring range, with higher scores indicating more advanced computational thinking skills.

2.2.5. Learning Effectiveness Evaluation Questionnaire

To measure learning achievements of students in the Jiangnan traditional architecture course, this study developed a learning effectiveness evaluation questionnaire. Administered during the final week of the course, the questionnaire contains 10 items covering five areas: learning attitude, academic performance, learning efficiency, learning pleasure, and learning outcomes. The key objective is to compare the AI group, VR group, and control group in terms of academic performance, learning efficiency, and learning outcomes. The questionnaire uses a 5-point Likert scale, where higher scores signify greater learning effectiveness.

2.3. Adaptive Evaluation Indicator System

This study established an adaptive evaluation system for the Jiangnan traditional architecture course (Table 1), designed to assess students across four key dimensions: architectural knowledge, architectural design, architectural computation, and architectural learning, with a total of 20 specific indicators.

(1) Architectural knowledge dimension: This dimension evaluates the grasp of Jiangnan traditional architectural knowledge. It focuses on three key areas: spatial creation, major wooden structures, and minor wooden decorations. Specific indicators include single space, space combinations, column and beam construction, typical structure, typical styles, and material craftsmanship.
(2) Architectural design dimension: The focus here is on cultivating design thinking skills, with specific indicators including empathy, define, ideate, and prototype stages.
(3) Architectural computation dimension: This dimension measures computational thinking capabilities of students, covering five specific indicators: creativity, algorithmic thinking, collaboration, critical thinking, and problem-solving.
(4) Architectural learning dimension: This dimension assesses learning effectiveness based on five indicators: learning attitude, academic performance, learning efficiency, learning pleasure, and learning outcomes.

Table 1. Adaptive evaluation indicator system for the Jiangnan traditional architecture course.

Adaptive Evaluation System	Adaptive Evaluation Items	Adaptive Evaluation Indicator	Adaptive Evaluation Sub-Indicators
Architectural knowledge dimension	Cognition of Jiangnan traditional architecture	Spatial creation of architecture	Single space Space combination
		Major wooden structures	Column and beam construction Typical structure
		Minor wooden decorations	Typical styles Material craftsmanship
Architectural design dimension	Design thinking		Empathize Define Ideate Prototype
Architectural computation dimension	Computational thinking		Creativity Algorithmic thinking Cooperativity Critical thinking Problem solving
Architectural learning dimension	Learning effectiveness		Learning attitude Academic performance Learning efficiency Learning pleasure Learning outcomes

3. Materials and Methods

3.1. Experimental Background

In the spring semester of 2024, a 10-week course on Jiangnan traditional architecture was introduced, consisting of 48 class hours and granting three academic credits. This course integrated artificial intelligence and virtual reality technologies alongside traditional teachings on the spatial layouts, major timber structures, and decorative elements of Jiangnan architecture. By analyzing quantitative data from four key areas—architectural knowledge, architectural design, architectural computing, and architectural learning—the course sought to evaluate the applicability, effectiveness, and differences in how these technologies enhance traditional architectural education.

Sixty undergraduate and graduate students from the majors of environmental art design, architectural design, and design studies were randomly and voluntarily divided into three groups—AI, VR, and control groups—with 20 students per group. Special consideration was given to ensure that VR group participants experienced no dizziness during their use of virtual reality equipment. After explaining the objectives, methods, privacy rights, and withdrawal rights, the students received adaptive training in artificial intelligence and virtual reality technologies. Each group then applied these technologies to complete design projects centered on Jiangnan traditional architecture.

3.2. Experiment Participants

This study recorded social-demographic data from the participants. The age was distributed between 18 and 25 years old, with 70% being 18 to 20 years old. A total of 61.7% were female and 38.3% were male. In total, 71.7% of the participants majored in environmental art design, 11.7% in architectural design, and 16.7% in design studies. In terms of education level, 83.3% were undergraduates and 16.7% were graduate students. In terms of software experience, 15% had experience with artificial intelligence software, and 13.3% had experience with virtual reality software (Table 2).

Table 2. Social–demographic data of the students.

Social–Demographic Items	AI Group		VR Group		Control Group		Total	
	Number	%	Number	%	Number	%	Number	%
Age (Years)								
18–20	15	75.0	13	65.0	14	70.0	42	70.0
21–22	2	10.0	3	15.0	3	15.0	8	13.3
23–25	3	15.0	4	20.0	3	15.0	10	16.7
Gender								
Female	12	60.0	14	70.0	11	55.0	37	61.7
Male	8	40.0	6	30.0	9	45.0	23	38.3
Major								
Environmental art design	14	70.0	14	70.0	15	75.0	43	71.7
Architectural design	3	15.0	2	10.0	2	10.0	7	11.7
Design studies	3	15.0	4	20.0	3	15.0	10	16.7
Educational level								
Undergraduate students	17	85.0	16	80.0	17	85.0	50	83.3
Graduate students	3	16.0	4	20.0	3	12.0	10	16.7
AI and VR software proficiency								
AI software proficiency	3	15.0	4	20.0	2	10.0	9	15.0
VR software proficiency	2	10.0	3	15.0	3	15.0	8	13.3

An independent samples *t*-test indicated that there were no statistically significant differences in demographic characteristics among the AI, VR, and control groups, suggesting that these variables did not impact the results of the experiment.

