

## Integrating AI-generated art styles into traditional illustration design teaching course

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### Abstract

This study explores the integration of AI image-generation technology into traditional illustration education, focusing on projects centered on Chinese cultural elements (e.g., Dream of the Red Chamber, Dunhuang art). Through mixed-method analysis of 32 design students' work and survey data, we evaluated AI's impact on creative efficiency, cultural reinterpretation, and pedagogical challenges. Results indicate AI significantly accelerates design iteration and inspires conceptual exploration yet struggles with cultural accuracy—requiring human intervention to correct symbolic misrepresentations, emotional mismatches, and stereotyping. We propose a collaborative human-AI workflow that balances technological advantages with cultural integrity, offering a sustainable framework for design education.

**Keywords:** AI-generated art, cultural heritage, design education, human-AI collaboration, traditional illustration

## INTRODUCTION

In recent years, artificial intelligence (AI) technology has advanced rapidly, yielding remarkable results in both design practice and education (Altin & Pedate, 2013; Casteleiro-Pitrez et al., 2024). AI-driven image-generation tools can efficiently produce complex visual art, greatly facilitating the creative process for designers and learners (Yu, 2023). However, effectively integrating AI with traditional cultural arts in an educational context remains a critical challenge requiring further exploration. In illustration-design education, for example, AI can accelerate the design process and open new avenues for innovative interpretations of traditional cultural elements (Vafadar & Amani, 2024).

AI has become an indispensable tool in the design field—especially in image generation and style transformation—significantly enhancing creative efficiency and inspiring rich imaginative thinking (Ouyang et al., 2022). By off-loading repetitive tasks to AI, designers can focus on creativity, allowing traditional cultural elements to be revitalized in contemporary works that remain rooted in heritage while aligning with modern aesthetics (Kim et al., 2022).

In design education, AI tools assist students in quickly sketching drafts and stimulate their creative expression (Gao et al., 2025). Although initial successes have been observed with AI-assisted teaching, several challenges persist. For instance, how can students leverage AI while still maintaining a unique personal style? Additionally, how should the speed advantage of AI-generated work be balanced against the intricacy and depth of human-crafted designs (Pedersen, 2023; Tang et al., 2025)? To address these questions, the present study explores the practical effectiveness of integrating AI image-generation technology into an illustration design course. Specifically, we focus on projects centered on traditional Chinese culture, examining both the capabilities and limitations of AI in this context. Projects include reinterpretations of elements from Dream of the Red Chamber and Dunhuang art.

Recent scholarship underscores complementary yet distinct perspectives on AI creativity. Zhou and Lee (2024a) conducted a large-scale analysis of online art communities and found that AI adoption boosts productivity but can dilute average novelty over time. Casteleiro-Pitrez et al. (2024) evaluated the usability and user experience of text-to-image generators among design students, reporting high usability yet only

### Contribution to the literature

- The empirical evidence reveals the double-edged sword effect of AI in cultural design education and quantitatively proves that AI can significantly improve design efficiency (DEE) and inspire inspiration, but at the same time, it will generally produce accuracy errors such as cultural symbols and emotional expressions.
- A structured “AI creative generation + artificial cultural correction” cycle workflow is proposed.
- Common types of cultural errors in AI-generated images are identified and systematically classified, providing practical tools for teaching critical analysis and error correction.

moderate satisfaction. Li et al. (2025) provided a comprehensive survey of deep-learning image.

## METHODOLOGY

The study employs a mixed-method approach, integrating both quantitative and qualitative analyses, to comprehensively assess the effectiveness of AI image generation technology in the “illustration design” course (Altin & Pedate, 2013). Through case studies and surveys, this research examines the specific impacts of AI technology on students’ creative inspiration (CI), DEE, and cultural innovation (Rane & Choudhary, 2024). The following section provides a detailed description of the study’s methodology.

