Computers & Education 239 (2025) 105419

Contents lists available at ScienceDirect

Computers & Education

journal homepage: www.elsevier.com/locate/compedu

AI-assisted design communication in ceramic-crafts education: Investigating image generation tools for concept representation and pedagogical practice

Woojin Kang [a], Hyun-Soo Lee [b,*], Jin-Hyuk Hong [a,**]

[a] Department of AI Convergence, Gwangju Institute of Science and Technology, Gwangju, Republic of Korea
[b] Industry-Academy Cooperation, Hanyang Women's University, Seoul, Republic of Korea

ARTICLE INFO

Keywords:
Applications in subject areas
Human-computer interface
Improving classroom teaching
21st century abilities

ABSTRACT

This study examines the implementation and effectiveness of AI-assisted visualization tools in ceramic-crafts education, with a specific focus on improving design communication and feedback exchange between instructors and students. Through empirical investigation, we developed and evaluated an AI-assisted visualization tool that leverages state-of-the-art image-generation models to enhance concept articulation in ceramic design practice. Our investigation, involving 12 first-year ceramic-crafts students and nine instructors, revealed significant improvements in three key areas: design communication clarity, feedback quality, and technical vocabulary acquisition. The findings demonstrate how AI tools can effectively augment specific aspects of ceramic-crafts education, particularly in bridging the gap between conceptual design and physical implementation. We analyze the tool's impact on student learning processes, instructor feedback mechanisms, and the preservation of traditional craft practices. The study contributes to the understanding of technology integration in craft-based education by providing empirical evidence of how AI tools can enhance specific pedagogical challenges while maintaining the essential tactile and experiential aspects of ceramic crafts. Additionally, we address critical considerations for implementing AI tools within traditional craft education, including the maintenance of hands-on learning experiences and artistic authenticity. Our research provides practical insights for ceramic-crafts educators seeking to integrate technological support while preserving fundamental craft-based teaching methodologies.

1. Introduction

With cultural, period, and national characteristics, ceramic-crafts have been constantly evolving and are being imparted not only for their functional purposes but also as a treasure trove of aesthetic values (Yao, 2020). Owing to the complexity of their design, material selection, and professional production methods, ceramic-crafts require comprehensive and specialized training, and there are various technical demands for producing work and transferring knowledge. The traditional ceramic-crafts education practices can be characterized by the experiential transfer of craftsmanship from experts to novices (Zou, 2019). However, this apprenticeship approach has inherent limitations, such as time constraints, so as to hinder the quality and efficiency of interactions between the

* Corresponding author.
** Corresponding author.
E-mail addresses: wjkang619@gm.gist.ac.kr (W. Kang), veronica713@hanmail.net (H.-S. Lee), jh7.hong@gist.ac.kr (J.-H. Hong).

https://doi.org/10.1016/j.compedu.2025.105419
Received 17 May 2024; Received in revised form 20 February 2025; Accepted 27 July 2025
Available online 7 August 2025
0360-1315/

experts and novices. Recently, various attempts are being made to address the challenges through the incorporation of intelligent technologies into the ceramic-crafts education and production process to facilitate efficient transfer of knowledge and creative work production. For example, Moradi et al. (Moradi et al., 2022) sought to computerize the glaze recipes of ceramics artisans to understand their material properties. Manitsaris et al. (Manitsaris et al., 2014) explored the use of AI to understand the gestures of ceramic-crafts experts at the pottery wheel. Huson (Huson, 2011) explored the possibilities of using 3D printers to create artwork.

In universities, where ceramic-crafts are mainly taught, students learn from practices of designing and making ceramics in their semester-long course (Guan et al., 2023). In common craft classes, as shown in Fig. 1, they spend most of the class making ceramics, but a little time is given to students to get inspired, refine and confirm their idea through image prototyping. Consequently, professors and students have less interaction, where the actual transfer of knowledge takes place in ceramic-crafts education. In order to make this class more efficient, we have to make the fewer interactions count, i.e., professors should be able to give quality feedback at every opportunity.

The proper communication between professors and students is important to get valuable and professional feedback, where the students create image prototypes by drawing directly on paper or utilizing design editing tools such as Adobe Illustrator to share their ideas with the professors. The current practices of image prototyping are mostly based on manual sketch (MS), and as mentioned earlier, the students have to complete their manual sketch within the limited timeframe. Currently, MS is a common practice frequently used in educational settings, which is highly important to share ideas in the ceramics production process. The quality of the sketch is directly related with the quality of the feedback and the final product; a higher-quality image prototype signifies that the design concept is clear and confirmed (Corremans et al., 2018).

To get an in-depth understanding of craft education in the real classroom, we performed interviews and surveys with 62 first-year ceramic-crafts students and three professors in the department of craft in a university, and identified a particular difficulty with the MS practice: design limitations due to manual skill. Students consistently reported difficulties in effectively communicating their design concepts through traditional sketching methods, with many expressing frustration at the disconnect between their creative vision and their ability to represent it visually. One student noted: "*I often have clear ideas in my mind, but translating them into sketches that accurately convey my intentions to professors becomes a significant challenge.*" This sentiment was echoed across multiple interviews, highlighting a systemic challenge in current ceramic-crafts education. Through thematic analysis of the interview data, we identified that students spent an average of 65 % of their design time focusing on technical drawing aspects rather than creative exploration. This imbalance significantly impacts the quality of student-instructor interactions and potentially limits students' creative development. Furthermore, instructors reported difficulty in providing precise feedback when working with unclear or technically limited sketches, often requiring multiple revision cycles that consumed valuable instructional time. Students have been struggling with their lack of design skills even when they use some editing tools such as Illustrator (Shi et al., 2023). As a result, inexperienced or less skilled students tend to naively express their intentions. Instructors (professors) struggle to understand the design intent of such naïve image prototypes sketched by them, and often misinterpreted them because of the low-quality sketches (Virzi et al., 1996). After the actual work is produced, they often realize that the intent had not been properly expressed and shared. It is important to improve the quality of image prototypes to reduce such misunderstandings; otherwise, both students and professors have to put much effort on the multiple iterations of revision until the correct communication is made. In the real classroom, where there are only one professor and a large number of students, the situation is even worse. Unfortunately, many times they are not allowed to have time and effort enough to make such high quality image prototypes.

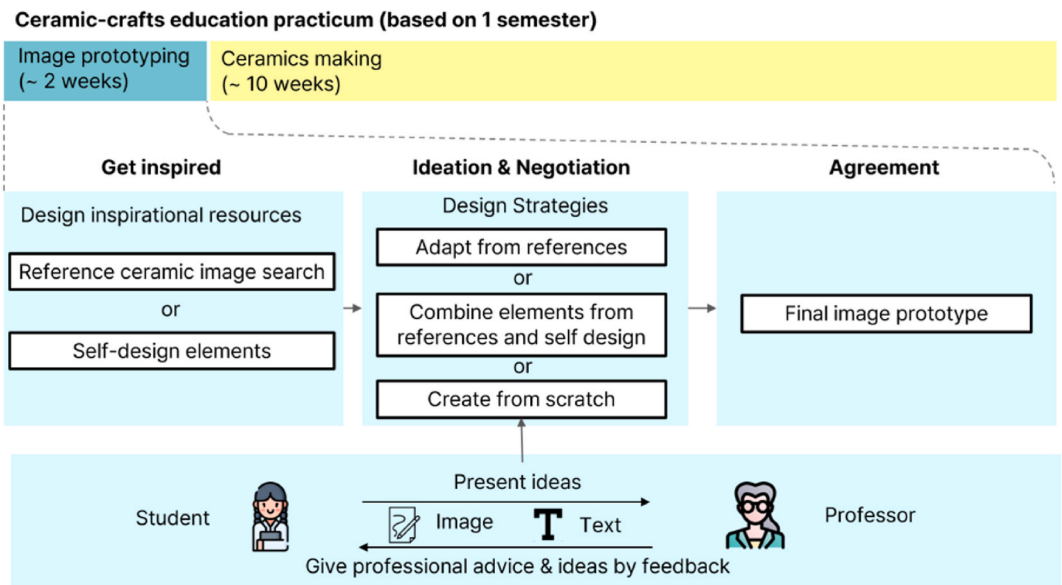

Fig. 1. Typical hands-on ceramic-crafts design course at a university.

The field of ceramic-crafts education faces specific challenges in facilitating effective design communication between instructors and students, particularly in the representation and refinement of complex design concepts. Traditional manual sketching, while fundamental to the craft, often presents limitations in accurately conveying design intentions and receiving precise feedback (Putra et al., 2022). These challenges are especially pronounced in educational settings where time constraints and varying levels of drawing proficiency can impede effective concept communication. Recent technological advances in AI-assisted visualization present opportunities to address these specific pedagogical challenges while maintaining the essential hands-on nature of ceramic crafts education (Zhang, 2024). The global shift towards digital literacy and technological integration in education (Ramli & Nurazidawati, 2023) raises important questions about the role of AI in developing students' creative and technical skills. How can AI image-generation models be effectively incorporated into educational curricula to enhance student learning outcomes? What are the implications of AI-assisted design processes on students' creativity and problem-solving abilities? How does the integration of AI tools affect the dynamics between instructors and students in creative disciplines? These questions are not only relevant to ceramic-crafts education but have broader implications for Visual Arts Education globally. By addressing these questions, we aim to contribute to the ongoing dialogue about the future of education in an AI-augmented world and provide insights that can inform educational policies and practices across different cultural contexts.

Improving the quality of students' design process and enabling better interaction between professors and students will improve their educational landscape. Here, we believe that AI image-generation models, which allow users to quickly generate new realistic and stylized ceramic-craft images with easy and comfortable input (e.g., text and image) (Zhan et al., 2023), work a great role for these purposes. Thus, we implemented the AI Ceramics Imagination Tool (AICIT), which supports students to complete their high-quality image prototypes, and verified its capability and potentials in ceramic-crafts education with addressing the following research questions.

- RQ1. How effectively do AI image-generation tools enhance concept representation and communication in ceramic-crafts design education?
- RQ2. What specific impacts do AI-assisted visualization tools have on instructor-student feedback exchanges in ceramic-crafts education?
- RQ3. How do AI tools influence technical vocabulary acquisition and design comprehension in ceramic-crafts learning?
- RQ4. What considerations are critical for integrating AI tools within traditional ceramic-crafts education while preserving essential craft practices?

Building upon Halverson's (Halverson, 2013) analytical framework for digital art-making processes in education, we examine the implementation of AI-assisted visualization tools in ceramic-crafts instruction. Our investigation focuses specifically on how these tools mediate design communication and concept representation within the unique context of ceramic-crafts education, where physical materiality and tactile understanding are fundamental to the learning process. Through systematic analysis of student-instructor interactions, we investigate the potential for AI-assisted visualization tools to supplement traditional craft-based teaching methods, particularly in addressing documented communication challenges during the design phase.