3.3. Experimental Plan and Content

The Jiangnan traditional architecture course is structured into four main phases: the Jiangnan traditional architecture explanation stage, the pre-test data survey stage, the technology-assisted Jiangnan traditional architecture design stage, and the data analysis stage, as shown in Figure 4. This study utilized a suite of advanced software tools, including ChatGPT version 4.0, Midjourney version 6.0, SketchUp 2022, Runwayml Gen-3, Sheencity Mars 2022, Tilt Brush version 16, and Premiere Pro 2023. The total cost of the software was approximately CNY 3280. The equipment deployed for the research comprised an Pico 4 headset (manufactured by Pico Interactive, headquartered in Beijing, China) with accompanying controllers and sensors, a high-performance computer, headphones, and a microphone. The total cost of the hardware was approximately CNY 21,800. Additionally, the study incorporated technical training focused on artificial intelligence and virtual reality software operation, installation and handling of virtual reality equipment, and immersive experience training. The training expenses amounted to approximately CNY 6000.

In this study, the AI group used ChatGPT (version 4.0) for generating design concepts, MidJourney (version 6.0) for creating storyboards and visual design images, and Runwayml (Gen-3) for video editing. The authors reviewed and edited all outputs and take full responsibility for the content presented in this paper.

3.3.1. Jiangnan Traditional Architecture Explanation Stage

During the initial two weeks, students are introduced to the theoretical foundations of Jiangnan architecture, including its spatial layout, major timber structures, and decorative elements. This phase equips students with an understanding of the creative process behind Jiangnan traditional architecture, guiding them through the analysis of exemplary design cases and assisting them in defining their specific design targets.

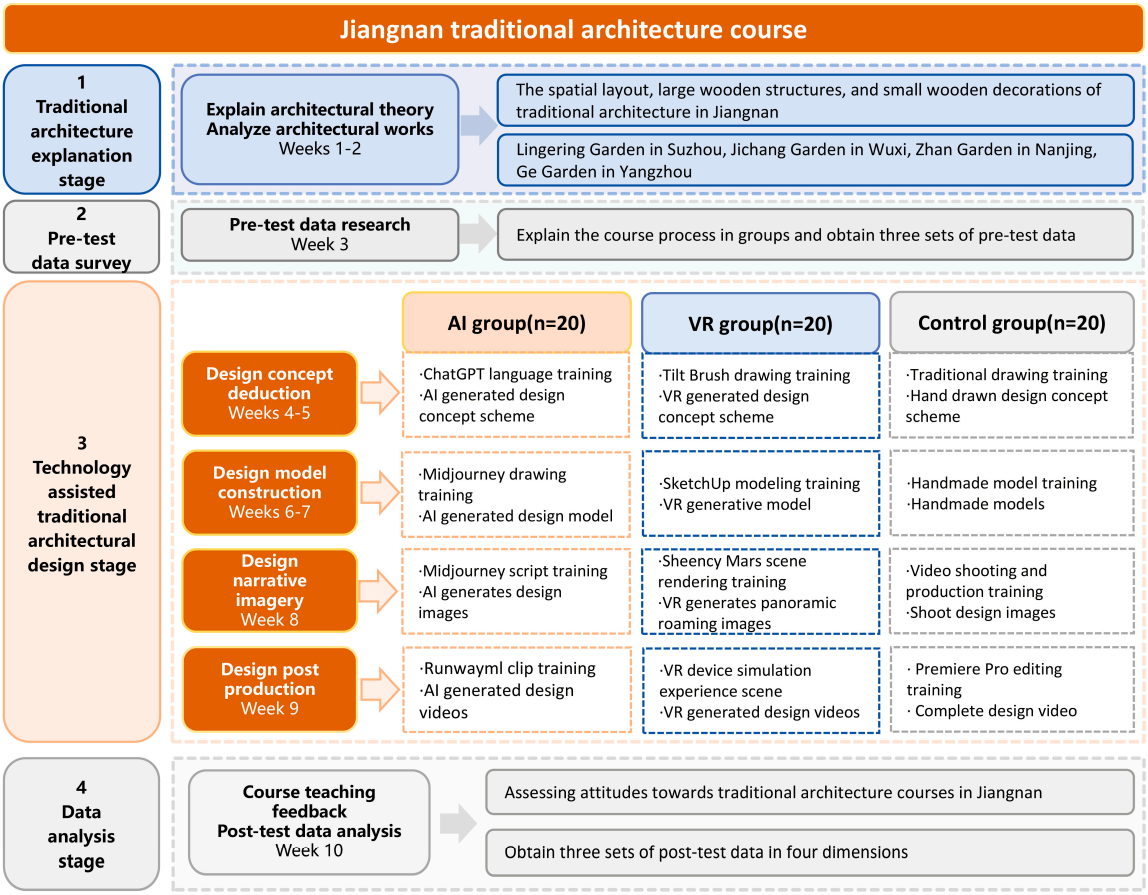


Figure 4. The experimental plan of the Jiangnan traditional architecture course.

3.3.2. Pre-Test Data Survey Stage

In the third week, the 60 undergraduate and graduate students are randomly assigned into the AI group, VR group, and control group. They are then tasked with completing a basic information survey, the Jiangnan traditional architecture cognition scale, the design thinking scale, and the computational thinking scale. These scales gather pre-test data on demographics, knowledge of traditional architecture, design thinking, and computational thinking across the three groups.

