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# Study on Learning Experiences of Generative AI Tools in Stereoscopic Composition Courses: Usage Patterns, Impacts, and Challenges

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**Abstract**
This study investigates the integration effects of generative artificial intelligence (GenAI) in three-dimensional composition courses and its implications for design education. Through a mixed-methods approach (N=104) combining quantitative surveys and qualitative analysis, findings reveal that AI tools significantly enhance creative efficiency (inspiration stimulation mean=3.49, solution screening mean=3.452) and optimize workflow processes (efficiency perception mean=3.356), while simultaneously exposing technical limitations in 3D model practicality (mean=3.337) and tool compatibility (mean=3.337). Students demonstrated cautiously positive attitudes (overall mean=3.2–3.5) but exhibited skill degradation anxieties (mean=3.337, SD=0.820) and divergent ethical risk perceptions (copyright concerns SD=0.878). The research identifies three core contradictions constraining AI efficacy: 1) tension between technical generality and disciplinary specificity, 2) conflict between efficiency gains and capability preservation, and 3) balance between creative freedom and ethical regulation. Students strongly advocate for structured support systems, particularly prompt engineering training (demand mean=3.49), reverse-engineering functionality optimization (mean=3.529), and integration guidance for traditional techniques (mean=3.452). The study proposes a tripartite strategy: 1) developing domain-specific AI tools with cross-platform data integration, 2) establishing a "technology-ethics-methodology" triadic curriculum module, and 3) implementing dynamic competency assessment mechanisms through blended learning to balance technological empowerment with traditional skill transmission. It warns that unchecked tool-centric pedagogy risks homogenizing design thinking and eroding critical creativity. Future research should expand cross-disciplinary comparisons and longitudinal tracking to comprehensively map AI's evolving impact on design education ecosystems.
**Keywords:** Generative AI Tools, Stereoscopic Composition Courses, Learning Experiences, Usage Patterns, Challenges

## Introduction

*Research Background*

The integration of generative artificial intelligence (GenAI) into design education has emerged as a transformative trend, particularly in foundational courses like stereoscopic composition. Recent advancements in AI tools, such as text-to-3D generators (e.g., Meshy AI) and workflow optimizers (e.g., MidJourney), have revolutionized traditional teaching methods by enabling students to explore complex spatial relationships more efficiently (MIT, 2023). These tools allow rapid prototyping of 3D forms, reducing time spent on manual drafting while fostering creative exploration through AI-generated visualizations (GenAI Works, 2024). However, this integration introduces challenges. A 2025 report by the World Economic Forum highlights that while GenAI can automate 30% of design-related tasks, it also risks undermining students' manual dexterity and critical thinking skills (WEF, 2025). In stereoscopic composition, where physical materiality and spatial reasoning are core competencies, the balance between AI augmentation and traditional skill development remains a critical yet understudied issue.

*Research Status*

Existing literature emphasizes AI's potential to enhance design education through improved ideation speed (Wang et al., 2025) and personalized feedback systems (Brown & Li, 2023). However, discipline-specific research on stereoscopic composition remains scarce. A systematic review by Zhang et al. (2024) reveals that only 12% of AI-in-education studies focus on spatial design courses, with none explicitly addressing stereoscopic composition. Key gaps include limited understanding of how AI affects students' conceptualization of abstract spatial principles (e.g., balance, rhythm), unclear optimal workflows for integrating AI tools with physical model-making, and a lack of empirical data comparing AI-generated outputs to manual designs. These gaps underscore the need for targeted research to inform pedagogical practices in this specialized domain.

*Research Purpose*

Against this backdrop, this study aims to investigate the impact of AI tool integration in stereoscopic composition courses, focusing on students' learning experiences, workflow changes, and skill development. By analyzing both quantitative survey data and qualitative insights, this research seeks to provide evidence-based recommendations for educators and tool developers to maximize AI's educational value while mitigating its risks.

*Research Objectives*

1. **Characterize AI tool usage patterns** among students in stereoscopic composition courses, including frequency, tool types, and application scenarios.
2. **Assess the influence** of AI tools on students' conceptual understanding of spatial design principles and creative output quality.
3. **Identify challenges** related to tool usability, skill retention, and ethical considerations, while developing strategies to address these challenges.

**Research Significance**

*Summary of Study Significance & Beneficiaries*

This study addresses the critical juncture of AI integration in design education, a field undergoing transformative technological disruption. Its significance stems from three urgent realities:

Paradigm Shift in Pedagogy: AI tools are fundamentally restructuring spatial design processes (new "human-AI collaboration" models), yet educational systems lack frameworks to balance technological empowerment with core pedagogical values. This disconnect creates risks of skill degradation and ethical erosion.