Drawing on established pedagogical principles in craft education, our study examines three critical aspects of AI integration: design concept articulation, technical knowledge acquisition, and preservation of traditional craft practices. This investigation extends current understanding of technology integration in craft-based education by providing empirical evidence of how AI-assisted visualization tools can support specific pedagogical challenges while maintaining essential hands-on learning experiences (Jinhee et al., 2024). The research specifically addresses the documented difficulties of communicating complex three-dimensional design concepts through traditional sketching methods, while considering the importance of preserving tactile learning experiences fundamental to ceramic-crafts education.

2. Related works

2.1. Pottery class and design support tools

A traditional ceramic-crafts curriculum (Fang, 2011; Peterson & Peterson, 2003) typically includes instruction on the following topics: (1) the history of ceramic-crafts; (2) the theory of form, based on the works of traditional and contemporary potters; (3) the properties of clay suitable for constructing these forms; (4) the properties of materials, such as glazes, which can be used to express color and texture; and (5) fabrication techniques. The theory and practice that a beginner needs to learn is long, complex, and materially expensive. Fortunately, digital tools have been developed to support this educational process both directly and indirectly. Kumar et al. (Kumar, Sharma, Bhowmick, & Technology, 2011) developed an early wheel-throwing simulator, which generates 3D pottery models from a 2D generatrix. Souper et al. (Souper et al., 2023) made an AI tool to predict color mixing results based on the spectral data of ceramic components (pigments and glazes), showing its potential to improve color mixing procedures. Google Arts & Culture's "3D Pottery[1]" presented a gamified support tool that allows users to simulate the pottery production process using the simple mouse manipulation of shapes, materials, colors, and patterns on the web. In addition, to provide a more immersive pottery production

[1] https://artsandculture.google.com/experiment/3d-pottery/nwHg1D0riJ1ltA.

experience for beginners, supporting tools have been developed to allow users to simulate pottery production using gesture manipulation in augmented reality (AR) (Gao et al., 2018) and virtual reality (VR) environments (Arango & Neira, 2016).

These tools all have one thing in common: they provide a brief taste of the pottery-making process, which can help spark interest and excitement in pottery for beginners. However, they are not enough to support users for more specific and specialized training, where the users may experience only a predetermined design of the process, or represent colors using RGB color codes rather than fully reflecting material properties. Owing to practical limitations, such as the need for certain equipments like VR, it is difficult to find confirmed cases of the effectiveness of such design support tools in the field of ceramic-crafts education. We aim to address the difficulties encountered with the MS practice, mainly used in ceramic-crafts education, by exploiting minimal equipments (PC or smartphone) and an AI image-generation model.

2.2. Design support tools based on AI image-generation models

Recent studies have been actively researching the use and development of AI techniques specifically for motivating and aiding novices in their design tasks, such as recommending design elements (Shi et al., 2023) and automatic combination of design elements (Zhao et al., 2021). In particular, AI image-generation models, which are a subset of generative AI models that automatically generate realistic images from certain sentences or simple sketches of users, have recently received considerable attention as design assistance tools (Haoran et al., 2023). Generative adversarial networks (GAN) and diffusion models are common approaches to implement those image-generation models, and they have evolved further and now work with many different kinds of input modalities such as text, image, and sound (Zhan et al., 2023).

In addition, design support using AI image-generation models has been actively applied to a variety of fields. In the fashion industry, for example, people developed various models, including colorization techniques to support coloring (Wu et al., 2023), image-manipulation techniques to modify garment designs (Dong et al., 2020), and virtual try-on techniques to enable people to try on virtual garments (He et al., 2022). It has even been reported that designers have displayed garments produced using AI image-generation models in a New York fashion show.[2] Similarly, in the architecture field, there are works on the development and use of architectural design support tools (Chang et al., 2021).

In addition to these concerns, it is crucial to situate our work within the broader context of AI-supported creative education research. Prior studies in architect design (Ceylan, 2021), architecture education (Tian et al., 2022), and digital art pedagogy (Halverson, 2013) have explored how AI tools can support ideation and iteration. However, most of these studies focus on digital media-based creative practices, where AI serves as a design automation tool rather than a co-creative assistant. In contrast, our work investigates how AI can function as a concept-sharing enhancer in a physical craft-based educational setting, where tactile and material considerations are paramount. Moreover, the ethical implications of potentially replacing human creativity with machine-generated designs are subjects of ongoing debate (Ali et al., 2021). Despite these complexities, the field remains a hotbed of innovation and rigorous academic investigation.

In summary, the potential applications of AI image-generation models are increasingly being recognized in a wide array of contexts. It is within this promising landscape that we aim to investigate the applicability and efficacy of these technologies in the specific context of ceramic-crafts education.

3. Method

3.1. AI Ceramics Imagination Tool

For our implementation of the AI-assisted visualization tool, AI Ceramics Imagination Tool (AICIT), we utilized and optimized existing state-of-the-art image-generation models. Specifically, we employed a "Stable Diffusion," (Rombach et al., 2022) a representative model to generate images from text input (T2I), and "ControlNet," (Zhang et al., 2023) a representative model to generate images from image input (I2I), as shown in Fig. 2. The Stable Diffusion, composed mainly of contrastive language-image pretraining (CLIP), U-Net, and a variational autoencoder, introduces autoencoders in the front and back to insert/remove noise in latent space and generates 512×512-resolution images operating with a single graphics card. For this study, we chose the pretrained 1.5 version of the Stable Diffusion model. On the other hand, ControlNet is a model for quickly and effectively training a pretrained large diffusion model, such as Stable Diffusion, for additional conditions even with small datasets (<50k) and is capable of generating high-quality image prototypes with various types of control conditions (e.g., edge map, segmentation map, keypoint, open pose, and scribble). For this study, a ControlNet model pretrained with scribble conditions was selected to enable students to convert idea sketches, which are the main types of graphics used in ceramic-crafts education, into high-quality image prototypes. This implementation allows for precise control over visual elements while maintaining artistic coherence.

To ensure the models working appropriately to generate images styled of Korean ceramics, we first obtained the consent of 170 Korean ceramic-artists, and then collected a total of 52,100 images for model training through multi-angle photography of their 4017 ceramics. The data collection process adhered to comprehensive ethical guidelines, particularly regarding the acquisition and usage of AI training data. We obtained informed consent from 170 Korean ceramic artists through a structured process that included detailed

[2] https://www.lgresearch.ai/news/view?seq=177.

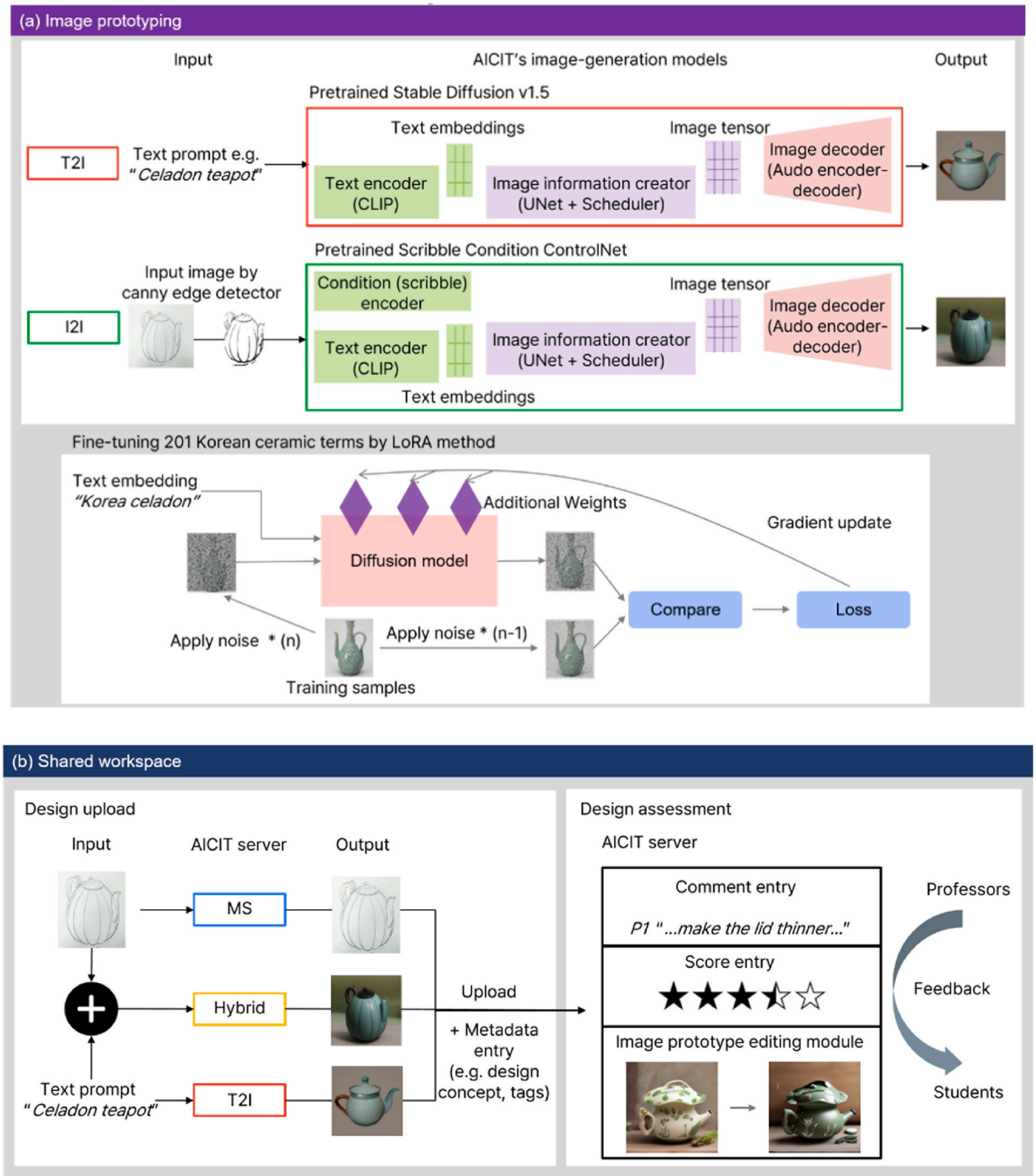

Fig. 2. Overview of the implementation of AICIT.

explanations of how their work would contribute to the AI model's development. Each artist received comprehensive documentation describing the potential implications of AI integration in ceramic education and retained the right to withdraw their contributions at any time. This ethical framework ensured transparency while preserving artistic integrity and intellectual property rights. We then annotated the 52,100 images based on 201 technical terms corresponding to the Korean ceramic classification system (material, form, pattern, and production technique) (Na et al., 2022). The dataset was trained on AICIT's two text encoders with low-rank adaptation (LoRA) (Hu et al., 2021), where the LoRA reduces the size of the data required for fine-tune the two text encoders and consequently reduces the training time required. This retraining process required 1 week to complete using nVIDIA A100 GPU × 3.