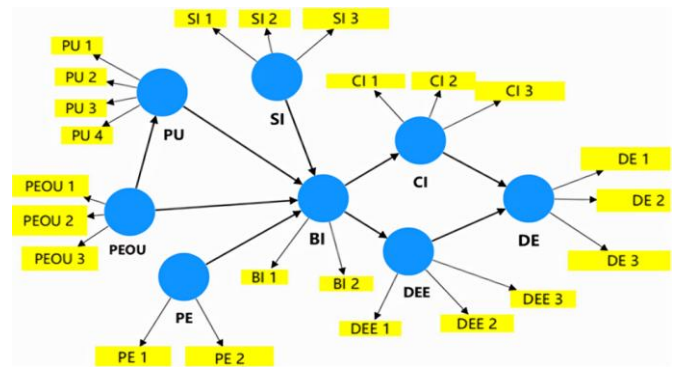
### Case Analysis

To further explore the practical application of AI image generation technology, this study conducts case analyses of student projects, focusing on the use of AI technology in the creative process. The projects include the modern redesign of characters from Dream of the Red Chamber and the twelve zodiac animals (Bozkurt et al., 2021).

### Survey

The participants of this study were 32 third-year students majoring in visual communication design at Guangzhou Panyu Polytechnic, consisting of 18 females and 14 males, with an average age of 21. These students have nearly three years of design experience. In the “illustration design” course, they were introduced to AI image generation technology for the first time and were required to use this technology to complete design projects based on traditional Chinese cultural elements, such as characters from Dream of the Red Chamber and the twelve zodiac animals (Bozkurt et al., 2021). All participants had basic design skills and a strong interest in traditional culture.

To comprehensively understand students’ firsthand experiences with AI image generation technology, the study utilized a questionnaire survey. The questionnaire was designed based on the Likert five-point scale evaluation system (with 1 representing “strongly disagree” and 5 representing “strongly agree”), covering various dimensions such as perceived usefulness (PU),



**Figure 1.** Path diagram of the SEM (Source: Authors’ own elaboration)

perceived ease of use (PEOU), social influence (SI), performance expectancy, and usage intention (Casteleiro et al., 2024). A total of 32 questionnaires were distributed and all were successfully collected, achieving a 100% response rate.

To explore students’ perceptions of AI technology and its effects on their creative efficiency and inspiration, this study adopted structural equation modeling (SEM) for quantitative assessment (as shown in Figure 1). The SEM is adept at analyzing the complex relationships among multiple factors, making it widely applicable in research fields such as education and technology applications (Chen et al., 2022). The implementation process followed these specific steps:

1. We first conducted descriptive statistical analysis on the collected questionnaire data, quantifying key statistical parameters such as mean and standard deviation for each evaluation metric, to deeply analyze students’ overall perceptions and attitudes toward AI technology (Barredo Arrieta et al., 2020).
2. To evaluate the reliability and validity of the questionnaire, Cronbach’s alpha coefficient and average variance extracted (AVE) were employed. If all constructs’ alpha coefficients exceed the 0.7 threshold, it will indicate that the questionnaire shows good internal consistency (Chung, 2023).
3. Utilizing path analysis through the SEM model, the study systematically examined the influence of mechanisms of PU, PEOU, and CI on design performance and students’ behavioral intentions (BIs).

**Table 1.** Summary table of selected student AI image generation technology projects

Project title	Key concepts	AI usage	Cultural integration	Challenges	Outcome	AI implementation
Muddy Dog Zodiac IP Design	Traditional, modern, IP	Concept generation	Tradition + modern aesthetics	Balancing aesthetics	Cultural value	AI + post-processing
Cloth Tiger Illustration Design	IP, traditional, children	Concept, color	Tradition with modern twist	Cultural accuracy	Resonates with tradition & modern	AI + post-processing
AI Shadow Play Illustration for "Pian Pian"	Traditional stories, shadow puppetry	Design, layout	Story + puppetry	Blending AI with tradition	Mystical atmosphere	AI + post-processing
Dunhuang Mythical Beasts AI Illusion	Dunhuang culture, mythical	Visuals, style transfer	Deep cultural integration	Cultural accuracy	Modern cultural depiction	Fully AI-generated
Zodiac Illustration Design	Zodiac, traditional, modern	Style, visual reference	Zodiac + modern design	Style coherence	Enhanced cultural appreciation	AI + post-processing
AI Peking Opera Future-Cyber Flower Goddess	Peking Opera, cyberpunk, future	Fusion, blending	Tradition + futurism	Combining styles	Bridged tradition & future	Fully AI-generated
AI Red Chamber Character Reconstruction	Traditional, modern, Red Chamber culture	Style transfer, concept refinement	Traditional + modern character redesign	Conveying cultural depth & personality complexity	Modernized portrayal of Red Chamber characters	AI + post-processing