3.3.3. Technology-Assisted Jiangnan Traditional Architecture Design Stage

The 6-week technology-assisted design phase for Jiangnan traditional architecture focuses on producing design proposals, models, and videos. This phase includes 30 lessons, scheduled two times per week, with each session lasting 45 min. The design process is structured into four distinct phases: design conception, design modeling, design narrative, and design post-production.

(1) Design conception phase (weeks 4–5). In this initial phase, students develop design proposals through creative sketches (Table 3). The AI group leverages ChatGPT software to generate design concepts, the VR group employs Tilt Brush software to sketch out their proposals, and the control group utilizes traditional drawing tools for their designs.

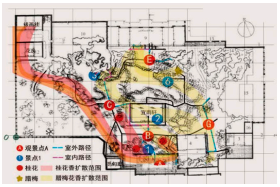
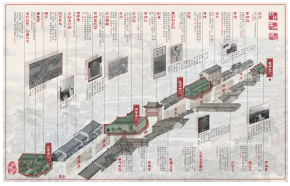
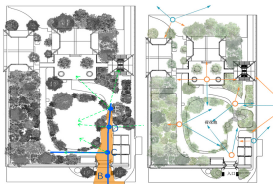
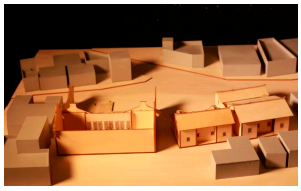
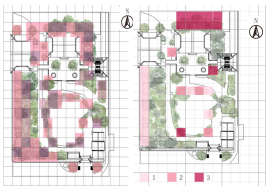
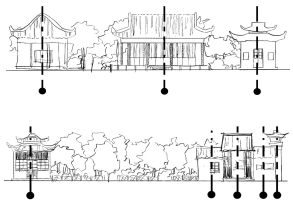
(2) Design modeling phase (weeks 6–7). The students create physical or digital models based on their design proposals. The AI group generates models using Midjourney software, as shown in Figure 5a; the VR group constructs virtual models in Sketchup software; and the control group handcrafts their models, as shown in Figure 5b.

(3) Design narrative phase (week 8). The focus of this phase is the creation of design visuals. The AI group uses Midjourney software to generate storyboards and visual

designs; the VR group uses Mars software to produce immersive panoramic visuals, as shown in Figure 5c; and the control group shoots their design visuals using mobile devices.

(4) Design post-production phase (week 9). In the final phase, students work on creating the final design videos. The AI group employs Runwayml software for video editing, the VR group utilizes virtual reality headsets to experience and finalize their virtual design videos, and the control group edits their videos using Premiere Pro software.

Table 3. Learning outcomes in the technology-assisted Jiangnan traditional architecture design stage. (Images in the AI group of Table 3 were generated using the AI software Midjourney).

Groups	Design Conception Phase	Design Modeling Phase	Design Narrative Phase	Post-Production Phase
AI group	Project		AI design tools	
	Traditional architecture of Ge Garden in Yangzhou		ChatGPT, Midjourney, Runwayml	
				
	Site plan	Architectural model	Architectural narrative	Architectural rendering
VR group	Project		VR design tools	
	Traditional architecture of Jianjia Lane in Suzhou		TiltBrush, SketchUp, Mars, VR equipment	
				
	Site layout	Architectural model	Spatial narrative	Architectural roaming
Control group	Project		Design tools	
	Traditional architecture of Xu Garden in Yangzhou		Premiere Pro, drawing tools, mobile phone	
				
	Traffic and sightline	Architectural model	Plant configuration	Architectural section



(**a**)



(**b**)



(**c**)

Figure 5. Learning scenarios of the AI, VR, and control groups: (**a**) design images generated by the AI group; (**b**) handcrafted models created by the control group; (**c**) virtual experience by the VR group.

3.3.4. Data Analysis Stage

In the final week of the course (week 10), students are invited to complete the learning effectiveness evaluation questionnaire of Jiangnan traditional architecture course. Additionally, they are required to retake the Jiangnan traditional architecture cognition scale, the design thinking scale, and the computational thinking scale. The post-test data from these assessments are then compared with the pre-test data, enabling an evaluation of impact on teaching effectiveness across four key dimensions: architectural cognition, architectural design, architectural computation, and architectural learning.

4. Results

For data processing, tabulation, and statistical analysis, this study used SPSS software version 25.0. Continuous variables were presented as means and standard deviations, while categorical variables were expressed as percentages and frequencies.

(1) To ensure the accuracy and consistency of the data, reliability and validity tests were performed. A Cronbach α value exceeding 0.8 was taken as an indicator of strong reliability, and a KMO value greater than 0.6 indicated strong validity (see Figure 6).