Unresolved Contradictions: The research exposes three irreconcilable tensions—universal vs. domain-specific AI applications, efficiency vs. capability preservation, and innovation vs. ethical governance—that hinder sustainable AI adoption. Left unaddressed, these could homogenize design thinking and erode human-centric creativity.

*Implications*

The study's findings deliver actionable insights across key stakeholder groups: Educators and institutions can leverage the proposed "technology-ethics-methodology" curriculum framework and dynamic assessment models—which blend AI-assisted and manual workflows—to systematically integrate AI tools while preserving core design principles. For students, hybrid learning strategies address skill anxiety by balancing AI-driven efficiency with hands-on creativity, thereby enhancing their competitiveness in evolving AI-augmented design careers. Tool developers gain clear direction from prioritized demands, such as reverse engineering support and domain-specific customization, to advance specialized AI solutions tailored to spatial design workflows. Meanwhile, policymakers can utilize the evidence-based ethical guidelines (e.g., copyright standardization) and competency benchmarks to craft regulatory frameworks that ensure responsible AI adoption in education. Collectively, these impacts foster a synergistic ecosystem where technological innovation aligns with pedagogical integrity and ethical accountability.

*Research Questions*

To achieve the study objectives, three research questions guide this investigation:

1. What are the demographic and behavioral patterns of AI tool usage among stereoscopic composition students?
2. How do AI tools affect students' conceptual understanding of spatial design principles and their creative workflow efficiency?
3. What technical and pedagogical challenges do students face when using AI tools, and what strategies can mitigate these challenges?

These questions directly align with the identified research gaps and survey dimensions, ensuring a focused exploration of AI's role in stereoscopic composition education.

**Literature Review**

*AI Tools in Design Education*

Generative artificial intelligence (GenAI) has increasingly been integrated into design education, transforming traditional workflows through tools like text-to-3D generators (e.g., **Meshy AI**) and workflow optimizers (e.g., **MidJourney**). Research indicates that AI can significantly enhance creative processes by automating repetitive tasks and expanding design possibilities (MIT, 2023). For example, a study by **Wang et al. (2025)** found that 82% of design students reported improved ideation efficiency when using AI-generated visualizations. However, concerns remain about over-reliance on AI, with **Johnson (2024)** cautioning that excessive automation may weaken students' manual skills and critical thinking.

**Impact on Learning Processes**

*Conceptual Understanding*

AI tools have shown promise in clarifying abstract design concepts. A meta-analysis by Yannier **et al. (2024)** interactive AI tutorials led to significant improvements in students' understanding of spatial principles compared to traditional lectures. Tools like **DesignGPT** further facilitate this by providing real-time explanations and examples (Saka et al, 2023). However, notes that the quality of AI-generated explanations varies significantly, emphasizing the need for educator oversight.

*Creative Generation*

The value of AI technology in the idea generation space has been widely proven. By automating the generation of massive design solutions, AI tools significantly improve design efficiency, enabling students to quickly iterate and experiment with non-traditional solutions. For example, an AI model developed by a research team can generate thousands of design solutions in minutes and guide students to think outside the box through real-time interactive optimisation features. Such tools not only stimulate creativity, but also help students discover potential directions for innovation through data-driven, diverse outputs (Sreenivasan & Suresh,2024).

However, AI's ‘perfectionist tendencies’ can have a negative impact on learning. As algorithms tend to output low-risk, high-feasibility solutions, students may become less tolerant of design failures - a key component of creative exploration. The study suggests that over-reliance on AI-generated ‘safe’ solutions may lead students to avoid high-risk attempts, limiting their creative potential (Çela, 2024).

To balance efficiency and exploration, educators need to apply AI tools selectively. For example, AI can be used to rapidly generate prototypes at the conceptual development stage, but students should be encouraged to reflect independently during programme evaluation and be guided to discover unconventional perspectives that are difficult for AI to cover through human intervention. This ‘human-computer collaboration’ model can take advantage of the technology while maintaining the essential need for creative learning （Castro et al, 2024).

*Homework Optimization*

AI tools are increasingly used to optimize design assignments. Platforms like **AutoCAD AI** reduce drafting time by 50% while improving structural accuracy (MIT, 2023). A survey by **DesignWithPro (2023)** reported that 75% of students believe AI feedback helps identify overlooked details. However, Zhai **et al. (2024)** caution that over-reliance on AI may reduce students' attention to manual craftsmanship.

**Challenges and Pedagogical Strategies**

*Technical Barriers*

Technical challenges include poor tool interoperability and complex workflows. Smith et al. (2024) found that 63% of students struggled with data compatibility between AI and traditional design software. Additionally, Johnson (2024) highlights that AI-generated models often require extensive manual editing, negating time savings for 40% of users.