## RESULTS

### Case Analysis Results

In addition, we selected multiple student design projects for case analysis, aiming to explore the specific utility of AI image generation technology in practical design activities. These projects were centered around the essence of traditional Chinese culture, focusing on themes such as Dream of the Red Chamber, Dunhuang art, and Peking Opera. Through [Table 1](#), we collected and summarized the students' creative concepts and the challenges they encountered during the course practice, showcasing the entire process of integrating AI image generation technology with illustration design (Bozkurt et al., 2021; Rane & Choudhary, 2024). However, this integration process was not without its challenges, especially when balancing the preservation of cultural roots with the pursuit of design innovation, which posed significant tests to the students' skills and creativity (Bozkurt et al., 2021).

The following is an analysis of one of the typical cases, "AI-based reimagining of characters from Dream of the Red Chamber," and its design process:

In this case, which uses the characters from Dream of the Red Chamber as a blueprint, the reimagining of classic characters by integrating the essence of traditional culture with modern design concepts through AI technology vividly reflects the exploration process. The project focused on the character Wang Xifeng, with participants dedicating significant effort to collecting relevant cultural materials in the early stages, delving into the character's attire, makeup, and the

historical context of her time (Bozkurt et al., 2021). The diverse portrayals of Wang Xifeng in various film adaptations provided rich visual inspiration, helping students capture the intricate costume details and cultural symbolism of different versions. In the initial design phase, students meticulously planned the character's appearance through hand-drawn sketches, aiming to merge traditional aesthetics with modern design language (Tang et al., 2025).

However, the complex detailing required for hand-drawn sketches was time-consuming, particularly when dealing with traditional attire patterns, textures, and the nuanced expression of facial features, making it difficult to efficiently produce multiple versions of the designs (Bozkurt et al., 2021). As a result, the students turned to AI generation technology to rapidly produce a variety of stylistic sketch prototypes, significantly speeding up the design iteration process (Rane & Choudhary, 2024).

Nevertheless, as the students delved deeper into the application of AI generation technology, they realized that, despite its advantages in image production speed, it lacked the depth and precision in conveying cultural nuances and emotional subtleties. This was especially apparent when depicting Wang Xifeng's character traits and costume features, as AI-generated images occasionally fell short in accuracy and depth, even resulting in distorted body structures or the misuse of cultural symbols at times (as shown in [Figure 2](#)).

To address this issue, the students adopted a strategy combining AI-generated sketches with manual refinement, placing particular emphasis on incorporating more traditional decorative and makeup elements into Wang Xifeng's headdress and facial