For the experiment, we additionally implemented an online workspace, where students can upload image prototypes made by

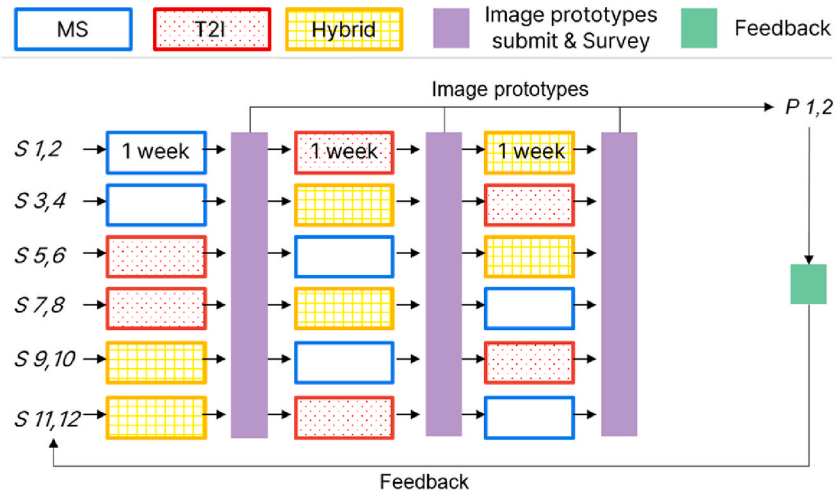

Fig. 3. A summary of the experimental process over participants.

manual sketch or the T2I and I2I functions of the AICIT, as shown in Fig. 2(b). It supports students and professors to have interaction by submitting the image prototypes and providing feedback on them.

3.2. Experimental setup

Two professors (*P1, P2*) and 12 first-year university students (*S1–S12*) from the ceramic-crafts department in a university in {Anonymized countries} were recruited for the evaluation of approaches of ceramics imagination. To ensure the global relevance of our study, we carefully considered the diversity of our participant pool, including students from various cultural backgrounds within the university. Note: This study was conducted at a women's university, and thus all 12 participants were biologically female. The potential influence of sex and gender was not addressed within the scope of this research. In this experiment, we asked the students and professors to follow the typical image prototyping process of ceramic crafts design class as shown in Fig. 1. The students were asked to use three image prototyping methods (MS, T2I, and Hybrid(I2I + T2I)) to complete their image prototypes for given three ceramics design tasks, usually used as the course content taught by the professors. The first task did not restrict the type of ceramic the students wanted to design and allowed them to perform creative work through the free exploration of ceramic design. The second task asked them to design a functional and practical kettle, which is often used to evaluate design mistakes of students in the class. The third task asked to design a creative and artistic kettle.

The students used each method for one week to perform the three tasks. In the MS image prototyping practice, the students were asked to prototype images on paper or tablets without restrictions on color expression, etc., as they usually did, whereas in the T2I image prototyping method, the students prototyped images as they wanted to express without restrictions on keywords. In the Hybrid image prototyping method, they were asked to manually sketch their ideas and input keywords to complete prototype images by using both of the I2I and T2I functions. For the Hybrid method, we asked them not to use any sketches obtained by MS. As shown in Fig. 3, we counterbalanced the order of the three image prototyping methods and asked the students to keep logbooks during each task. The logbooks included the time spent on activities related to the design task, websites visited, search terms used, and intermediate outputs. Because the time required for design varied by student, we did not limit the time spent on the tasks and obtained the number of times and time spent on the design process from voluntary measurements by them. As a result, they performed each method in a randomized order for one week, finalized three image prototypes by each method, wrote a description of the design in free form, and uploaded them to the shared workspace.

For the image prototypes submitted by the students, two professors were asked to evaluate them and leave feedback in free-form sentences in the shared workspace after each student submitted all nine image prototypes (3 methods x 3 tasks). Especially, the professors' evaluations on the image prototypes were based on their expectations of the final ceramic product, as they would do in their classroom. The experiment was approved by the institutional review board (IRB).

3.3. Evaluation metrics

The two ceramic-crafts professors evaluated for image prototypes with respect to Aesthetics, Usability, Feasibility, and Creativity, designed based on the sketch design evaluation criteria (Kudrowitz & Wallace, 2013), on a 5-point Likert scale. The feedback written by the professors was categorized as shown in Table 1, including Form, Material, and Technique, and the aforementioned four criteria.

Table 1
Feedback classification criteria and examples.

Feedback content	Feedback levels	
	Abstract	Detailed
Form	"It's a plain looking kettle."	"Above a certain size, you can safely make a hole for water to come out while maintaining proportion"
Material	"Looks like a material modification is needed."	"If you used colored clay, work with the red pigment, then apply black makeup and sculpt to reveal the red pigment."
Technique	"The lines of the jar are represented by the spinning wheel."	"Apply the black and red clay in sequence to create the body, then carve and the casting is complete."
Aesthetic	"cute"	"The difference in thickness of the celadon glaze on the celadon clay creates a beautiful coloring of the pattern"
Usefulness	"Less practical"	"The typical kettle design has a high spout, which requires a lot of tilting."
Creativity	"creative"	"The bottom is wider and shorter than a typical jar, so it resembles the specialty earthenware of Jeju Island and looks interesting."
Functionality	"I think it's an object"	"The actual jar itself doesn't have much functionality, but I think it would be interesting to develop various jars by changing the counterweight in different directions."

The level of feedback was analyzed after keyword tagging using ATLAS.ti,[3] a qualitative research software tool developed by Scientific Software Development GmbH. For the given feedback, the students also evaluated if their original design concepts were well shared by their image prototypes with the professors or not.

For the analysis, we investigated how the students conceptualize their design with the three methods, by analyzing the search terms in their logbooks and the prompts they used to create image prototypes. We also conducted surveys to measure their experience with each method in terms of satisfaction and educational effectiveness. For satisfaction, we exploited survey items, including some related to the System Usability Survey (SUS) (Brooke, 1996), the Usefulness, Satisfaction, and Ease of use (USE) questionnaire (Lund, 2001), and some items used in recent generative AI research (e.g., whether the product is recognized as user-made; novelty of the product) (Hitsuwari et al., 2023; Pidhorskyi et al., 2018). We also used the NASA task load index (NASA-TLX) (Hart & Staveland, 1988) survey to measure the degree of cognitive load of the methods. For educational effectiveness, we asked whether each method affected the students' expressiveness and understanding of the craft. All these survey results were statistically analyzed using one-way repeated-measures analysis of variance (ANOVA).

4. Results

In this section, we answered our research questions (RQs) by qualitatively analyzing the results of our user study, by which we were able to identify that the AI image-generation model correlates with an increase in the range of design domains explored by students, an increase in design quality, and the improved interaction between students and professors.

4.1. RQ1. How much do AI image-generation models improve students' ceramics image prototyping?

We analyzed the amount of time spent on the design process and the number of design iterations the students worked on. Here, we referred to the exploration for design inspiration, including web searches, as "Exploring," and the act of designing, e.g., expressing ideas into concrete design prototypes on paper or in the digital workspace as "Designing." (Dam & Siang, 2020). In comparison, we counted the design outputs for non-duplicated input prompts only, to control the effect of the image-generation model's repeatedly producing outputs on the same input prompt.

As shown in Fig. 4(a), with MS, the students spent much time exploring for inspiration (7.5h), and in the actual design (4.75h) on average. The number of image prototypes submitted was much fewer than other methods (T2I and Hybird) because they had to spend much time to create one image prototype and were reluctant to repeat the process many times, *S11*: *"I sketch by hand, but it's difficult and annoying to modify the color, so I didn't do it much."* Among the three methods, T2I required the least amount of time for exploration and design, while producing the highest number of image prototypes. They easily obtained a number of designs by simply typing in keywords with T2I, enabling them to iterate many times in a short period of time. With Hybrid that embraces the MS practice and T2I, the students spent less time exploring than in MS and more time designing than in T2I. As a result, the students created more image prototypes in less time than MS as a percentage of the total design process time.

We analyzed the user experience to investigate the reasons for the differences in design process time and number of image prototypes between the three methods. Students felt that MS did not reflect their design intent (Fig. 5(a1). Avg. = 3.08), and also thought that it was not easy to reflect their intent into the image prototypes well enough with the MS practice (Fig. 5(a.2). Avg. = 3.16). This is in line with the results of the preliminary survey. We can also see that the process of producing image prototypes with MS was cognitively demanding (see Fig. 5(b)). As a result, the students found it tedious (see Fig. 5(a.6). avg. = 3.25) and burdensome to create image prototypes by the MS practice, and therefore performed fewer iterations of the design process.

[3] https://atlasti.com/.

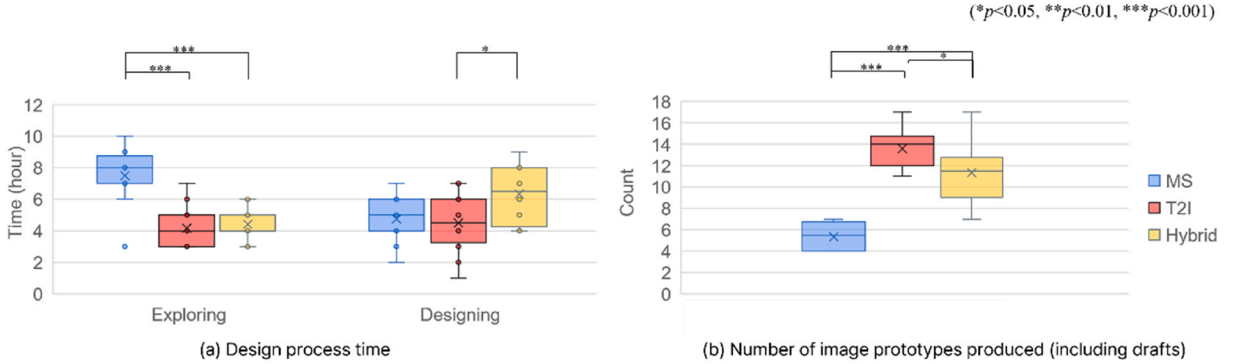

Fig. 4. Productivity analysis.