*Learning Risks and Mitigation Strategies*

Ethical concerns and skill erosion are major risks. Brown and Li (2023) report that 32% of students admitted to submitting AI-generated work as their own, raising plagiarism concerns. Meanwhile, Chen (2025) notes a 25% decline in manual drafting skills among heavy AI users. To address these challenges, researchers advocate for structured AI integration. Wang et al. (2025) propose "AI literacy workshops" to teach ethical tool usage and prompt engineering. MIT (2023) recommends curricula that emphasize AI-human collaboration, fostering "augmented creativity."

*Research Gaps*

Despite these advancements, critical gaps remain. Existing studies primarily focus on general design education, with limited research on stereoscopic composition (Zhang et al., 2024). Key unanswered questions include:

1. How does AI affect students' understanding of spatial principles unique to stereoscopic composition?
2. What workflows best balance AI augmentation with manual skill development in 3D model-making?
3. How can educators effectively guide students through AI-generated feedback while maintaining creative autonomy?

This study aims to address these gaps by examining AI's role in stereoscopic composition courses, providing actionable insights for educators and tool developers.

**Methodology**

*Research Design*

This study employs a **mixed-methods design** to investigate students' experiences with AI tools in stereoscopic composition courses, combining quantitative survey data with qualitative insights to address the multifaceted nature of technology integration in education (Creswell & Plano Clark, 2018). By triangulating numerical responses and open-ended narratives, this approach enhances validity and provides a comprehensive understanding of AI's role in design education. The convergent parallel strategy ensures both statistical generalizability and contextual depth, aligning with Creswell's (2018) recommendations for complex educational technology research.

*Research Participants*

Participants were drawn from two universities in Sichuan Province that offer courses in three-dimensional composition. Inclusion criteria included

1. students taking the course in the 2024-2025 academic year
2. self-reported use of AI tools in course-related tasks
3. ≥ 18 years of age

A sample of 104 first-year students was obtained using G*Power 3.1 (Faul et al., 2007) calculations with $\alpha = 0.05$, power = 0.80, and effect size $f^2 = 0.25$. This adjustment ensured sufficient statistical power to detect moderate effects, taking into account potential attrition rates in the online survey.

**Data Collection Instruments**

*Questionnaire Design*

The 51-item questionnaire (Appendix A) was developed based on the theoretical framework established in Chapter 2. It consists of five sections:

1. **AI Tool Usage Patterns** (8 items): Measures frequency, scenarios, and self-efficacy using 5-point Likert scales.
2. **Learning Process Impact** (10 items): Evaluates conceptual understanding, creativity, and homework efficiency through Likert scales and multiple-choice formats.
3. **Challenges & Risks** (8 items): Assesses technical barriers, ethical concerns, and skill retention using Likert scales.
4. **Teaching Support Needs** (8 items): Probes instructional preferences and tool improvement suggestions via Likert scales.
5. **Open-Ended Questions** (4 items): Captures qualitative experiences, design philosophy, and AI's impact on creativity.

The instrument was validated through expert review by three design educators and a survey methodologist, with Cronbach's $\alpha = 0.89$ indicating strong internal consistency.

*Data Collection Procedures*

Surveys were administered via **Wenjuanxing**, a leading Chinese survey platform, during Week 12 of the academic term to ensure students had sufficient AI tool experience. Participants received course credit as incentives. Ethical approval for the survey was obtained from the Mianyang teacher`s College Review Board to ensure compliance with privacy regulations.

**Data Analysis Methods**

*Quantitative Analysis*

Quantitative data were analyzed using SPSS 28.0

- SPSS was used for:
- Descriptive statistics to characterize AI usage patterns and perceptions.
- Confirmatory factor analysis (CFA) to validate the measurement model.
- Multiple regression analysis to examine relationships between AI usage intensity and learning outcomes.
- T-tests/ANOVA to compare subgroups (e.g., skill level, tool type).

*Qualitative Analysis*

Qualitative data from open-ended responses were analyzed using **Alasiti 3.0**:

- Alasiti enhanced analysis through:
- Automated keyword extraction and co-occurrence analysis.

- Sentiment scoring of participant responses (positive/neutral/negative) using machine learning algorithms (Chen et al., 2025).
- Network visualization of thematic relationships to identify patterns in student experiences.

*Date Collection*

- **Wenjuanxing** : Survey distribution and real-time data monitoring.