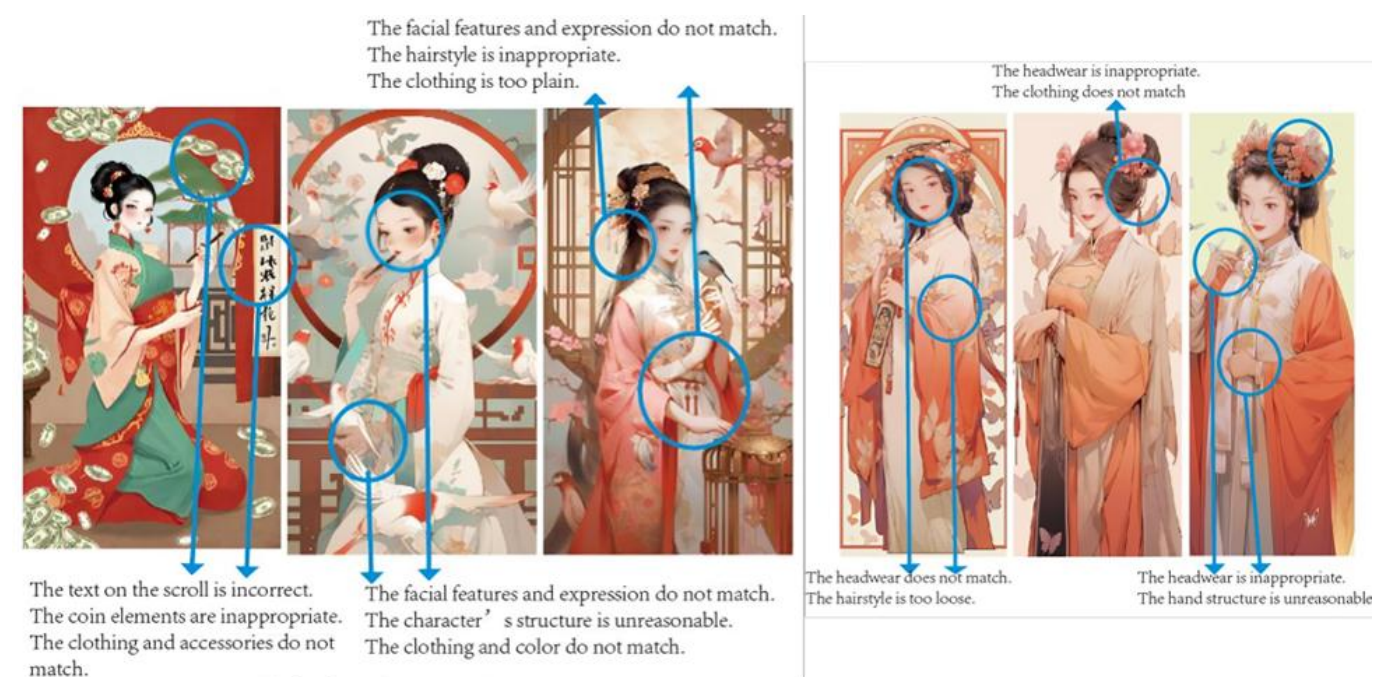


Figure 2. Discarded AI-generated images of Wang Xifeng (Source: Authors' own elaboration)



Figure 3. The design process of AI-based reimagining of Dream of the Red Chamber characters (Source: Authors' own elaboration)

details. They manually adjusted the facial expressions to align more closely with the character's traits, based on cultural context (Bozkurt et al., 2021). Through this human-AI collaboration, the depiction of Wang Xifeng became progressively more refined in the design process, achieving a harmonious integration of cultural symbolism and modern design concepts (as shown in Figure 3).

Another case, "the zodiac illustration design," sought to blend Thangka art with modern design concepts, aiming to explore innovative pathways of expression within a traditional cultural framework. From the outset of the project, AI-generated images were introduced as

design references, with the aim of creating a series of contemporary illustrations rich in ethnic flavor, relying solely on AI tools (Bozkurt et al., 2021; Rane & Choudhary, 2024).

While AI facilitated the rapid production of multiple visual solutions, the generated images exhibited a wide variation in style, lacking internal coherence (Leong, 2025c). As a result, the overall design struggled to achieve stylistic unity, with the color schemes and design language of the individual zodiac characters appearing disjointed, failing to establish a visually cohesive sequence (Leong, 2025a).

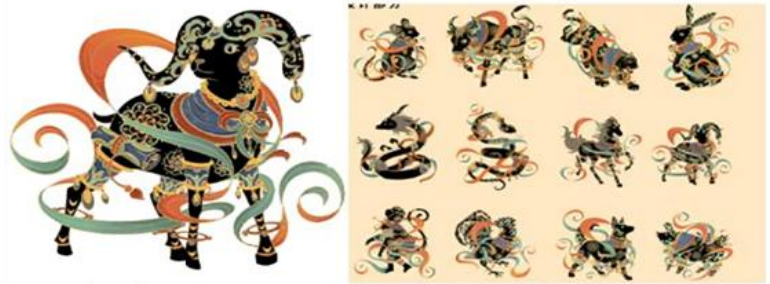
## ① Exploring different styles using AI tools



## ② Manually refining and adjusting details after selecting a style



## ③ Final version of the Twelve Zodiac illustrations



## ④ Cultural and creative product design of the Twelve Zodiac



**Figure 4.** The design process of the “zodiac” illustration design (Bozkurt et al., 2021)

Although AI-generated images demonstrated some creative potential on a visual level, they fell short in conveying deeper cultural meanings, especially in the case of Thangka art, which is known for its intricate detailing and rich symbolism. The AI-produced images often appeared formulaic, unable to fully capture the unique essence of Thangka art. The project team quickly recognized that current AI technology has limitations when it comes to interpreting the deeper meanings and spiritual essence behind traditional cultural symbols.