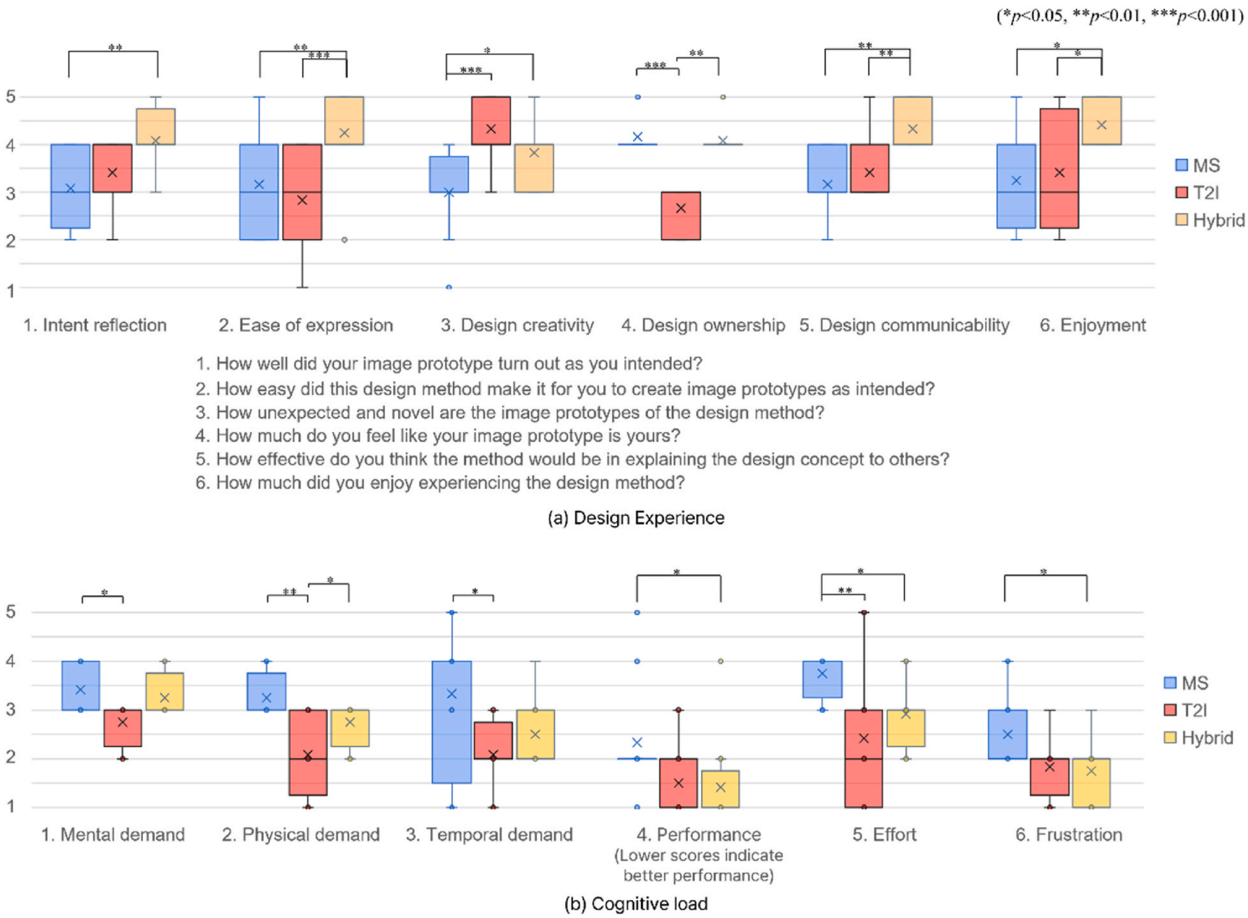

Fig. 5. Result of user experience.

With respect to the T2I image prototyping method, the students were able to modify their input queries several times until they were able to express their intentions to some extent (Fig. 5(a.1). Avg. = 3.42), but sometimes found it difficult to find the right keywords to match their intentions (Fig. 5(a.2). Avg. = 2.83). Students were able to easily modify their input queries and produce many image prototypes (see Fig. 4(b)), they felt that T2I was the least cognitively demanding (see Fig. 5(b)). More importantly, they did not feel the outputs produced by T2I as their own (Fig. 5(a.4). Avg. = 2.67). Nonetheless, T2I has a great potential in the area of design exploration, as mentioned by *S1 "I repeated it several times until something similar to the design I wanted was generated, and in the process, some designs were generated by chance that I liked better."* Many students indicated that they were able to find many unexpected and novel designs by T2I, unlike other methods, as shown in Fig. 5(a.3). *S1* said, *"As the design was generated quickly, it felt like searching* *on Pinterest, so I repeated it until I found a design I liked rather than searching."* The students used fewer web searches and rather used T2I to explore more design examples, indicating that the image-generation model could partially replace traditional search engine.

With respect to the Hybrid image prototyping method, students, who input a simple sketch and a few words, were generally very satisfied with producing high-quality image prototypes that met their intentions. They felt that Hybrid helped them express their ideas more accurately, easily, and effectively (see Fig. 5(a.1&2&5)). In terms of cognitive load, it asked less effort than MS and had the lowest failure rate among the three methods (see Fig. 5(b.4-6)). Unlike T2I, students felt a sense of ownership in Hybrid (see Fig. 5(a.4). Avg. = 4.08), which was the same as MS, because they used their own idea sketches as input queries and iterated until they obtained an image prototype they wanted. *S12* said, *"It was really good because the image that I sketched down and input some words to the color changed into a picture of real pottery. There were other creative things produced that were different from the pottery I thought of, but it was solved by repeating it several times."* Based on the interviews, it seems that producing image prototypes by Hybrid provided some of the same experiences as Exploring. *S1* said, "*It was fun because I just had to make a rough sketch and input some words on the elements of the pottery I wanted to make, and the design came out similar to what I had in mind.*" As such, it seems that designing with Hybrid was enjoyable (see Fig. 5(a.6) avg. = 4.42) for them and its high-quality image prototypes motivated them to repeat the design process even though it took a lot of time in Designing. One student (*S7*) noted: *"I initially felt that the AI-generated images were too polished and didn't reflect my unique artistic style. But after iterating with my own sketches and modifying AI outputs, I felt more in control of the design process."* Faculty members also observed that students who engaged in AI-supported design tended to revise and refine more, leading to richer final concepts.

In summary, the AI image-generation model could help students produce image prototypes according to their intentions or explore novelty image prototypes by helping them be less influenced by their hand-sketching skill level. It also makes the time-consuming process more enjoyable for students, getting them in the virtuous cycle of creating high-quality image prototypes. These findings align with global trends in educational technology that emphasize the importance of student engagement and self-directed learning (Evirgen, Ruolin, & Xiang'Anthony, 2024).

4.2. RQ2. How do AI image-generation models impact instructor–student interaction?

To further explain how professors evaluated the image prototypes, we qualitatively analyzed their feedback within the seven categories, as shown in Table 2. In terms of the quality of feedback, the professors provided with detailed feedback in a great portion when given the prototypes created by T2I (84.2 %) and Hybrid (77.5 %), where MS shows a much less portion of detailed feedback (54.1 %). For Technique, interestingly, T2I and Hybrid have elicited 6.58 and 6.59 feedback statements per a prototype on average while MS only elicited 2.91. In Material and Creativity, T2I drew out detailed feedback (96.9 % and 95.8 % out of 5.5 and 6.84 statements, respectively) greatly against abstract feedback. Hybrid could obtain quality feedback for Form (91.3 % out of 5.85 statements). Particularly, MS failed to elicit detailed feedback for Form (41.2 %/6.58), Aesthetic (38.7 %/6.25) and Creativity (4.63 %/6.84), whereas T2I and Hybrid showed their potentials, e.g., *P1*'s comment: "*The center of mass of the pottery seems to be at the top, so it would be better to expand the bottom to lower the center of mass*." The fact, that the image prototypes produced by T2I and Hybrid received more detailed feedback than MS, indicates that students could present their concept clearly on the realistic image prototypes generated by T2I and I2I functions. This is supported by *P2*'s abstract comment on *S2*'s MS image prototype, "*I don't understand the intention with this sketch*." whereas for *S2*'s another prototype by T2I, he gave more specific feedback, "*The height of the spout of the kettle is high, which is a disadvantage that requires a lot of tilting, and the size of the lid and its bite with the body needs to be checked.*" AICIT also helps instructors modify image prototypes in limited feedback time. "*Through AI simulation design, I can not only understand the student's intention immediately, but I can also directly correct the student's design through this system, which will have a great teaching effect,*" as P2 said in the interview. With the proposed AICIT, the image prototye in ceramics is no longer a sketch, but a reality check without a real product.

Qualitative analysis of student experiences revealed distinctive patterns in how students integrated AI tools into their creative process. Students demonstrated an evolutionary approach to tool usage, beginning with broad conceptual exploration and progressively moving toward refined design iterations. As *S4* explained: "*The AI tool allowed me to rapidly visualize different possibilities, helping me understand how subtle variations in form and texture could impact the final piece.*" This iterative exploration process facilitated deeper engagement with traditional ceramic principles while enabling more efficient concept communication.

Table 2
The frequency of professors' feedback on image prototypes (standard deviations in parentheses).

Feedback category	Feedback quality								
	Abstract			Detailed			Total		
	MS	T2I	Hybrid	MS	T2I	Hybrid	MS	T2I	Hybrid
Form	3.83 (2.25)	0.50 (0.80)	0.50 (0.67)	2.75 (2.38)	3.83 (2.17)	5.25 (2.70)	6.58	4.33	5.75
Material	1.83 (1.34)	0.17 (0.39)	1.58 (1.08)	2.50 (2.20)	5.33 (2.19)	3.67 (2.39)	4.33	5.50	5.25
Technique	1.08 (0.90)	0.83 (0.94)	1.67 (0.78)	1.83 (2.12)	5.75 (2.22)	4.92 (2.31)	2.91	6.58	6.59
Aesthetic	3.83 (1.27)	0.92 (0.67)	0.83 (1.11)	2.42 (2.47)	5.08 (2.47)	4.17 (1.75)	6.25	6.00	5.00
Usefulness	1.67 (0.49)	1.67 (0.78)	1.50 (0.80)	2.92 (1.51)	4.25 (2.45)	4.00 (1.86)	4.59	5.92	5.50
Creativity	3.67 (1.50)	0.17 (0.39)	0.83 (0.72)	3.17 (1.70)	3.92 (2.27)	3.58 (2.02)	6.84	4.09	4.41
Functionality	1.67 (0.98)	2.00 (0.60)	1.50 (1.00)	3.50 (2.28)	3.58 (1.56)	3.42 (2.27)	5.17	5.58	4.92
Sum	17.58	6.26	8.41	19.09	31.74	29.01	36.67	38.00	37.52

As shown in Fig. 6(a), the students reviewed the feedback of the professors and answered if their design intentions were well shared with them. With the T2I and I2I functions, the students thought that the professors caught the point they wanted to deliver in general. Interestingly, contrary to the results in Fig. 5(a.1&2) that they felt it difficult to present their intentions in their image prototypes with T2I, but T2I obtained the highest success rate in sharing ideas with the professors (see Fig. 6(a). Avg. = 91.6 %).

With respect to the aesthetic evaluation on the prototypes, MS received the lowest scores for all the criteria, whereas T2I and Hybrid show their distinct superiority in Aesthetic and Feasibility, respectively (see Fig. 6(b)). These findings are in line with the results from RQ1, which showed that the students were able to create image prototypes that not only reflected their intentions but also generated them in high-quality by the T2I and I2I functions. We think the reason for the highest Aesthetic rating (see Fig. 6(b.Aesthetic). Avg. = 4.00) and success rate of intention sharing of T2I is that T2I allows students to explore their designs more freely and to generate more novel image prototypes while both MS and Hybrid require an initial constraint (i.e., sketch) to envision a basic form.