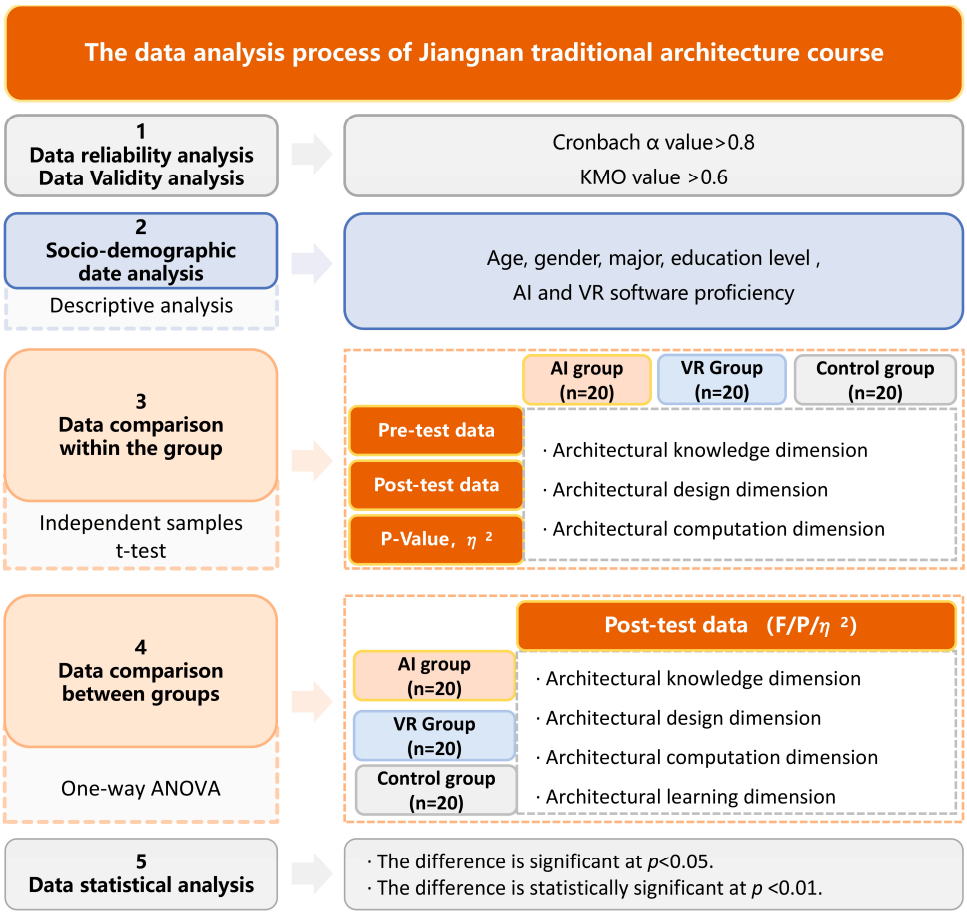


Figure 6. Data analysis process.

(2) Descriptive analysis was used to illustrate social–demographic characteristics of the participants, such as age, gender, major, educational level, and experience with AI or VR software, ensuring no statistically significant differences across the three groups.

(3) An independent samples *t*-test was conducted to compare the pre-test and post-test results for architectural knowledge, architectural design, and architectural computation within the AI, VR, and control groups, with significance set at $p < 0.05$.

(4) A one-way ANOVA was used to assess differences in post-test results across the four dimensions—architectural knowledge, architectural design, architectural computation, and architectural learning—among the AI, VR, and control groups. The threshold for statistical significance was $p < 0.05$.

4.1. Data Analysis of the Architectural Knowledge Dimension

4.1.1. Spatial Creation of Architecture

The data on architectural spatial creation reveal that the VR group achieved higher average scores than both the control group and the AI group (Table 4). The VR group exhibited significant improvements in understanding both single space ($p = 0.002$, $\eta^2 = 0.164$) and space combinations ($p = 0.010$, $\eta^2 = 0.141$). The control group performed better in single space (1.70 ± 0.92, $p = 0.042$) compared to in space combinations (1.50 ± 0.69, $p = 0.083$). Meanwhile, the AI group showed slight improvement in space combinations ($p = 0.021$, F = 6.153).

Table 4. Data analysis of the architectural knowledge dimension between the AI group, VR group, and control group.

Architectural Knowledge Dimension		Groups	Cognitive Function (Mean ± SD)			Group Comparison		
			Pre	Post	*p*-Value	F	*p*	η^2
Spatial creation of architecture	Single space	AI group	1.45 ± 1.00	1.60 ± 1.10	0.083			0.164
		VR group	2.20 ± 0.95	2.60 ± 1.10	0.002 **	5.595	0.006 **	
		Control group	1.50 ± 0.83	1.70 ± 0.92	0.042 *			
	Space combination	AI group	1.25 ± 0.72	1.50 ± 0.89	0.021 *	6.153	0.004 **	0.141
		VR group	2.00 ± 0.79	2.30 ± 0.92	0.010 *			
		Control group	1.35 ± 0.59	1.50 ± 0.69	0.083			
Major wooden structures	Construction column and beam	AI group	1.90 ± 0.91	1.95 ± 0.89	0.330			0.102
		VR group	2.45 ± 0.76	2.80 ± 0.89	0.005 **	5.224	0.008 **	
		Control group	1.75 ± 0.91	2.05 ± 0.94	0.010 *			
	Typical structure	AI group	2.25 ± 0.79	2.55 ± 0.89	0.010 *	5.654	0.006 **	0.130
		VR group	2.70 ± 0.80	3.25 ± 0.91	0.001 **			
		Control group	2.15 ± 0.75	2.40 ± 0.75	0.056			
Minor wooden decorations	Typical styles	AI group	2.15 ± 0.75	2.55 ± 0.89	0.002 **			0.104
		VR group	1.85 ± 0.81	2.05 ± 0.69	0.297	3.306	0.044 *	
		Control group	1.80 ± 0.62	2.00 ± 0.65	0.104			
	Material craftsmanship	AI group	2.00 ± 0.86	2.35 ± 0.93	0.005 **			0.069
		VR group	1.65 ± 0.75	1.85 ± 0.88	0.163	2.114	0.130	
		Control group	1.80 ± 0.70	1.90 ± 0.72	0.428			

Note: * The difference is statistically significant at $p < 0.05$. ** The difference is statistically significant at $p < 0.01$.