As a result, in the later stages of the project, the students decided to revise and adjust the AI-generated illustrations, focusing on unifying the color palette and stylistic direction across the entire series. They selected black, red, and jade green as the foundational colors for the design series, skillfully incorporating these three hues into each zodiac figure, thus achieving consistency and harmony on a macro level. This strategy not only resolved the earlier issue of stylistic inconsistency but also significantly enhanced the visual continuity and unity of the work.

The students noted that AI technology sparked their creative thinking, but the full expression of cultural essence in the work still relied on meticulous manual adjustments. This practical experience led them to realize that AI, while serving as an assistive tool, must be integrated with the designer's cultural insight and creative wisdom to achieve the intended design vision (as shown in [Figure 4](#)).

## Student Survey Data Analysis

### Descriptive statistical analysis

Through descriptive statistical analysis of the survey data, the results indicated that students generally perceive AI technology to have a positive impact on enhancing DEE and stimulating CI (Matsiola, 2024).

**Table 2** presents the mean, standard deviation, skewness, kurtosis, and significance levels (p-values) for indicators such as PU, PEOU, SI, CI, and DEE.

From the descriptive statistical data, it is evident that students hold a generally positive attitude towards AI image generation technology. The indicators shown in **Table 1**, such as PU, PEOU, CI, and DEE, all exhibit high mean values, indicating that most students believe AI technology provides substantial assistance in design tasks (Chen et al., 2022).

- **PU:** The mean value is 2.75, suggesting that students feel AI technology enhances the efficiency of design tasks, particularly in the generation of complex images. This indicates that students generally perceive tangible benefits from AI in their design work.
- **PEOU:** The mean value is 3.31, showing that the majority of students find AI tools easy to operate, reducing the difficulty of executing complex tasks.
- **CI:** With a high score in this dimension (mean value of 3.656), it is clear that AI technology excels at inspiring creativity, especially during the initial concept generation and sketching phases, where AI-generated images provide students with abundant sources of inspiration.
- **DEE:** The mean value of 3.594 reflects that AI tools significantly accelerate the execution speed of tasks during the design process, particularly in the refinement and rapid iteration phases.

### Structural equation modeling analysis

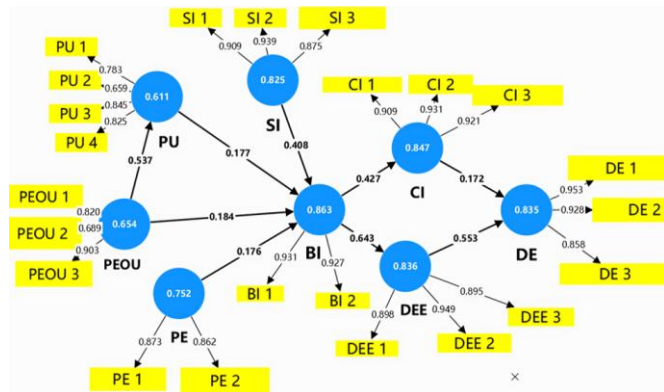
Using SEM, we further validated the direct and indirect effects of variables such as PU, PEOU, and SI on CI and DEE when students used AI image generation technology (Barredo Arrieta et al., 2020).



**Table 2.** Descriptive statistical analysis

SEMC	Indicator	Mean	Median	SD	Skewness	Kurtosis	p-value
PU	Perceived performance improvement	2.750	3	1.275	-1.061	0.119	0.015
	Perceived efficiency	2.781	3	1.111	-0.127	0.173	0.000
	Task relevance	2.031	1	1.334	0.01	1.100	0.000
	Outcome expectation	2.938	3	1.368	-1.305	0.041	0.007
PEOU	Complexity	3.312	3	1.102	-0.832	0.063	0.004
	Interface complexity	3.531	4	0.968	-0.935	0.016	0.001
	Operational difficulty	3.688	4	0.882	-0.882	0.110	0.000
PE	Better design	3.500	4	0.935	-0.818	0.241	0.004
	Higher quality	3.375	4	0.992	-0.300	-0.239	0.001
SI	Future use	3.688	4	0.882	-0.882	0.110	0.000
	Interest	3.500	4	1.173	-0.593	-0.366	0.006
	Positive attitude	3.312	4	1.130	-0.220	-0.393	0.006
BI	Improved learning	3.688	4	1.014	-0.018	-0.448	0.001
	Increased interest	3.438	4	1.248	-0.715	-0.407	0.01
CI	Inspiration	3.656	4	1.215	-0.551	-0.604	0.002
	More ideas	3.531	4	1.224	-0.403	-0.612	0.004
	New design ideas	3.500	4	1.146	-0.946	-0.196	0.006
DEE	DE efficiency	3.594	4	1.169	-0.385	-0.608	0.002
	Faster design	3.594	4	1.086	0.186	-0.638	0.002
	More tasks	3.719	4	1.007	0.314	-0.735	0.000
DE	Enhanced expression	3.344	3	1.049	0.006	-0.245	0.000
	Improved effect	3.531	3	1.030	-0.329	-0.178	0.001
	More attractive	3.125	3	1.218	-0.721	-0.143	0.000