Fig. 7 presents some examples that show how the AICIT supports instructor-student interaction and influences the design quality. *S2* is a student who spent more time in her sketch and drew relatively poor sketches than the other students with the MS practice (Exploring = 8 h vs Avg. 7.5 h, Designing = 7 h vs Avg. 4.75 h, # of sketches = 7 vs Avg. 5.33); however, the quality of her image prototypes significantly improves by exploiting the T2I and I2I functions. The professors either failed to identify *S2*'s intentions or made abstract comments on the image prototypes she produced with MS, but when she produced image prototypes with T2I or I2I, they succeeded in identifying her intentions and could give her more specific feedback. As the result, she got high aesthetic scores on her prototypes by the T2I and I2I functions, because they determined that her final work would be of high quality. She even achieved the Usefulness and Feasibility scores higher than the other students (T2I: Usefulness = 4.0 vs Avg. 3.5, Feasibility = 4.0 vs Avg. 3.0 | Hybrid: Usefulness = 3.5 vs Avg. 3.5, Feasibility = 4.5 vs Avg. 4.0). As a good hand drawer, *S12* created image prototypes with multiple views, and even drew an image prototype at an oblique angle to deliver the design intent as much as possible. Her potential on expressiveness was also shown with T2I and Hybrid, implying that the AICIT did not interfere with or impede her performance. The professors provided detailed feedback on all of *S12*'s image prototypes because they understood her intentions and gave her high aesthetic scores for her final work.

These aesthetic score improvements demonstrate the positive impact of the AI image-generation models. However, the difference in scores between the students in their T2I and Hybrid suggests that although the image-generation model helps the students share their design intentions better, it would still require continuous effort on the part of each student to hone their creativity and achieve their best results. The improved quality of instructor feedback facilitated by AI-generated prototypes addresses a universal challenge in visual arts education: bridging the gap between students' conceptual ideas and their visual representation.

4.3. RQ3. What are the pedagogical benefits of AI image-generation models?

To check whether the use of the AI image-generation model has an effect on expanding students' interest and professional knowledge in ceramic-crafts, we collected the logbook entries and prompts entered by the system and analyzed the types, as shown in Fig. 8(a). The overall number of keywords used increased when the AI image-generation models were used, while the students prompted more words with T2I, which is a natural result. For MS, not only were there fewer search terms in total, but also there was less use of technical and professional terms, such as words related to the Korean pottery classification system. For example, to express the color of a design, the word "blue" was used directly rather than some words for the material, e.g., celadon clay, with MS. Simple words such as "bottle" were often used instead of technical words to describe shapes, e.g., double gourd body shaped bottle (Korean "PyoHyeongByeong"). By contrast, they used more technical terms with T2I and Hybrid. Interviews such as that with *S12* ("*I tried to put in terms I didn't know in order to design a creative and artistic kettle.*") and the results in Fig. 8(b.2&3) show that T2I is very helpful to get new design ideas and technical knowledge about ceramic-crafts. Furthermore, when asked if this design method was effective at helping them learn the concepts of the terms, *S8* said, "*Yes. I designed a vase in the shape of a wave, and it was good to learn about colored soil.*" This and other interviews, in conjunction with the results shown in Fig. 8(b.3), imply that T2I was effective at helping the students conceptualize new and unfamiliar terms. Meanwhile, whereas Hybrid showed similar trends as those exhibited by T2I, it appeared to

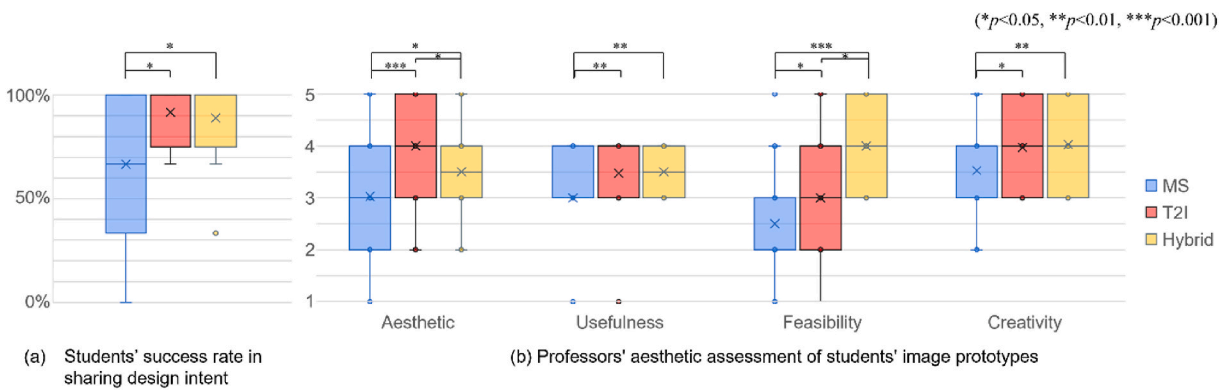

Fig. 6. Assessment of feedback and image prototypes.

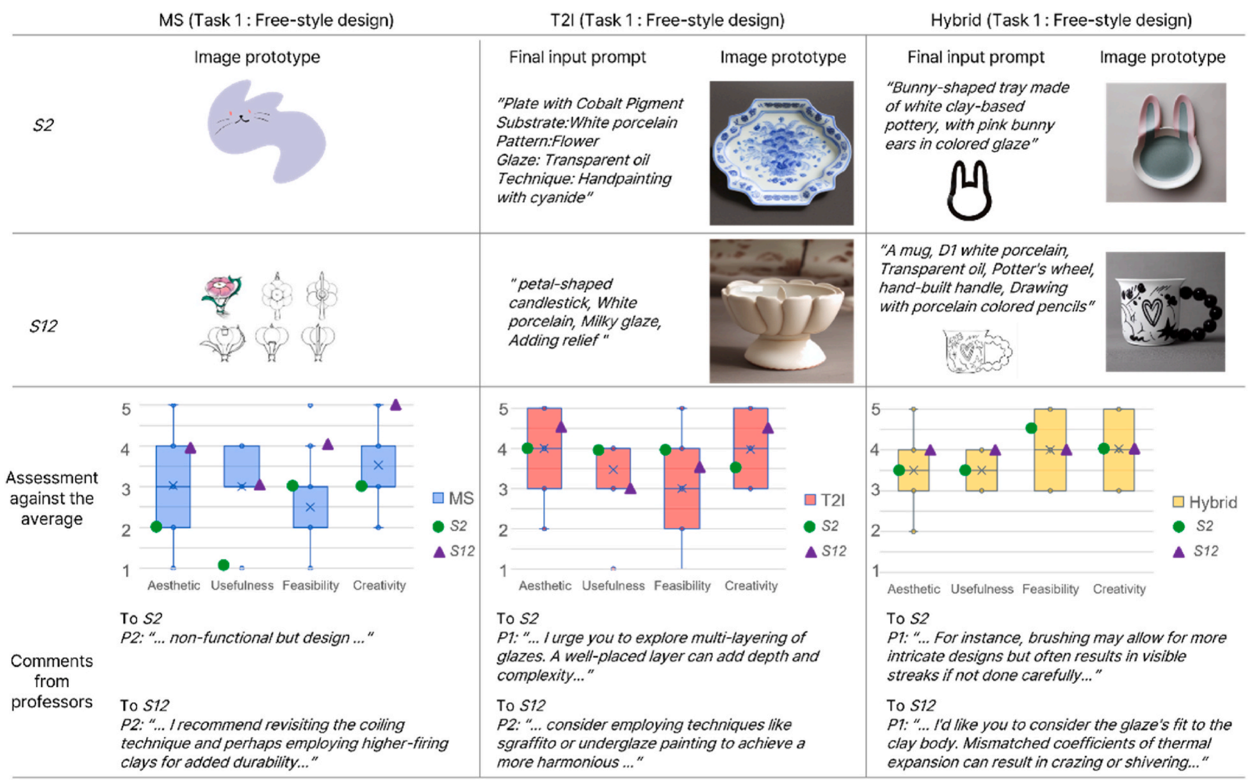

Fig. 7. Designs of participating students; *S2* showed the largest score improvement by T2I and Hybrid, and *S12* obtained the highest score over the methods.

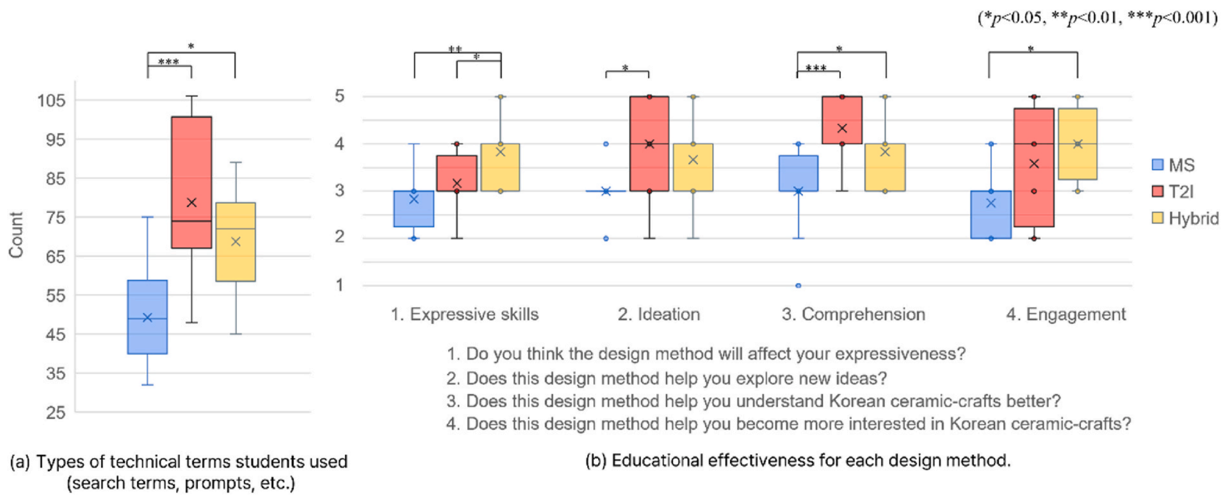

Fig. 8. Qualitative analysis of educational impact.

have greater potential than T2I in improving instructional effectiveness through physical design representation (Fig. 8(b.1)) and engagement (Fig. 8(b.4)).

These findings, including the interviews, suggest that the T2I and Hybrid methods can collaborate with each other (although Hybrid actually embraces T2I), because T2I supports the exploration of primitive concepts while the I2I function in Hybrid improves the accuracy and refinement of ideas. In other words, T2I is suitable for partially fulfilling the role of a search engines in exploring initial ideas, while Hybrid is suitable for fulfilling the role of an efficient design editor. By integrating these tools, the AICIT can play a bridging role in solving the difficulties of applying traditional search engines and design editors to ceramic-crafts education. The observed increase in students' use of technical terminology and understanding of ceramic-crafts concepts reflects the potential of AI tools to enhance domain-specific knowledge acquisition, a finding that resonates with recent global research on AI in specialized education (Harisankar et al., 2024).