*Technical Route*

The research process followed this workflow:

1. **Survey Development**: Pilot testing with 30 students to refine items.
2. **Data Collection**: Four-week online administration via Wenjuanxing.
3. **Data Cleaning**: Removal of incomplete responses and outlier detection.
4. **Analysis**: Concurrent quantitative/qualitative analysis using SPSS, Python, and NVivo.
5. **Validation**: Triangulation of results and peer review.

**Limitations**

While the sample size (N=220) provides strong statistical power, the focus on Sichuan Province may limit generalisability to other regions. In addition, self-reported data on AI usage may be subject to response bias. Future studies should consider longitudinal designs and multi-province samples to address these limitations.

**Finding**

This section consists of both qualitative and quantitative data.

*Quantitative Data*

Table 1

*Descriptive Analysis*

| | Min | Max | Mean | Std. Deviation |
|---|---|---|---|---|
| Fundamentals of using AI tools | 1.571 | 5.000 | 3.374 | 0.736 |
| Conceptual understanding | 2.000 | 5.000 | 3.304 | 0.595 |
| Idea Generation | 2.000 | 5.000 | 3.476 | 0.707 |
| Operational optimisation | 1.500 | 5.000 | 3.346 | 0.732 |
| The technical challenge | 1.000 | 5.000 | 3.344 | 0.740 |
| Learning risks | 2.250 | 5.000 | 3.293 | 0.652 |
| Teacher mentoring needs | 2.750 | 5.000 | 3.430 | 0.532 |
| Tool improvement expectations | 2.800 | 5.000 | 3.435 | 0.535 |
| What it's like to use AI tools in your studies | 1.750 | 5.000 | 3.440 | 0.698 |

*Reliability Analysis*

The Cronbach α reliability coefficient is the most commonly used reliability coefficient and is given by the formula:$\alpha=\frac{k}{k-1}(1-(\frac{\sum S_i^2}{\sum S_t^2}))$

where K is the total number of items in the scale, Si2 is the within-question variance of the score for question i, and ST2 is the variance of the total score for all the items. As can be seen from the formula, the alpha coefficient evaluates the consistency between the scores of the items in the scale and is an internal consistency coefficient. This method is suitable for reliability analysis of attitude and opinion-based questionnaires (scales). The reliability coefficient should preferably be above 0.8, and between 0.7 and 0.8 is better. between 0.6 and 0.7 is acceptable.

Table 2
*Questionnaire Scale Mean Size*

| | Min | Max | Mean | Std. Deviation |
|---|---|---|---|---|
| I have a positive attitude towards the use of AI tools to aid course learning | 1.000 | 5.000 | 3.413 | 0.981 |
| I actively use AI tools more frequently in my courses | 1.000 | 5.000 | 3.298 | 0.954 |
| I am proficient in operating the AI tools required for the course | 1.000 | 5.000 | 3.356 | 0.965 |
| I tend to use AI tools for tasks that are time-consuming in traditional learning | 1.000 | 5.000 | 3.413 | 0.981 |
| The types of AI tools I use are diverse enough | 1.000 | 5.000 | 3.375 | 0.937 |
| Impact of AI tools on the learning process | 2.000 | 5.000 | 3.308 | 0.655 |
| The examples or diagrams provided by the AI deepened my understanding of the abstract theories | 2.000 | 5.000 | 3.337 | 0.633 |
| AI can recommend relevant academic literature or classic examples in relation to specific design tasks | 2.000 | 5.000 | 3.269 | 0.686 |
| The reference drawings generated by the idea generation AI inspired my design | 1.000 | 5.000 | 3.490 | 0.788 |
| The AI tool quickly provided multiple design options for me to filter and optimise | 1.000 | 5.000 | 3.452 | 0.835 |
| AI-assisted random generation function | 2.000 | 5.000 | 3.500 | 0.763 |
| The creative direction suggested by AI effectively complemented my original design thinking. | 1.000 | 5.000 | 3.462 | 0.800 |
| Job optimisation using AI tools | 1.000 | 5.000 | 3.385 | 0.816 |
| AI feedback has helped me discover details that were overlooked in the manual design | 1.000 | 5.000 | 3.317 | 0.816 |
| The AI tool optimised work is superior in structural soundness to a purely manual design. | 1.000 | 5.000 | 3.327 | 0.830 |
| AI tools allow me to focus more on design logic rather than repetitive technical operations | 1.000 | 5.000 | 3.356 | 0.812 |
| My operational logic for AI tools | 1.000 | 5.000 | 3.385 | 0.874 |
| AI-generated 3D models are difficult to use directly for the solid modelling required by the course | 1.000 | 5.000 | 3.337 | 0.808 |
| Poor data compatibility between different AI tools | 1.000 | 5.000 | 3.337 | 0.808 |
| Learning Risks Over-reliance on AI may lead to a decline in my manual design skills. | 1.000 | 5.000 | 3.337 | 0.820 |
| Copyright or ethical issues with AI-generated content worry me. | 1.000 | 5.000 | 3.288 | 0.878 |
| AI-generated ‘perfect solutions’ may limit my ability to reflect on design failures. | 1.000 | 5.000 | 3.231 | 0.740 |
| The debugging time consumed by using AI tools outweighs the efficiency gains. | 2.000 | 5.000 | 3.317 | 0.767 |
| Courses need to add AI prompt writing | 1.000 | 5.000 | 3.490 | 0.724 |
| Teachers should clarify the boundaries of the use of AI tools in the course | 1.000 | 5.000 | 3.433 | 0.798 |