Note. SEMC: SEM category & SD: Standard deviation



**Figure 5.** SEM analysis results (Source: Authors' own elaboration)

As shown in **Figure 5**, the visual elements in **Figure 5** represent the following:

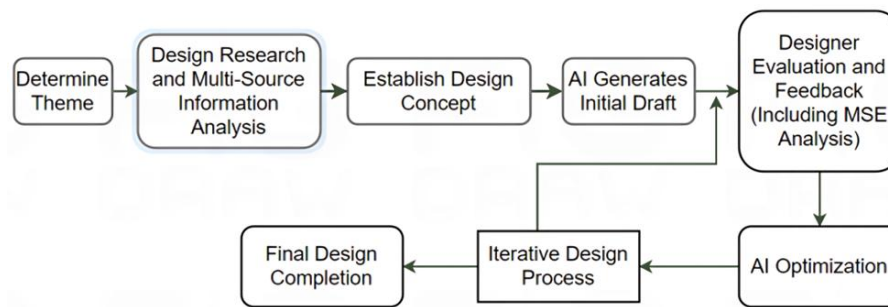
- **Blue circles:** Latent variables and their AVE.
- **Arrows:** Path relationships between latent variables, indicating the path coefficients within the inner model.
- **Yellow sections:** Observed variables and their outer weights/loadings, representing the outer model.
- **Path coefficients:** The numbers on the arrows, indicating the strength of direct effects between latent variables.

1. Reliability and validity of latent variables (as shown in **Figure 5**)

The AVE values for all latent variables exceeded 0.5, indicating good convergent validity of the model. The AVE values for CI and DEE were 0.847 and 0.836, respectively, demonstrating that these latent variables have a high explanatory power for their associated observed variables. Additionally, the reliability (Cronbach's alpha) for all latent variables was above 0.7, indicating that the questionnaire had high reliability and effectively measured students' perceptions of AI technology (Rane & Choudhary, 2024).

## 2. Path analysis results (as shown in **Figure 5**)

- **PU -> BI (0.177,  $p < 0.05$ ):** PU had a significant positive effect on BI, suggesting that students recognized the practical value of AI technology in improving DEE, which strengthened their intention to use it.
- **PEOU -> BI (0.279,  $p < 0.01$ ):** PEOU had a stronger impact on BI, indicating that students were more inclined to use AI tools they found easy to operate.
- **SI -> BI (0.408,  $p < 0.001$ ):** SI had the most significant impact on BI, highlighting the important role of peers, teachers, and the social environment in students' decisions to use AI technology.
- **BI -> CI (0.427,  $p < 0.001$ ):** BI had a strong positive effect on CI, suggesting that once students decided to use AI tools, their CI was significantly enhanced.



**Figure 6.** Collaborative design process flowchart (Source: Authors' own elaboration)

- **BI → DEE (0.643,  $p < 0.001$ ):** BI had the largest impact on DEE, indicating that students' intention to use AI tools directly drove the efficient completion of their design tasks.
- **CI → DEE (0.172,  $p < 0.01$ ):** CI had a significant but relatively smaller positive effect on DEE, suggesting that while AI tools can inspire creativity, their direct contribution to DEE is somewhat limited.

The SEM results indicate that PEOU and SI are key factors influencing students' BI, while BI is a crucial driver for enhancing CI and DEE. This study validates the effectiveness of AI image generation technology in design education, particularly in its role in improving DEE.