5. Discussion

To comprehensively address RQ4 regarding the practical implications and future directions of AI integration in ceramic-crafts education, we conducted a systematic two-phase expert consultation process. The initial phase involved detailed discussions with four ceramic-crafts professors (*E1-E4*) and one design professor (*E5*), who evaluated the implementation of AI image-generation models in their specific disciplinary context. These experts conducted thorough reviews of student-generated image prototypes and personally evaluated the AICIT system to provide informed perspectives on its educational applications. Building upon these initial insights, we expanded our investigation through a second phase of expert consultations, incorporating perspectives from broader visual arts disciplines. This extended panel included professors specializing in sculpture (*E6*), painting (*E7*), visual communication design (*E8*), and digital media arts (*E9*). This methodological expansion was strategically designed to examine the broader applicability of AI-augmented visual arts education across different creative disciplines and to identify common pedagogical patterns and challenges. The integration of perspectives from both phases of expert consultation revealed several crucial insights regarding the implementation of AI tools in visual arts education. Our analysis framework incorporated three primary dimensions: pedagogical effectiveness, technological integration, and preservation of artistic development. This structured approach enabled us to identify both discipline-specific considerations and cross-disciplinary patterns in AI tool adoption within visual arts education.

5.1. AI-assisted design communication in ceramic-crafts education: mechanisms and impacts

Current AI image-generation models are trained to produce images as realistic as possible. This can lead to the generation of images that are not practical but only photorealistic, for a user input that may have some conflicts in the taxonomy combinations. Fig. 9 shows an example that S2 input some words, e.g., celadonite and super white, and produced an image of a cup constituted as specific soils (e.g., porcelain clay), which is practically impossible to make with current ceramic techniques. The professors argued that the AICIT is more useful as an educational support tool when being used under a supervision of instructors, because otherwise, it could lead to incorrect conceptualizations when used by novice students alone. The AICIT currently produces anything according to users' input. In particular, *E1* said, *"When educating students about possible designs, it is expected that the effect of using* AICIT *with an instructor will be greater than the existing educational method."*

As shown in Fig. 7(b), overall, the quality of image prototypes produced using AI was rated higher than that of image prototypes produced traditionally. Even students who produced low-quality image prototypes by their own showed a significant improvement in the quality of their designs by actively utilizing the AI tool. In many other fields, there have been concerns about people becoming dependent on AI. As Kahneman (Kahneman, 2011) stated, people often rely on instinctive thinking without trying to think rigorously. We also raised concerns about the AI image-generation models, simply amplifying the instinctive thinking in the ceramic design process. On the other hand, *E3* believes that through proper distribution of the time for design exploration and design discussion using AI within the controlled design-education time, educational effectiveness can be improved compared to that of existing design exploration through web search engines and manual sketches. These opinions tend to differ from the concerns voiced by the educational community regarding large-language models (LLM), another kind of generative AI (Dwivedi et al., 2023). According to a recent

Fig. 9. Image prototype example of incorrect combination results for porcelain clay. There are no ceramic techniques to implement this in real, at least so far.

multidisciplinary discussion, the impression regarding ChatGPT, a representative service example of an LLM, is that it will spread innovation across the ecosystem in industry, whereas in education, the dominant opinion is that AI-dependent students will not learn good ways to write because of the simplicity and convenience of text generation (Darvishi et al., 2024; Liu et al., 2023).

However, unlike various fields where LLMs or image-creation models are recklessly used, the field of ceramic-crafts can be differently characterized by students going through a series of processes to feel and modify their designs while physically creating their works. *E3* stated: "*I don't think it's a problem for students to use AI because they're constantly tweaking their designs, not only in the design process, but also in the production process, so they're creating their own unique style.*" In ceramic-crafts education, the manual learning process and the tangible nature of the work could undermine concerns about relying on AI. Furthermore, implementing designs materialized with the help of AI in the physical world can provide students with multidimensional feedback that spans both digital and physical worlds.

In this study, it also shows another perspective on AI reliance. In the experiment, we asked the students to use the I2I function with their own idea sketches as input, but some students used some images collected from the web, as shown in Fig. 10. When we interviewed the students about this, *S6* responded, *"I don't think it's different from the inspiration process in general because it's a different material than ceramics,"* and *S7* said, *"I think it's an homage, not plagiarism."*

The professors presented different opinions regarding this behavior. E1 said, "I think there is a concern about design plagiarism," whereas E2 said, "I think the level of imitation determines whether it is plagiarism or not, which is the same as the existing sketching method, and I see this experimental results as reinvention."

Creativity is often inspired by existing work (Okada & Ishibashi, 2017). Although the tools have changed in the digital age, the fundamental process of finding inspiration remains the same (Ornes, 2019). Professor *E2*'s perspective, in that the degree of imitation determines the classification of a work, recognizes that all creative processes, even those augmented by technology, involve some degree of imitation. It also acknowledges professor *E1*'s concern about design plagiarism, especially given that the I2I function has been demonstrated to be able to easily reproduce or copy existing designs.

The key to creating honestly inspired designs, while avoiding inadvertently plagiarizing another person's work, is to add value to the output, whether it is a new interpretation, unique combination of elements, or significant departure from the original. The perspectives of *E1 and E2* are not mutually exclusive. To address this underlying concern, we are encouraging a culture of transparency. We expect that encouraging students and professionals to disclose the tools and methods they use in the creative process would not only build trust but also create an environment that recognizes innovation and encourages reinvention. This is in line with the recent policy of some article publishers to allow the use of generative AI tools such as ChatGPT but with the requirement to disclose their use (Brainard, 2023).

5.2. AI-assisted design communication in ceramic-crafts education: framework and implementation

Our findings demonstrate how AI-assisted visualization tools can effectively support specific aspects of ceramic-crafts education when properly integrated into the learning process. Through systematic analysis of our empirical results, we identify key mechanisms through which AI tools can enhance concept communication and design feedback while preserving essential craft-based learning experiences. This integration advances our understanding of how technological support can augment traditional ceramic-crafts education practices.

The implementation of AI-assisted visualization tools in ceramic-crafts education encompasses several key aspects: concept articulation support, iterative design refinement, technical vocabulary development, and preservation of traditional craft practices. These tools specifically enhance students' ability to communicate design intentions and receive detailed feedback while maintaining

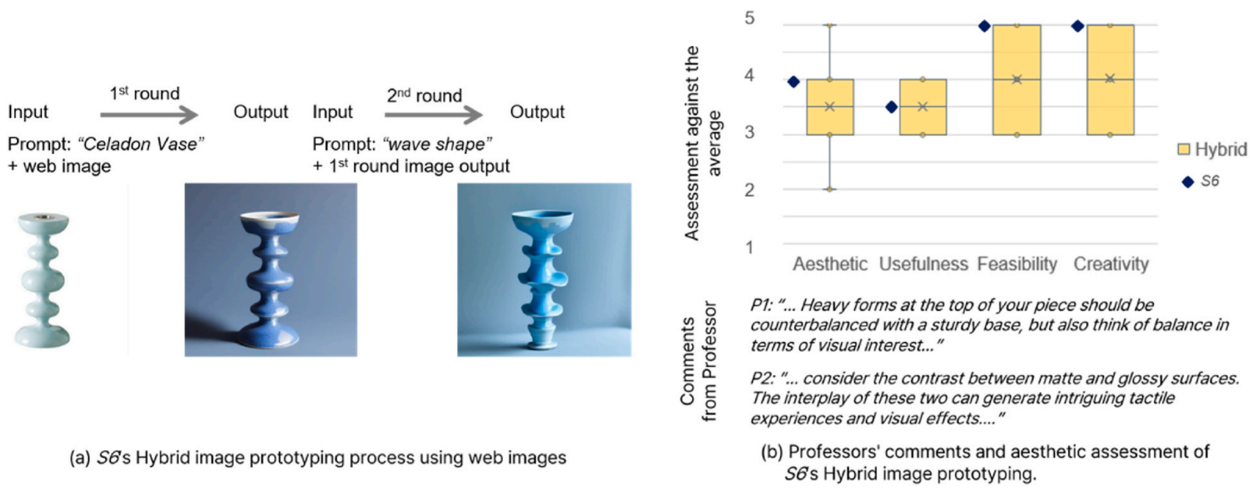

Fig. 10. *S6* used web images instead of her own idea sketches.

the essential hands-on nature of ceramic crafts education. This was evident in our study, where students using AICIT were able to generate and explore a wider range of design ideas than those using traditional methods. The rapid prototyping capabilities of AI-generated image prototypes allow for quick visualization and iteration of ideas, accelerating the design process. This acceleration was particularly noticeable in our study, with students using AICIT producing significantly more design iterations in less time compared to manual sketching.

High-quality AI-generated prototypes enhance the clarity of concept communication between students and instructors. Our results showed that professors were able to provide more detailed and constructive feedback on AI-generated prototypes compared to manual sketches, indicating improved communication of design concepts. Furthermore, interaction with AI tools encourages students to engage with and learn domain-specific technical vocabulary and concepts. We observed an increase in the use of technical terminology among students using AICIT, suggesting enhanced technical skill development.

The process of guiding AI tools to produce desired outputs encourages students to reflect on their own creative processes and decisions, fostering metacognitive awareness(Hutson & Peter, 2023). In our study, students using AICIT demonstrated increased awareness of their design choices and creative processes, as they had to articulate their ideas clearly to generate appropriate AI outputs.

This approach to integrating AI tools in ceramic-crafts education builds upon established pedagogical principles in craft-based learning. It specifically addresses the challenge of concept communication in physical craft practices while preserving the experiential learning aspects essential to ceramic-crafts education. The implementation focuses on enhancing, rather than replacing, traditional pedagogical interactions between instructors and students. AICIT providing immediate, personalized scaffolding, thus extending Vygotsky's concept of the Zone of Proximal Development (Simms, 2024) and demonstrated this by generating diverse design prototypes that challenged students' preconceptions and expanded their design possibilities.

5.3. Material and digital integration: implications for craft-based education

To examine the broader implications of our findings, we conducted additional interviews with experts from related visual arts disciplines. These experts included professors specializing in sculpture (*E6*), painting (*E7*), visual communication design (*E8*), and digital media arts (*E9*), complementing insights from instructors (*E1-E5*). This cross-disciplinary investigation revealed both promising opportunities and significant challenges in AI integration across visual arts education.