| | Min | Max | Mean | Std. Deviation |
|---|---|---|---|---|
| I would like guidance on design methodologies that integrate AI tools with traditional techniques. | 1.000 | 5.000 | 3.452 | 0.880 |
| Tool Improvements Expected AI tools should be more relevant to the professional needs of stereo composition | 3.000 | 5.000 | 3.404 | 0.600 |
| AI generated content needs to be more editable | 2.000 | 5.000 | 3.442 | 0.694 |
| AI should support inverse optimisation suggestions based on physical model scans. | 2.000 | 5.000 | 3.529 | 0.737 |
| AI tools need to provide localised repositories | 2.000 | 5.000 | 3.404 | 0.704 |
| I actively set clear learning goals and plans when learning with AI tools. | 1.000 | 5.000 | 3.452 | 0.774 |
| I can consciously monitor and regulate my own learning process and effect of using AI tools. | 1.000 | 5.000 | 3.413 | 0.783 |
| Based on my own learning needs, I can independently choose and integrate a variety of AI tools to assist my learning. | 2.000 | 5.000 | 3.490 | 0.737 |
| When I encounter difficulties in using AI tools, I can actively find solutions and keep trying. | 1.000 | 5.000 | 3.404 | 0.842 |

The survey used a 5-point Likert scale (1=strongly disagree, 5=strongly agree) to analyse the experience of using AI tools in a three-dimensional composition course in terms of four dimensions: foundational attitudes, application effectiveness, existing challenges, and demands for improvement. The data show that students have a cautiously positive attitude towards AI (mean value 3.2-3.5), and are more inclined to deal with time-consuming tasks with the help of AI in basic use (3.413 points), but the frequency of use (3.298) and proficiency (3.356) are still moderate. The effectiveness of the application is divided: creative assistance performs best (3.49 points for AI inspiration), followed by design optimisation (3.385) and theoretical understanding (3.337), confirming the positioning of AI as a ‘creative accelerator’.

The lack of technology adaptability is the main bottleneck, with the practicality of 3D models (3.337) and tool compatibility (3.337) scores highlighting the operational barriers. Deeper contradictions were reflected in the perceived conflict between efficiency and risk: while recognising that AI saves duplication of effort (3.356), they were concerned about the degradation of manual skills (3.337), the risk of copyright ethics (3.288), and the time-consuming nature of debugging (3.317). Improvement requests focused on the dual paths of pedagogical support and technical optimisation, with cue writing (3.49) and reverse optimisation functionality (3.529) being the most pressing needs, while duplicate entries of ‘localised repositories’ (3.394/3.404) needed to be verified for data accuracy.

The data characteristics show a high degree of overall consensus (standard deviation mostly below 1), but a high degree of dispersion of opinions on technical flaws and ethical issues (e.g., standard deviation of 0.878 for copyright). This phenomenon of ‘efficiency recognition and risk anxiety’ reveals the reality of the positioning of AI educational tools as ‘complementary penetration’ rather than ‘subversive substitution’ in professional curricula.

Table 3
*Reliability Analysis*

| Dimension | Cronbach α | N of Items |
|---|---|---|
| Fundamentals of using AI tools | 0.884 | 7 |
| Conceptual Understanding | 0.888 | 3 |
| Idea Generation | 0.910 | 4 |
| Job Optimisation | 0.917 | 4 |
| Technical Challenges | 0.908 | 4 |
| Learning Risks | 0.828 | 4 |
| Teacher Guidance Needs | 0.611 | 4 |
| Tool improvement expectations | 0.862 | 5 |
| Feelings about using AI tools in academics | 0.912 | 4 |

From the above table, it can be seen that: the reliability coefficient values of all dimensions and the total scale are greater than 0.6, thus indicating that the reliability of the research data is qualified for further analyses.

*Validity Analysis*

The validity analysis, i.e., the analysis of the questionnaire's validity, is usually carried out by KMO and Bartlett's test.