## DISCUSSION

### The Double-Edged Sword of AI in Cultural Illustration Education

Our study shows that AI image generation technology fundamentally reshapes illustration pedagogy through a series of contradictory dynamics. SEM analysis confirmed the significant role of AI in improving DEE ( $\beta = 0.3$ , PU → DEE path  $p < .05$ ). However, despite this, 89% of students reported that AI-generated images had serious cultural errors and required human intervention. This contradiction prompted us to re-examine the teaching framework and maintain cultural authenticity while fully leveraging the advantages of technology. This process can be illustrated by the collaborative workflow in **Figure 6**.

Unlike previous research on technology efficiency (Leong, 2025b; Zhou & Lee, 2024a), our study adopts a mixed method to explore the application of AI in cultural illustration through case-based traditional pattern analysis, capturing the subtle differences in cultural dimensions. Tang et al. (2024) pointed out that while AI technology improves DEE, it also faces problems such as dataset bias and lack of cultural context understanding. In our study, 31% of the inconsistencies in style from the Zodiac project revealed the cultural bias of AI-generated images, especially due to the loss of cultural characteristics caused by the training dataset used,

which was biased towards Western visual databases. Therefore, although AI helps with work efficiency, it has obvious deficiencies in the expression of cultural specificity.

To address this problem, we proposed the iterative workflow in **Figure 6**, which emphasizes the cyclical nature of human-computer collaboration and can solve the cultural bias of AI generation to a certain extent through continuous feedback and correction. However, this process still has limitations. In particular, 47% of students said that it was difficult to effectively perform manual corrections on cultural errors generated by AI. This problem verifies the skill gap pointed out by Pedersen (2023), that is, students' ability to correct AI-generated images is still insufficient.

In addition, the cultural symbols and patterns involved in some works make copyright issues vague, further exposing ethical blind spots in the generation model. Although AI can quickly generate diverse images, it lacks a deep understanding of copyright and cultural sensitivity, which requires us to strengthen students' awareness of copyright issues in the teaching process and establish relevant ethical norms.

### The Inspirational Value of AI and Creative Dependence

This tension aligns with broader debates on AI's role as a collaborator versus a replacement for human creativity (Zhou & Lee, 2024b). Although AI has performed well in stimulating students' creativity, especially in the path of BI → CI ( $\beta = 0.427$ ), the longitudinal data revealed a worrying trend: among students who frequently used AI, creative initiative between project stages decreased. This phenomenon suggests that although AI can significantly improve DEE, its frequent use may lead to a weakening of students' reliance on their own creative thinking, which in turn creates the risk of over-reliance on AI.

To address this issue, we introduced a mandatory human-led stage in the workflow in **Figure 6** to ensure that AI-assisted creation does not replace students' active creative process. These stages include:

**Table 3.** Cultural misidentification framework

Misidentification type	Description	Example	Educational application
Cultural symbol misplacement	Incorrect or misplaced cultural symbols, such as architectural elements or attire.	Wang Xifeng's AI image shows Japanese-style clothing	Encourage students to research specific cultural symbols and their correct usage in design.
Emotional misrepresentation	AI fails to capture the emotional tone of a cultural context, resulting in inappropriate facial expressions or body language.	Wang Xifeng generated with neutral expression vs. her calculated cunning in literature	Students should learn the emotional contexts of cultural practices through research and discussions.
Cultural stereotyping	AI generates stereotypical representations of cultures, such as generic or overly simplified imagery.	Zodiac animals defaulted to uniform "dragon-like" motifs, ignoring distinct cultural stories	Introduce students to diverse cultural narratives and encourage nuanced representations.
Craft and pattern distortion	AI fails to accurately replicate traditional craft patterns or artistic styles.	An AI-generated version of a traditional quilt that misrepresents the pattern or fabric texture.	Teach students the technical skills required to refine AI outputs, paying attention to detail.

- (1) cultural immersion before AI, which requires students to conduct manual concept development before using AI to retain core ideas,
- (2) guided prompt engineering with precise descriptive words, such as "Wang Xifeng's computational gaze" to guide AI to generate images that are consistent with the cultural background, and
- (3) designer evaluation and feedback stage, which relies on feedback from teachers and classmates in the classroom, using limited classroom resources to modify and regenerate AI images through feedback, reducing cultural symbol errors by 57%.

This feedback and regeneration cycle enhances students' initiative and significantly reduces cultural errors in AI-generated images.