The potential for enhanced visual communication emerged as a consistent theme across disciplines. *E6,* a sculpture professor, observed: "*The AI tool's ability to rapidly generate multiple viewpoints could transform how we teach form and space. However, this efficiency might inadvertently diminish students' developmental process of understanding three-dimensional relationships through traditional sketching.*" Another crucial aspect raised in the expert interviews was the impact of AI tools on narrative development in artistic practice. *E7*, a painting professor, noted: "*While AI can accelerate visual exploration, students sometimes struggle to embed their personal or cultural narratives into AI-generated images. The process of manually sketching often helps them discover deeper symbolic meanings, which may be less apparent when relying solely on AI outputs.*" This observation suggests that while AI aids in visual articulation, it may require additional pedagogical strategies to ensure that students' artistic narratives are not diluted. From the visual communication design perspective, *E8* emphasized both opportunities and concerns: "*The rapid visualization capabilities could revolutionize visual arts education by accelerating the iterative process. However, we've observed that students might become overly dependent on AI-generated solutions, potentially limiting their ability to develop original design thinking strategies.*" This aligns with broader concerns in the field of AI-assisted creativity. Recent studies (Hang et al., 2024) suggest that AI-reliant students may exhibit reduced problem-solving flexibility, as they tend to select AI-generated results rather than critically iterating on their own concepts. This raises important pedagogical questions about how AI tools should be integrated into curricula to foster, rather than inhibit, independent creative problem-solving skills. *E9*, specializing in digital media arts, provided a critical perspective on technological integration: "*While the ceramic study demonstrates immediate benefits in concept visualization, we must consider the long-term implications for artistic practice. There's a risk that AI tools might standardize visual expressions, potentially homogenizing creative outputs across different cultural contexts.*" This observation highlights the need for careful consideration of cultural preservation in AI-augmented arts education.

5.4. Methodological considerations and future research directions

While our study provides valuable insights into the integration of AI tools in visual arts education, several methodological, technical, and contextual limitations warrant careful consideration. These limitations not only frame the scope of our current findings but also illuminate promising directions for future research in this domain.

Our investigation into AI-augmented visual arts education, while yielding significant insights, necessitates careful examination of several methodological, technical, and contextual limitations. These constraints not only delineate the boundaries of our current findings but also illuminate critical trajectories for future scholarly inquiry in this emerging domain of educational technology research. The methodological framework of our study exhibits several inherent limitations that affect the generalizability of our findings. The relatively concentrated participant sample ($n = 12$) from a single institutional context potentially constrains the comprehensive representation of diverse student experiences and learning patterns in visual arts education. The homogeneous participant demographic—comprising first-year university students from a specific cultural context—limits our understanding of AI-augmented tool efficacy across varied educational levels and cultural settings. Moreover, the temporal scope of our study, primarily focused on immediate learning outcomes, precludes thorough evaluation of longitudinal impacts on artistic development and skill acquisition. Our data collection methodology, particularly the observational logbooking approach, while effective for analyzing web-based design inspiration sources, demonstrated limitations in capturing the full spectrum of creative inspiration. For instance, as evidenced by participant S10's experience, students often derived inspiration from diverse sources such as musical stimuli, which were only partially captured in their logbooks. The phenomenon of students finding design inspiration from naturalistic sources (Mumcu & Yılmaz, 2018) further exemplifies this limitation. While we incorporated students' representational interpretations in our analysis, following Eckert & Stacey's (Eckert & Stacey, 2000) framework for implicit inspiration sources, this methodological constraint warrants acknowledgment, despite its minimal impact on our primary analytical findings.

Technical limitations of the current AICIT implementation present additional considerations. While the integration of T2I and I2I functionalities demonstrates efficacy, the system's potential could be enhanced through advanced interaction methodologies. The implementation of intuitive real-time image modification capabilities, such as those demonstrated in DragGAN (Pan et al., 2023), represents one such opportunity for enhancement. A significant technical limitation emerges in the system's current restriction to 2D image generation, whereas participant feedback consistently indicated the necessity for 3D modeling capabilities in ceramic education contexts. This limitation particularly affects the representation of cross-sectional design elements and physical properties crucial to ceramic crafts.

Through comprehensive discussions with our expert panel (*E1-E9*), representing diverse disciplines from ceramic arts to digital media, we identified several critical directions for future research that address the current limitations while advancing the field of AI-augmented visual arts education. Our longitudinal investigation priorities emerged from extensive dialogue with educational experts (E1-E5), who emphasized the necessity of tracking student development trajectories over extended periods. These experts particularly stressed the importance of understanding how AI integration influences artistic growth patterns and technical skill acquisition over time. Visual arts experts (*E6-E9*) further emphasized the need for systematic assessment of how AI tools impact creative development across different stages of artistic maturity.

Technical enhancement priorities were synthesized from discussions with both traditional craft experts (*E1-E4*) and digital media specialists (*E8-E9*). These discussions highlighted the critical need for three-dimensional visualization capabilities that accurately represent spatial relationships in ceramic work. The experts collectively emphasized the importance of developing advanced material property simulation systems and integrating haptic feedback mechanisms to bridge the gap between digital representation and physical craft experience. In terms of pedagogical research extensions, our expert panel identified several crucial areas for investigation. Education specialists (*E1-E5, E7*) emphasized the need for developing comprehensive assessment frameworks that effectively evaluate both technical proficiency and artistic development in AI-augmented learning environments. The preservation of cultural and traditional aspects of art education while leveraging technological advances emerged as a particular concern among traditional craft experts (*E1-E4*).

Despite these constraints, our findings contribute substantially to the discourse on AI integration in creative education globally. The observed enhancements in creative exploration and instructor-student interactions align with contemporary educational technology trends emphasizing creativity and innovation skill development (Jianzheng & Zhang, 2023). Our results demonstrate AI tools' efficacy as scaffolding mechanisms for domain-specific knowledge acquisition, corroborating recent research on AI-enhanced learning outcomes across diverse educational contexts (Weng et al., 2024). The implications of AI integration extend to broader considerations in curriculum design and pedagogical approaches. The adaptive potential of AI tools suggests opportunities for personalized learning experiences in creative education, consistent with emerging trends in adaptive learning systems (Weng et al., 2024). Furthermore, the enhanced quality of design prototypes necessitates reconsideration of assessment methodologies in creative disciplines, particularly within AI-augmented learning environments. The ethical considerations surrounding AI integration, particularly regarding plagiarism and creative authenticity, necessitate continued scholarly attention. The establishment of ethical guidelines for AI utilization in creative education represents a critical global concern, as does ensuring equitable access to these technologies across diverse socio-economic contexts. These research directions should maintain methodological rigor while acknowledging the complex interplay between technological innovation and traditional artistic practices.

6. Conclusion

This study provides empirical evidence for the effectiveness of AI-assisted visualization tools in addressing specific pedagogical challenges within ceramic-crafts education. Our findings demonstrate several key contributions: (1) AI-assisted visualization tools significantly enhanced design concept communication, particularly in representing complex ceramic forms and technical specifications (RQ1). (2) The integration of these tools facilitated more precise and constructive feedback exchanges between instructors and students, enabling detailed discussion of design refinements (RQ2). (3) Students demonstrated improved technical vocabulary acquisition and deeper understanding of ceramic-crafts concepts through tool engagement (RQ3). (4) The study identified critical considerations for maintaining traditional craft practices while integrating technological support, emphasizing the importance of supervised implementation and preservation of hands-on learning experiences (RQ4).

Comparing our findings with current research up to 2024, we observe that our results align with and extend recent studies on AI in education. For instance, a study (Yuldashev et al., 2024) reported improved student engagement with AI tools in general education, which our study confirms specifically in the context of creative arts education. However, our research goes further by demonstrating the specific mechanisms through which AI image-generation tools can enhance both the learning process and the quality of educational outcomes in visual arts.

The research advances our understanding of how targeted technological integration can enhance specific aspects of craft-based education while preserving essential tactile learning experiences. These findings provide concrete guidance for ceramic-crafts educators seeking to address communication challenges in design instruction while maintaining the integrity of traditional craft-based teaching methodologies.

The findings from this study have specific implications for craft-based educational contexts where concept visualization and communication are crucial components of the learning process. Future research directions should focus on: (1) Longitudinal assessment of how AI-assisted visualization tools impact technical skill development and craft mastery in ceramic education. (2) Investigation of how these tools can be optimized for different skill levels within ceramic-crafts curricula. (3) Development of specific guidelines for integrating technological support while preserving traditional craft teaching methodologies. These research directions aim to further our understanding of how technological tools can enhance specific aspects of craft education while maintaining its fundamental hands-on nature.

CRediT authorship contribution statement

Woojin Kang: Conceptualization, Methodology, Writing – original draft, Formal analysis, Software. **Hyun-Soo Lee:** Validation, Writing – review & editing, Project administration, Investigation, Data curation, Supervision. **Jin-Hyuk Hong:** Resources, Funding acquisition, Supervision, Writing – review & editing.

Acknowledgments

This work was supported by the AI-based GIST Research Scientist Project grant funded by GIST in 2025 and by the National Research Foundation of Korea (NRF) grant funded by the Korean government (MSIT) (RS-2025-16902996). The two grants contributed equally (50%/50%) to this research.

Data availability

Data will be made available on request.

References

Ali, S., DiPaola, D., Lee, I., Hong, J., & Breazeal, C. (2021). Exploring generative models with middle school students. In *Proceedings of the 2021 CHI conference on human factors in computing systems* (pp. 1–13). https://doi.org/10.1145/3411764.3445226

Arango, J. S. M., & Neira, C. C. (2016). POTEL: low cost realtime virtual pottery maker simulator. In *Proceedings of the 2016 virtual reality international conference* (pp. 1–4). https://doi.org/10.1145/2927929.2927949

Brainard, J. (2023). As scientists explore AI-written text, journals hammer out policies. *Science, 23*. https://doi.org/10.1126/science.adh2937

Brooke, J. (1996). Sus: a "quick and dirty'usability. *Usability evaluation in industry, 189*(3), 189–194.

Ceylan, S. (2021). Artificial intelligence in architecture: An educational perspective. In *Proceedings of the 13th international conference on computer supported education*. https://doi.org/10.5220/0010444501000107

Chang, K.-H., Cheng, C.-Y., Luo, J., Murata, S., Nourbakhsh, M., & Tsuji, Y. (2021). Building-GAN: Graph-conditioned architectural volumetric design generation. In *Proceedings of the IEEE/CVF international conference on computer vision* (pp. 11956–11965). https://doi.org/10.1109/ICCV48922.2021.01174

Corremans, J. A., Vaes, K. R., & Coppieters, W. (2018). Do better sketchers become better product designers?. In *Proceedings of the DESIGN 2018 15th international design conference* (pp. 2411–2420). https://doi.org/10.21278/idc.2018.0113

Dam, R. F., & Siang, T. Y. (2020). *Design thinking: Get started with prototyping*. Interaction Design Foundation.