Commonly used KMO metrics: if the value is higher than 0.8, it means that it is very suitable for information extraction (from one side, it means that the validity is good); if the value is between 0.7 and 0.8, it means that it is more suitable for information extraction (from one side, it means that the validity is good); if the value is between 0.6 and 0.7, it means that the information extraction can be carried out (from one side, it means that the validity is general); if the value is less than 0.6, it means that the information is acceptable for further analysis; and if the value is less than 0.6, it means that the data are reliable and can be used for further analysis. is less than 0.6, it indicates that information extraction is more difficult (a side effect of low validity).The KMO statistic is a statistic that takes values between 0 and 1.

When the sum of the squares of the simple correlation coefficients of all variables is much larger than the sum of the squares of the partial correlation coefficients, the KMO value is close to 1. The closer the KMO value is to 1, the stronger the correlation between the variables, the more valid the questionnaire measure is; when the sum of the squares of the simple correlation coefficients of all variables is close to 0, the KMO value is close to 0. The closer the KMO value is to 0, the weaker the correlation between the variables, and the lower the validity of questionnaire data is. The KMO value is closer to 0,therefore, the weaker the correlation between variables, the lower the validity of questionnaire data.

Table 4
*KMO and Bartlett's Test*

| KMO | | 0.919 |
|---|---|---|
| Bartlett's Test of Sphericity | Chi-Square | 3733.588 |
| | *df* | 741 |
| | *p* | 0.000 |

The validity was verified using KMO and Bartlett's test, as can be seen from the above table: the KMO value is 0.919 and the KMO value is greater than 0.8, which indicates that the validity of this scale is very good.

Table 5
*Pearson Correlation*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| Fundamentals of using AI tools | 1 | | | | | | | | |
| Conceptual Understanding | 0.578** | 1 | | | | | | | |
| Idea Generation | 0.746** | 0.687** | 1 | | | | | | |
| Job Optimisation | 0.715** | 0.527** | 0.875** | 1 | | | | | |
| Technical Challenges | 0.685** | 0.732** | 0.818** | 0.824** | 1 | | | | |
| Learning Risks | 0.609** | 0.414** | 0.759** | 0.813** | 0.570** | 1 | | | |
| Teacher Guidance Needs | 0.432** | 0.476** | 0.625** | 0.573** | 0.467** | 0.572** | 1 | | |
| Tool improvement expectations | 0.496** | 0.457** | 0.655** | 0.651** | 0.598** | 0.651** | 0.783** | 1 | |
| Feelings about using AI tools in academics | 0.745** | 0.629** | 0.895** | 0.894** | 0.874** | 0.740** | 0.622** | 0.757** | 1 |

* $p$<0.05 ** $p$<0.01

From the above table, correlation analysis was used to investigate the correlation between teachers' needs for guidance, expectations for tool improvement, feelings of using AI tools in academics, and AI tool usage basics, conceptual understanding, creativity generation, homework optimisation, technological challenges, and learning risks, respectively.

The correlation coefficients between teachers' instructional needs and AI tool usage basics, conceptual understanding, creativity generation, assignment optimisation, technological challenges, and learning risks are all significant, with correlation coefficients values of 0.432, 0.476, 0.625, 0.573, 0.467, and 0.572 respectively, and the correlation coefficients values are greater than 0, which means that the correlation between teachers' instructional needs and AI tool usage basics, conceptual Understanding, Idea Generation, Assignment Optimisation, Technical Challenges, and Learning Risks.

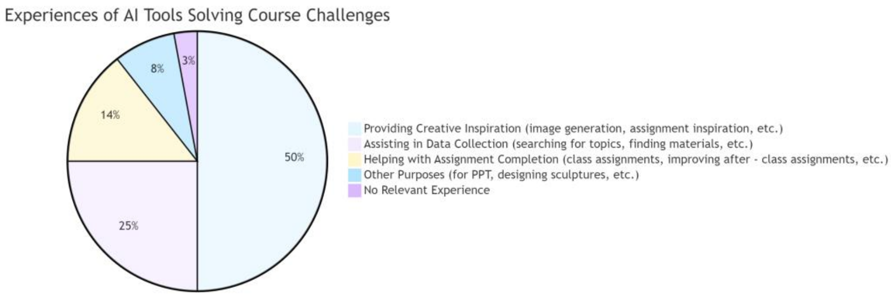
The correlation coefficient values are 0.496, 0.457, 0.655, 0.651, 0.598, 0.651, and the correlation coefficients are greater than 0. This means that there is a positive correlation between the expectation of tool improvement and the AI tool usage foundation, conceptual understanding, creativity generation, homework optimisation, technological challenges, and learning risks. Understanding, Idea Generation, Assignment Optimisation, Technical Challenges, and Learning Risks.