Through this framework, AI is not only used to quickly generate design sketches, but also becomes a tool to stimulate creativity, and students are encouraged to maintain creative dominance in the design process (Tang et al., 2024). This human-computer collaboration model ensures that students can not only benefit from AI and improve DEE but also maintain their creativity and sensitivity to cultural details (Tang & Leong, 2025).

### Cultural Misidentification Taxonomy

AI-generated images show many cultural misidentifications, such as inappropriate headwear, mismatched clothing, and inconsistency between facial expressions and cultural background. Due to resource constraints and the lack of formal expert evaluation, we can classify these errors and establish a cultural misidentification classification framework (as shown in Table 3). Teachers can use this classification framework to organize students to discuss and reflect, analyze the use of different cultural symbols and their performance in AI images, and improve students' understanding and processing capabilities of cultural differences. For

example, by analyzing the phenomenon that "Wang Xifeng's" facial expressions do not match the cultural background, students can learn how to guide AI to generate images that match the cultural background through AI input prompts (prompt engineering). At the same time, teachers can encourage students to give critical feedback on AI-generated work and cultivate students' cultural judgment and design capabilities. This framework provides a structured feedback tool for the classroom. It helps students identify errors in AI-generated images and guides teaching tasks. Ultimately, it enhances students' understanding and application of cultural elements, facilitating the effective integration of AI and traditional culture.

### Limitations and Future Directions

Although this study demonstrates the teaching potential of incorporating AI-generated art styles into traditional illustration design, there are still some limitations that deserve attention. First, the sample size was limited to 32 students from the same institution, which limits the generalizability of the findings. Second, the cultural fidelity assessment relied solely on the teacher's evaluation and students' mutual feedback; future research should incorporate expert evaluation (e.g., historians or traditional craftsmen) to objectively quantify the accuracy of AI in presenting cultural symbols. Third, the short-term course design cannot capture longitudinal effects, such as whether long-term use of AI will weaken students' hand-drawn illustration skills or creative autonomy.

To address these shortcomings, we recommend:

- **Cross-cultural validation:** replicate this study into different educational settings to test how AI handles different cultural elements, such efforts should also consider local educational infrastructures and cultural contexts, as environmental factors significantly mediate



technology adoption outcomes (Dabouba et al., 2023).

- **Ethical framework:** develop classroom guidelines to ensure compliance with copyright regulations and cultural sensitivity when using generative AI to reduce the risk of stereotyping or misappropriation (e.g., the misclassification method in Table 3).
- **Hybrid teaching model:** design longitudinal courses that alternate between AI-assisted and traditional modules to balance efficiency and skill retention. Integrating multimodal assessment frameworks, such as those deployed for anxiety reduction in speech training (Wang & Leong, 2025), could further optimize this hybrid approach.
- **Interdisciplinary collaboration:** collaborate with linguistics/history departments to strengthen just-in-time engineering strategies and ensure that AI outputs are consistent with contextual narratives.

## CONCLUSIONS

his study critically examines the integration of AI-generated art styles into traditional illustration design education, focusing on projects rooted in Chinese cultural heritage (e.g., Dream of the Red Chamber, Dunhuang art). Quantitative and qualitative analyses reveal that AI significantly enhances DEE and stimulates CI, as evidenced by high student ratings for PU (PU mean = 2.75) and CI (CI mean = 3.66). However, AI alone cannot replicate the depth of cultural nuance; 89% of outputs required manual refinement to correct symbolic inaccuracies (e.g., misplaced attire, emotional misrepresentation).

Our key contribution is the proposal of a human-AI collaborative framework (Figure 6). This framework strategically positions AI as an ideation catalyst, while prioritizing essential human oversight in cultural interpretation. This approach not only accelerates iterative design but also fosters critical engagement with tradition—transforming AI from a mere tool into a bridge between heritage and innovation. Nevertheless, educators must mitigate risks of creative dependency and ethical oversight through structured curricula that emphasize cultural literacy alongside technical skills.

Future work should expand to multi-institutional cohorts and longitudinal tracking to validate these findings. By embracing both the capabilities and limitations of AI, design education can harness technological advances without compromising the integrity of cultural storytelling.

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**Declaration of interest:** The authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

**Data sharing statement:** The data presented in this study are available on request from the corresponding author.

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