The superior performance of the VR group is due to their use of SketchUp software to construct virtual models of traditional architecture, facilitating the best analysis and understanding of spatial layouts. The control group, working with physical models, enhanced their comprehension of single spaces in traditional architecture. In contrast, the AI group, which relied on visualizing three-dimensional spaces from two-dimensional plans, had the weakest grasp of space, though their understanding of space combinations was stronger than that of single space.

4.1.2. Major Wooden Structures

Data on major wooden structures reveal that the VR group achieved higher average scores compared to both the control and the AI groups. The differences were most pronounced in the performance of the VR group in column and beam construction ($p = 0.005$, $\eta^2 = 0.102$) and typical structures ($p = 0.001$, $\eta^2 = 0.130$). The control group performed better in column and beam construction (2.05 ± 0.94, $p = 0.010$) than in typical structures (2.40 ± 0.75, $p = 0.056$), while the AI group showed some variability in their understanding of typical structures ($p = 0.010$, F = 5.654).

The advantage of the VR group is largely due to their immersive experience with virtual reality, which allowed students to engage deeply with the construction process,

leading to strong memory retention. The control group, working with physical models, enhanced their understanding of structural assembly, particularly in columns and beams. The AI group, tasked with understanding major wooden structures through two-dimensional and three-dimensional images, found this challenging, but they demonstrated a better grasp of typical structures (2.55 ± 0.89, $p = 0.010$) than of column and beam construction (1.95 ± 0.89, $p = 0.33$).

4.1.3. Minor Wooden Decorations

Data on minor wooden decorations show that the AI group scored the highest in typical styles (2.55 ± 0.89, $p = 0.002$), followed by the VR group (2.05 ± 0.69, $p = 0.297$), with the control group scoring the lowest (2.00 ± 0.65, $p = 0.104$). The AI group exhibited significant differences in typical styles ($p = 0.002$, $\eta^2 = 0.104$), because artificial intelligence software was used to generate numerous traditional architectural illustrations of minor wooden decorations, enhancing retention of decorative styles.

In terms of material craftsmanship, the AI group also had the highest average score (2.35 ± 0.93, $p = 0.005$), outperforming both the control group (1.90 ± 0.72, $p = 0.428$) and the VR group (1.85 ± 0.88, $p = 0.163$). The AI group showed significant differences in material craftsmanship ($p = 0.005$, $\eta^2 = 0.069$), which can be attributed to the ability of software to provide detailed insights into the materials and techniques used in minor wooden decorations. The control group, however, did not show significant differences in this area, due to the time-intensive nature of physically crafting the models, which made it harder to capture the intricate craftsmanship details.

4.2. Data Analysis of the Architectural Design Dimension

The data for the architectural design dimension show that the AI group outperformed both the VR group and the control group in the define ($p = 0.002$, $\eta^2 = 0.177$) and ideate aspects ($p = 0.001$, $\eta^2 = 0.161$) (Table 5), with highly significant results. This advantage stems from the AI groups using generative artificial intelligence technology, which excels at identifying design problems and offering solutions, thus broadening the creative ideation and problem-solving capacities of students.

Table 5. Data analysis of the architectural design dimension between the AI group, VR group, and control group.

Design Dimension	Groups	Cognitive Function (Mean ± SD)			Group Comparison		
		Pre	Post	*p*-Value	F	*p*	η^2
Empathize	AI group	2.20 ± 0.89	2.40 ± 0.99	0.042 *	1.568	0.217	0.052
	VR group	1.95 ± 0.83	2.10 ± 1.02	0.083			
	Control group	1.75 ± 0.91	1.85 ± 0.93	0.163			
Define	AI group	2.70 ± 1.03	3.10 ± 1.07	0.002 **	5.640	0.006 **	0.177
	VR group	1.95 ± 1.00	2.20 ± 1.20	0.021 *			
	Control group	1.80 ± 0.89	1.95 ± 1.00	0.083			
Ideate	AI group	2.45 ± 0.89	2.90 ± 0.91	0.001 **	5.301	0.008 **	0.161
	VR group	1.95 ± 1.10	2.15 ± 1.09	0.042 *			
	Control group	1.80 ± 1.06	1.85 ± 1.09	0.330			
Prototype	AI group	2.05 ± 0.69	2.20 ± 0.77	0.083	4.742	0.012 *	0.217
	VR group	2.30 ± 0.80	2.65 ± 0.93	0.005 **			
	Control group	1.80 ± 1.06	1.85 ± 1.09	0.163			

Note: * The difference is statistically significant at $p < 0.05$. ** The difference is statistically significant at $p < 0.01$.

In the prototype aspect, the VR group had a higher average score (2.65 ± 0.93, $p = 0.005$) compared to the AI (2.20 ± 0.77, $p = 0.083$) and control groups (1.85 ± 1.09, $p = 0.163$), with significant learning gains ($p = 0.005$, $\eta^2 = 0.217$), largely due to their virtual modeling exercises. In the empathize aspect, no significant differences were observed between the

groups, though the AI group exhibited slightly stronger results (p = 0.042, η^2 = 0.052) compared to the VR and control groups.