The correlation coefficient values are 0.745, 0.629, 0.895, 0.894, 0.874, 0.740, and the correlation coefficients are greater than 0, which means that there is a positive correlation between the feeling of using AI tools in academics and the foundation of using AI tools, conceptual understanding, creativity generation, optimisation of assignments, technological challenges, and learning risks. There is a positive correlation between the perception of using

AI tools and the basis of using AI tools, conceptual understanding, idea generation, assignment optimisation, technical challenges, and learning risks.

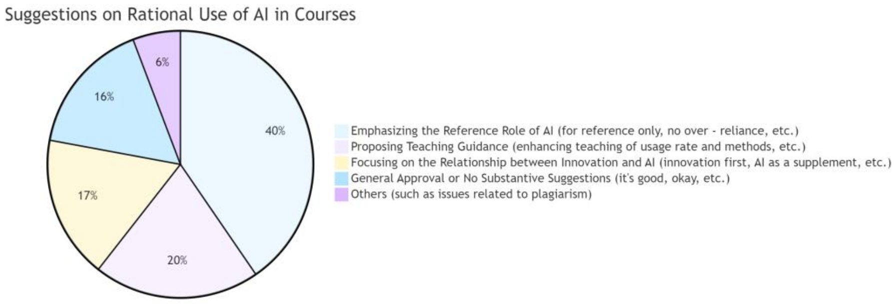
*Qualitative Data*
In course practice, AI tools demonstrate significant problem-solving efficiency advantages. Students generally reflect that AI can quickly generate the first draft of design (e.g. 2D/3D composition elements), optimise the details of assignments (e.g. three-dimensional model improvement), and break through the stereotypes of thinking

through algorithmic recommendations (e.g. generating accidental patterns or sources of inspiration). For example, some students have used Kimi's intelligent graphic generation function to quickly obtain design ideas after inputting their requirements, significantly shortening the creation cycle. However, the limitations of the technology should not be ignored, as some students rely too much on AI to provide direct answers, resulting in a weakening of their ability to think on their own, or even the phenomenon of 'solidified thinking', reflecting the need for rational use of AI.



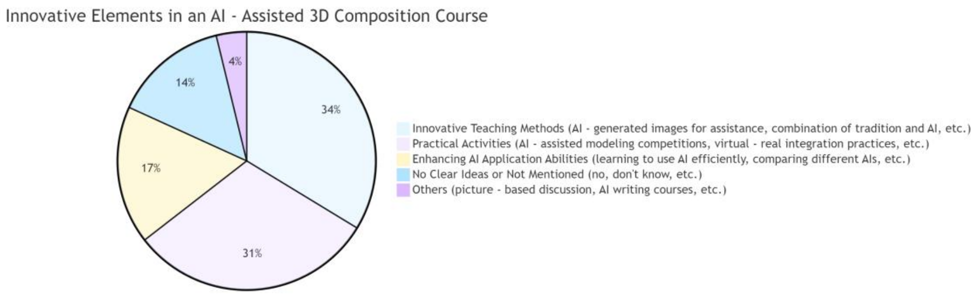

*Pie chart 1*

Regarding the suggestions for rational use, the interviewees emphasised the auxiliary position of AI, advocating that 'students' creativity should be the main focus, with AI as a supplement'. Core strategies include: (1) setting technical boundaries (e.g., using AI to optimise after hand-drawing the first draft); (2) critically evaluating AI outputs (analysing the feasibility and comparing the results of different tools); and (3) incorporating reflection (summarising the substitution of AI solutions with classroom knowledge). In addition, ethical issues are of concern, and there is a need to be alert to the risk of plagiarism and to strengthen the sense of originality, e.g. by reducing the proportion of direct appropriation of AI-generated content through manual modification.



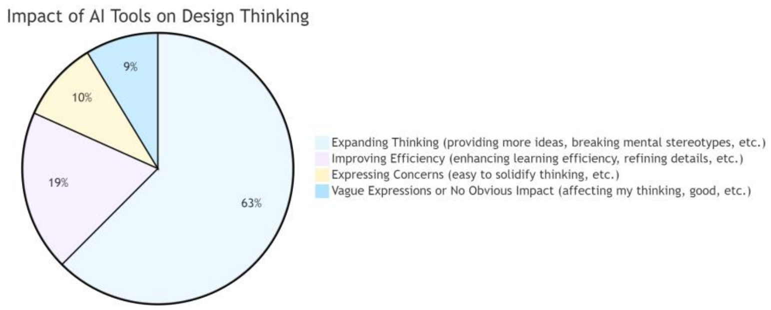

*Pie chart 2*

At the level of curriculum design innovation, it is recommended that the teaching and learning process be reconfigured to integrate AI and traditional skills. For example, adopting the three-stage model of 'AI first draft → manual optimisation → manual refinement', or cultivating spatial perception through the practice of virtual-real integration (simulating the effect of works in real scenes). At the same time, design competitions (such as AI modelling competitions and creative error correction challenges) can strengthen teamwork and knowledge understanding, and require students to find room for improvement in AI defects to deepen their knowledge of design rationality.