4.3. Data Analysis of the Architectural Computation Dimension

In the architectural computation dimension (Table 6), the VR group outperformed both the AI group and the control group in algorithmic thinking (p = 0.005, η^2 = 0.186), cooperativity (p = 0.004, η^2 = 0.179), and problem solving (p = 0.010, η^2 = 0.138), with significant results. This advantage arises from the fixed proportional relationships between components in Jiangnan traditional architecture. The VR group, through the virtual modeling process, had to calculate the precise dimensions of the wooden components, enhancing their algorithmic thinking and problem-solving skills. Additionally, the extensive modeling tasks required collaboration among team members to build different parts of the same traditional structure, which significantly improved their cooperative communication abilities.

Table 6. Data analysis of the architectural computation dimension between the AI group, VR group, and control group.

Architectural Computation Dimension	Groups	Cognitive Function (Mean ± SD)			Group Comparison		
		Pre	Post	p-Value	F	p	η^2
Creativity	AI group	2.75 ± 0.97	3.15 ± 0.99	0.002 **	5.483	0.007 **	0.161
	VR group	2.15 ± 0.59	2.35 ± 0.67	0.042 *			
	Control group	2.15 ± 0.99	2.30 ± 1.03	0.083			
Algorithmic thinking	AI group	1.95 ± 0.83	2.20 ± 0.89	0.021 *	6.500	0.003 **	0.186
	VR group	2.70 ± 0.66	3.05 ± 0.89	0.005 **			
	Control group	2.15 ± 0.81	2.25 ± 0.72	0.163			
Cooperativity	AI group	2.00 ± 0.86	2.30 ± 0.86	0.010 *	6.225	0.004 *	0.179
	VR group	2.45 ± 0.94	2.90 ± 0.85	0.004 **			
	Control group	1.85 ± 0.67	2.05 ± 0.60	0.042 *			
Critical thinking	AI group	1.95 ± 0.69	2.40 ± 0.82	0.001 **	0.577	0.565	0.020
	VR group	2.15 ± 0.75	2.20 ± 0.77	0.330			
	Control group	2.00 ± 0.65	2.15 ± 0.75	0.083			
Problem solving	AI group	2.20 ± 0.83	2.45 ± 0.83	0.021 *	4.304	0.018 *	0.138
	VR group	2.55 ± 0.76	2.85 ± 0.88	0.010 *			
	Control group	2.05 ± 0.60	2.10 ± 0.64	0.330			

Note: * The difference is statistically significant at $p < 0.05$. ** The difference is statistically significant at $p < 0.01$.

In the creativity (p = 0.002, η^2 = 0.161) and critical thinking (p = 0.001. η^2 = 0.020) aspects, the AI group scored higher than both the VR group and the control group, with notable learning gains. This can be attributed to the diverse range of information provided by artificial intelligence software, which stimulated creativity and critical thinking in the AI group. In contrast, the more traditional learning process of the control group limited their creativity.

4.4. Data Analysis of the Architectural Learning Dimension

In the architectural learning dimension (Table 7), the VR group scored higher than both the AI group and the control group in terms of learning attitude (2.95 ± 1.10, p = 0.001, F = 7.472, η^2 = 0.208) and learning outcomes (2.85 ± 1.27, p = 0.022, F = 4.067, η^2 = 0.125), with significant results. This advantage of the VR group is attributed to the structured and detailed approach to design steps and technological pathways, which fostered a positive learning attitude and better adherence to the process. The VR group also completed a significantly larger volume of design work and developed a high level of technical expertise with virtual reality software and hardware, enhancing their sense of achievement.

Table 7. Data analysis of the architectural learning dimension between the AI group, VR group, and control group.

Architectural Learning Dimension	Experimental Groups (Mean ± SD)			F	p	η^2
	AI Group	VR Group	Control Group			
Learning attitude	1.95 ± 0.94	2.95 ± 1.10	1.85 ± 0.93	7.472	0.001 **	0.208
Academic performance	2.70 ± 1.13	1.95 ± 1.05	1.70 ± 0.80	5.384	0.007 **	0.159
Learning efficiency	2.85 ± 1.23	1.85 ± 1.18	1.70 ± 1.08	5.764	0.005 **	0.168
Learning pleasure	2.30 ± 1.13	1.80 ± 0.70	1.55 ± 0.69	3.926	0.025 *	0.121
Learning outcomes	2.30 ± 0.86	2.85 ± 1.27	1.95 ± 0.83	4.067	0.022 *	0.125

Note: * The difference is statistically significant at $p < 0.05$; ** The difference is statistically significant at $p < 0.01$.

Meanwhile, the AI group excelled in learning efficiency (2.85 ± 1.23, p = 0.005, F = 5.764, η^2 = 0.168), academic performance (2.70 ± 1.13, p = 0.007, F = 5.384, η^2 = 0.159), and learning pleasure (2.30 ± 1.13, p = 0.025, F = 3.926, η^2 = 0.121), scoring significantly higher than both the VR group and the control group. The advantage of the AI group stemmed from not needing to engage in virtual or manual modeling, which saved time that was redirected to design narrative and post-production work. Additionally, the artificial intelligence software provided diverse generative content in a short timeframe, boosting learning efficiency and contributing to high-quality final designs.