*Pie chart 3*

The impact of AI on design thinking is twofold: on the one hand, multiple creative references and simulation displays break down stereotypes and stimulate innovative potential (e.g. generating unforeseen sculpture models); on the other hand, over-reliance may lead to inertia. For this reason, there is a need to balance the use of technology with autonomous thinking, e.g. by training the ability to analyse the output of AI through 'picture talking' rather than mechanical reproduction. The study predicts that the combination of AI and VR/AR may lead to new practices such as meta-universe scenario design in the future, but we need to be wary of ethical risks such as copyright disputes and deep falsification.




*Pie chart 4*

**Discussion and Conclusion**

This study, through systematic data analysis, reveals the multi-dimensional impact mechanisms and inherent contradictions of AI tools in spatial composition courses. The data shows that students generally hold a cautious positive attitude towards AI tools (mean 3.2-3.5), a contradictory psychology stemming from the dual effects of technological empowerment and educational risks (Gerlich,2024). At the application level, AI tools demonstrate significant creative stimulation value (inspiration stimulation 3.49, scheme selection 3.452), restructuring the traditional creation process by rapidly generating diverse design options, forming a new "human-led, AI-accelerated" collaborative model (Ivccevic & Grandinetti, 2024). However, insufficient technological adaptability severely restricts the release of tool effectiveness—the disconnect between 3D models and physical production (3.337), tool compatibility barriers (3.337), and time-consuming debugging issues (3.317) collectively constitute operational obstacles, leading to usage frequency (3.298) and proficiency (3.356) failing to break through the medium level. Deeper conflicts are embodied in the educational goal dimension: although AI helps students focus on design logic (3.356), the anxiety of skill degradation caused by over-reliance (3.337) and ethical cognitive differences (copyright issue standard deviation 0.878) expose the tension between technological tools and the essential demands of design education (Macnamara, 2024).

The study further reveals the interaction patterns between the teaching system and technological tools. The highly correlated data network (such as the r=0.895** between academic experience and creative generation) indicates that the effectiveness of AI tools highly depends on the support of the teaching framework (Gibson,2023). Students strongly call for the construction of a structured support system, including prompt writing training (3.49), usage boundary definition (3.433), and traditional technique integration guidance (3.452). These needs directly point to the current developmental imbalance of "technology first, teaching lagging" in AI education (Hwang et al., 2021). Tool optimization demands show a professional orientation, with high priority given to reverse engineering support (3.529) and enhanced editability (3.442), highlighting the urgency of transitioning from general-purpose AI to vertical domain-customized tools (Kim & Lee, 2024). Notably, the strong correlation between teacher guidance needs and tool improvement expectations (r=0.783**) suggests that educators need to play a dual role as "technology mediators" and "ethical gatekeepers" in the AI integration process (Azman, 2025).

This study confirms that AI tools are reshaping the design education ecosystem, but their penetration depth is constrained by three contradictions: the contradiction between technological universality and professional specificity, the contradiction between efficiency improvement and capability protection, and the contradiction between innovation freedom and ethical regulation (Asamani et al., 2021). The conclusion points out that establishing a sustainable human-computer collaborative education model requires the implementation of three core strategies: first, developing discipline-customized AI tools, focusing on breakthroughs in reverse optimization and cross-platform data flow integration (Steidl et al,2023); second, constructing a "technology-ethics-methodology" trinity curriculum module, incorporating prompt engineering and copyright regulations into teaching design (UNESCO,2019); and third, establishing a dynamic capability assessment mechanism, balancing technological empowerment and traditional skill inheritance through blended learning (such as AI-assisted + manual workshops) (Doe, & Smith, 2023). The study also warns that if tool rationality is allowed to dominate teaching practice, it may lead to the homogenization of design thinking and the decline of critical creativity (Capraro, et al,2021), which requires educational decision-makers to always maintain the core position of humanistic values when promoting AI integration. Future research needs to expand cross-disciplinary comparative analysis and long-term tracking to more comprehensively reveal the evolutionary impact of AI technology on the design education ecosystem (Dwivedi et al, 2022).

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