5. Discussion

5.1. Matching of Learning Tasks and Technology Applications in Each Phase

Inspired by recent research, this study integrates artificial intelligence and virtual reality technologies into the curriculum of traditional Jiangnan architecture. The study focuses on assessing the compatibility of these technologies with learning tasks across four critical stages: design conceptualization, design modeling, design narration, and post-design refinement (Tris et al., 2024) [31]. Building on previous studies, this research innovatively associates the language and drawing technologies of artificial intelligence capabilities with the design conceptualization and narration stages, while connecting the modeling and immersive roaming technologies of virtual reality to the design modeling and post-design stages. By analyzing the compatibility between learning tasks and technological applications in each phase, the study sheds light on the deeper factors influencing these alignments.

Artificial intelligence language technology was found to be the best match for the design conception phase. The use of ChatGPT software significantly enhanced the abilities to gather information, analyze design problems, and generate creative ideas. These results echo the findings of Jongsawas (2024), who highlighted the role of artificial intelligence in enhancing the ability of students to conceptualize their designs in creative thinking practices [32].

Virtual reality modeling and immersive roaming technologies were the most effective for the design modeling phase. Using Sketchup software to create virtual models and Mars software with virtual reality devices to generate panoramic tours greatly improved spatial awareness, construction skills, and material craftsmanship understanding. This aligns with the findings of Yang and Zhu (2023), who emphasized the capacity of virtual reality technology to stimulate creativity, critical thinking, and other higher-order cognitive skills among learners [33].

Artificial intelligence drawing technology had the strongest alignment with the design narrative phase. The use of Midjourney drawing software to generate narrative visuals of Jiangnan architecture based on scripts significantly boosted the script-handling and architectural storytelling abilities of students.

Virtual reality experiences and generative video technology were best suited to the post-production phase. Immersive experiences with virtual reality headsets and controllers, combined with the generation of design videos, significantly enhanced the virtual perception and design output skills of students.

5.2. The Relationship Between Technology Applications and Learning Outcomes in Various Dimensions of Architecture

Inspired by recent studies, this research developed an adaptive teaching evaluation index system, integrating the design dimension and the computational dimension into the foundational framework of the architectural knowledge dimension and the architectural learning dimension (Li et al., 2023) [34]. Expanding on earlier work, the study offers a comparative analysis of AI-driven language and drawing technologies versus VR-based painting and simulation technologies. It evaluates their impact on learning outcomes across four critical dimensions: architectural knowledge, architectural design, architectural computation, and architectural learning. By assessing the adaptability of these technologies to various learning objectives, the study delves into the deeper factors shaping these results.

Virtual reality drawing and simulation technologies proved to be the most effective in improving learning outcomes in the architectural knowledge dimension, particularly in the spatial layout and major wooden structures of Jiangnan traditional architecture. This is because, when comparing Sketchup modeling software of virtual reality to Midjourney drawing software of artificial intelligence, the former, which allows for the construction of three-dimensional virtual models, was far better suited for teaching the spatial and structural aspects of Jiangnan architecture. The latter required students to imagine three-dimensional spaces from two-dimensional images, which posed a greater challenge. Moreover, the immersive panoramic tours provided by Mars software of virtual reality heightened the sense of realism, greatly increasing interest of students in learning and enhancing their spatial awareness. Sandra (2022) supports this perspective, emphasizing that immersive virtual reality technology significantly boosts the engagement and outcomes of learners [35].

Artificial intelligence language and drawing technologies demonstrated superior learning outcomes in the architectural design dimension, especially in the empathize, define, and ideate aspects. Unlike the operation-focused virtual reality tools such as Tilt Brush software, Sketchup software, and Mars software, artificial intelligence tools like ChatGPT software and Midjourney software are better equipped to help students define design problems. By fostering empathy through human–machine interaction and offering diverse approaches to ideation, these artificial intelligence tools significantly boost creative thinking and innovation in design.

Virtual reality drawing and simulation technologies had the most substantial impact on learning outcomes in the architectural computation dimension, particularly in algorithmic thinking, cooperativity, and problem solving. The process of creating digital models of Jiangnan traditional architecture enabled students to understand the material proportions and modular systems inherent in traditional construction, thereby improving their algorithmic thinking. Moreover, the collaborative nature of large-scale virtual modeling projects encouraged group cooperation, enhancing systematic thinking and problem-solving abilities as team members combined different parts of the model. This is consistent with the results of Gustav (2023), who suggest that incorporating collaborative generative activities into virtual reality courses can more effectively improve learning abilities [36].

Artificial intelligence language and drawing technologies demonstrated outstanding performance in improving learning outcomes in the architectural learning dimension, especially in academic performance, learning efficiency, and learning enjoyment. The AI group achieved the best results in both the design conception phase and the design narrative phase. In terms of overall academic performance, their creativity and design expression were superior to those of the VR and control groups. The VR group spent much of their learning time on virtual modeling, while the control group focused on handcrafting physical models, which led to lower learning efficiency in both groups compared to in the AI group. The artificial intelligence tools, being easier to use, provided more frequent human–machine feedback and a greater amount of information. This enhanced the autonomy in learning and contributed to a higher level of enjoyment in the process.

5.3. Insights on the Application of Artificial Intelligence and Virtual Reality in Traditional Architecture Courses

This study proposes further implications for the application of artificial intelligence and virtual reality technologies in traditional architectural courses, which are inspired by recent studies. These include the mixed application of technologies at different stages, balancing interactive technological experiences with foundational learning practices (Zaher & Dalia, 2023) [37], and strengthening the adaptability of learners to technology (Marie et al., 2024) [38]. The equipment of virtual reality used in this study includes Pico 4 headset (manufactured by Pico Interactive, headquartered in Beijing, China), and the AI software used is Midjourney (developed by Midjourney, Inc., San Francisco, CA, USA).

5.3.1. Mixed Use of Technologies Across Different Phases

In future traditional architecture education, a phase-specific, mixed approach to technology can be adopted to maximize the benefits of different technologies and enhance student learning outcomes. In the design conception and design narrative phases, artificial intelligence language and drawing technologies should be the primary focus, supported by hand-drawn design concepts and narrative presentation techniques. In the design modeling and post-production phases, virtual reality drawing and simulation technologies should take precedence, with hand-built models and video editing as complementary tools.

5.3.2. Balancing Technology-Enhanced Interaction with Fundamental Learning

Artificial intelligence interactions and immersive virtual reality experiences significantly increase student engagement and design capabilities. However, it is important to balance these interactive elements with foundational learning in traditional architecture courses. Fundamental skills like architectural cognition, hand-drawing techniques, and spatial modeling training should not be overlooked. Overemphasizing technology-driven experiences at the expense of basic knowledge and training could hinder student development in core areas. This aligns with Dilay (2021), who highlight that while applying virtual reality technology to foundational architectural education, the effectiveness of paper-based design should not be overlooked [39].

5.3.3. Enhancing Learner Adaptation to New Technologies

At the beginning of each course stage, it is important to strengthen the adaptation of students to artificial intelligence and virtual reality technologies, taking into account their prior experience with such tools. This should involve essential training on the relevant software and ensuring students are proficient in using virtual reality headsets and controllers. As technological support is a core element of the course, continuous updates to training based on advancements in the hardware and software of artificial intelligence and virtual reality will help meet the evolving needs of traditional architecture education. This is also consistent with the conclusion of Daniel (2024), who believes that preparatory training for educators to adapt to new technologies is essential [40].

6. Conclusions

This study explored the integration of artificial intelligence language and drawing technologies, alongside virtual reality drawing and simulation technologies, into traditional architecture education. By establishing an adaptive evaluation system based on the learning objectives and outcomes of the course, this study compared the effects of artificial intelligence and virtual reality technologies across multiple phases and dimensions. Empirical research validated the differences in their application effectiveness.

On one level, the study assessed the alignment of technologies with learning tasks in the design conception, design modeling, design narrative, and design post-production phases. The findings reveal that students readily embraced both artificial intelligence and virtual reality technologies. The language and generative drawing tools of artificial intelligence demonstrated the best match for learning tasks in the design conception and

design narrative phases, while modeling and immersive roaming technologies of virtual reality showed the highest compatibility with learning tasks in the design modeling and design post-production phases.

On another level, this study evaluated the relationship between learning outcomes and technology applications across four key dimensions: architectural knowledge, architectural design, architectural computation, and architectural learning. The results highlight that artificial intelligence language and drawing technologies performed the best in enhancing learning outcomes in architectural design and learning, while virtual reality modeling and roaming technologies were most effective in improving learning in architectural knowledge and computation. The findings of this study offer new theoretical insights and practical approaches for integrating artificial intelligence and virtual reality technologies into traditional architecture education. Future courses could adopt a phase-specific mixed application of these technologies, maintaining a balance between interactive experiences and foundational learning, while enhancing the adaptability of students to these emerging tools to ensure more effective technology use. This would further explore the potential of artificial intelligence and virtual reality in sustainable educational practices, broaden sustainable architecture education approaches, and achieve broader sustainable education development goals.

This study identifies three key limitations. The first is its relatively short duration, as it is based on a 10-week course on traditional Jiangnan architecture. This limited timeframe may restrict the ability to comprehensively evaluate learning outcomes, knowledge retention, and the integration of technology into architectural education. To address this constraint, future research will design a series of interconnected courses on traditional architecture, enabling long-term and multi-phase tracking of the enduring impacts of artificial intelligence and virtual reality technologies on learning. Second, the adaptability of participants to artificial intelligence and virtual reality technologies may influence the effectiveness of the application. The third limitation is the financial cost associated with implementing artificial intelligence and virtual reality technologies, including expenditures on hardware, software, and technical training. These costs may impede the widespread adoption of the technology. However, the long-term benefits of artificial intelligence and virtual reality technologies, such as significantly enhanced teaching efficiency and learning outcomes, are expected to justify the initial investment. To reduce expenses and improve the accessibility of these findings, future efforts could utilize open-access resources, establish collaborative partnerships with technology companies, and apply for research grants that integrate academia, industry, and education. These strategies could help secure funding and sponsorships or discounts for required hardware and software. Additionally, phased implementation of technology solutions, tailored to available funding, would allow for gradual enhancements and system upgrades over time.

Future research will emphasize enhanced technology adaptation training at the start of traditional architecture courses or during the early phases of a course series, equipping participants to better utilize software and hardware tools. This will deepen our understanding of the relationship between artificial intelligence and virtual reality technologies and traditional architecture learning, driving innovation in teaching methods. This will enable students to implement sustainable design practices more effectively and efficiently, aligning with sustainable development principles.

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