Darvishi, A., Khosravi, H., Sadiq, S., Gašević, D., & Siemens, G. (2024). Impact of AI assistance on student agency. *Computers & Education, 210*, Article 104967. https://doi.org/10.1016/j.compedu.2023.104967

Dong, H., Liang, X., Zhang, Y., Zhang, X., Shen, X., Xie, Z., Wu, B., & Yin, J. (2020). Fashion editing with adversarial parsing learning. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition* (pp. 8120–8128). https://doi.org/10.1109/CVPR42600.2020.00814

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., & Ahuja, M. (2023). "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management, 71*, Article 102642. https://doi.org/10.1016/j.ijinfomgt.2023.102642

Eckert, C., & Stacey, M. (2000). Sources of inspiration: a language of design. *Design Studies, 21*(5), 523–538. https://doi.org/10.1016/S0142-694X(00)00022-3

Evirgen, N., Ruolin, W., & Xiang, A. C. (2024). From text to pixels: Enhancing user understanding through text-to-image model explanations. *Proceedings of the 29th international conference on intelligent user interfaces*. https://doi.org/10.1145/3640543.36451

Fang, L. (2011). *Chinese ceramics*. Cambridge University Press.

Gao, Z., Li, J., Wang, H., & Feng, G. (2018). Digiclay: an interactive installation for virtual pottery using motion sensing technology. In *Proceedings of the 4th international conference on virtual reality* (pp. 126–132). https://doi.org/10.1145/3198910.3234659

Guan, J.-Q., Wang, L.-H., Chen, Q., Jin, K., & Hwang, G. (2023). Effects of a virtual reality-based pottery making approach on junior high school students' creativity and learning engagement. *Interactive Learning Environments, 31*(4), 2016–2032. https://doi.org/10.1080/10494820.2021.1871631

Halverson, E. R. (2013). Digital art making as a representational process. *The Journal of the Learning Sciences, 22*(1), 121–162. https://doi.org/10.1080/10508406.2011.639471

Hang, L., Tianlong, X., Chaoli, Z., Eason, C., Jing, L., Xing, F., Haoyang, L., Jiliang, T., & Qingsong, W. (2024). Bringing generative AI to adaptive learning in education. arXiv preprint https://arxiv.org/pdf/2402.14601.

Haoran, X., Shuyao, C., & Zhang, Y. (2023). Magical brush: A symbol-based modern Chinese painting system for novices. In *Proceedings of the 2023 CHI conference on human factors in computing systems* (pp. 1–14). https://doi.org/10.1145/3544548.3581429

Harisankar, P. V., Sushant, M., & Jeevan, N. (2024). Analyzing the impact of AI on knowledge acquisition of students. *2024 international conference on current trends in advanced computing (ICCTAC)*. IEEE. https://doi.org/10.1109/ICCTAC61556.2024.10581301

Hart, S. G., & Staveland, L. E. (1988). Development of NASA-TLX (task load index): Results of empirical and theoretical research. *Advances in Psychology, 52*, 139–183. https://doi.org/10.1016/S0166-4115(08)62386-9

He, S., Song, Y.-Z., & Xiang, T. (2022). Style-based global appearance flow for virtual try-on. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition* (pp. 3470–3479). https://doi.org/10.1109/CVPR52688.2022.00346

Hitsuwari, J., Ueda, Y., Yun, W., & Nomura, M. (2023). Does human–AI collaboration lead to more creative art? Aesthetic evaluation of human-made and AI-generated haiku poetry. *Computers in Human Behavior, 139*, Article 107502. https://doi.org/10.1016/j.chb.2022.107502

Hu, E. J., Shen, Y., Wallis, P., Allen-Zhu, Z., Li, Y., Wang, S., Wang, L., & Chen, W. (2021). Lora: Low-rank adaptation of large language models. arXiv preprint https://arxiv.org/abs/2106.09685.

Huson, D. (2011). 3D printing of ceramics for design concept modeling. NIP & digital fabrication conference. *Society of Imaging Science and Technology, 27*. https://doi.org/10.2352/issn.2169-4451.2011.27.1.art00104_2

Hutson, J., & Peter, C. (2023). Generative AI tools in art education: Exploring prompt engineering and iterative processes for enhanced creativity. *Metaverse, 4*(1), 14. https://doi.org/10.54517/m.v4i1.2164

Jianzheng, S., & Zhang, X. (2023). Integration of AI with higher education innovation: Reforming future educational directions. *International Journal of Science and Research, 12*(10), 1727–1731. https://www.ijsr.net/getabstract.php?paperid=SR231023183401.

Jinhee, K., Yoonhee, H., & Sang-Soog, L. (2024). Differences in student-AI interaction process on a drawing task: Focusing on students' attitude towards AI and the level of drawing skills. *Australasian Journal of Educational Technology, 40*(1), 19–41. https://doi.org/10.14742/ajet.8859

Kahneman, D. (2011). *Thinking, fast and slow*. macmillan.

Kudrowitz, B. M., & Wallace, D. (2013). Assessing the quality of ideas from prolific, early-stage product ideation. *Journal of Engineering Design, 24*(2), 120–139. https://doi.org/10.1080/09544828.2012.676633

Kumar, G., Sharma, N. K., & Bhowmick, P. (2011). Wheel-throwing in digital space using number-theoretic approach. *International Journal of Arts and Technology, 4*(2), 196–215. https://doi.org/10.1504/IJART.2011.039845

Liu, M., Zhang, L. J., & Biebricher, C. (2023). Investigating students' cognitive processes in AI-assisted digital multimodal composing and traditional writing. https://doi.org/10.1016/j.compedu.2023.104977.

Lund, A. M. (2001). Measuring usability with the use questionnaire12. *Usability interface, 8*(2), 3–6.

Manitsaris, S., Glushkova, A., Bevilacqua, F., Moutarde, F. J. J.o. C., & Heritage, C. (2014). Capture, modeling, and recognition of expert technical gestures in wheel-throwing art of pottery. *Journal on Computing and Cultural Heritage (JOCCH), 7*(2), 1–15. https://doi.org/10.1145/2627729

Moradi, H., Nguyen, L. N., Nguyen, Q.-A. V., & Torres, C. (2022). Glaze epochs: Understanding lifelong material relationships within ceramics studios. In *16th international conference on tangible, embedded, and embodied interaction* (pp. 1–13). https://doi.org/10.1145/3490149.3501310

Mumcu, S., & Yılmaz, S. (2018). *Examining sources of inspiration in the conceptual design of landscape architecture. Ler: R. Efe, M. Zencirkiran ve İ. Curebal, recent researches in science and landscape management, Newcastle upon Tyne* (pp. 30–43). Cambridge Scholars Publishing.

Na, E. K., Lee, H. S., Kim, Y. W., & Yi, J. H. (2022). A study on the craft classification system for construction of craft Metadata. *Korean Society of Basic Design & Art, 23*(6), 111–128. https://doi.org/10.47294/KSBDA.23.6.8

Okada, T., & Ishibashi, K. (2017). Imitation, inspiration, and creation: Cognitive process of creative drawing by copying others' artworks. *Cognitive Science, 41*(7), 1804–1837. https://doi.org/10.1111/cogs.12442

Ornes, S. (2019). Computers take art in new directions, challenging the meaning of "creativity". *Proceedings of the National Academy of Sciences, 116*(11), 4760–4763. https://doi.org/10.1073/pnas.1900883116

Pan, X., Tewari, A., Leimkühler, T., Liu, L., Meka, A., & Theobalt, C. (2023). Drag your gan: Interactive point-based manipulation on the generative image manifold. In *ACM SIGGRAPH 2023 conference proceedings* (pp. 1–11). https://doi.org/10.1145/3588432.3591500

Peterson, S., & Peterson, J. (2003). *The craft and art of clay: a complete potter's handbook*. Laurence King Publishing.

Pidhorskyi, S., Almohsen, R., & Doretto, G. (2018). Generative probabilistic novelty detection with adversarial autoencoders. *Advances in Neural Information Processing Systems, 31*.

Putra, A. M., Hardiman, G., Sardjono, A. B., Madyatmadja, E. D., & Cahyandari, G. O. I. A. (2022). The effect of manual sketching on architectural design process in digital era. *Journal of Theoretical and Applied Information Technology, 100*(2).

Ramli, F. N. A., & Nurazidawati, M. (2023). A. Stem teacher digital literacy: Relationship between digital literacy and technology integration in teaching and learning post Covid-19. *Journal of Nusantara Studies (JONUS), 8*(2), 316–333. https://doi.org/10.24200/jonus.vol8iss2pp316-333

Rombach, R., Blattmann, A., Lorenz, D., Esser, P., & Ommer, B. (2022). High-resolution image synthesis with latent diffusion models. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition* (pp. 10684–10695). https://doi.org/10.1109/CVPR52688.2022.01042

Shi, X., Zhou, Z., Zhang, J. W., Neshati, A., Tyagi, A. K., Rossi, R., Guo, S., Du, F., & Zhao, J. (2023). De-Stijl: Facilitating graphics design with interactive 2D color palette recommendation. In *Proceedings of the 2023 CHI conference on human factors in computing systems* (pp. 1–19). https://doi.org/10.1145/3544548.3581070

Simms, R. C. (2024). Work with ChatGPT, not against: 3 teaching strategies that harness the power of artificial intelligence. *Nurse Educator, 49*(3), 158–161. https://doi.org/10.1097/NNE.0000000000001634

Souper, T., Morgado, A. C., Marques, A., Silva, I., & Rosado, L. (2023). Improving color mixture predictions in ceramics using data-centric deep learning. In *Proceedings of the 2023 8th international conference on machine learning technologies* (pp. 221–229). https://doi.org/10.1145/3589883.3589917

Tian, Q., Kuang, K., Jiang, K., Liu, F., Wang, Z., & Wu, F. (2022). ConfounderGAN: Protecting image data privacy with causal confounder. *Advances in Neural Information Processing Systems, 35*, 32789–32800.

Virzi, R. A., Sokolov, J. L., & Karis, D. (1996). Usability problem identification using both low-and high-fidelity prototypes. In *Proceedings of the SIGCHI conference on human factors in computing systems* (pp. 236–243). https://doi.org/10.1145/238386.238516

Weng, X., Huiyan, Y., Yun, D., & Oi-lam, N. (2024). Integrating artificial intelligence and computational thinking in educational contexts: A systematic review of instructional design and student learning outcomes. *Journal of Educational Computing Research.* , Article 07356331241248686. https://doi.org/10.1177/07356331241248686

Wu, D., Yu, Z., Ma, N., Jiang, J., Wang, Y., Zhou, G., Deng, H., & Li, Y. (2023). StyleMe: Towards intelligent fashion generation with designer style. In *Proceedings of the 2023 CHI conference on human factors in computing systems* (pp. 1–16). https://doi.org/10.1145/3544548.3581377

Yao, L. (2020). Study on the inheritance of traditional ceramic culture in the ceramic art of contemporary life. In *4th international conference on art studies: Science, experience, education* (pp. 455–458). Atlantis Press. https://doi.org/10.2991/assehr.k.200907.078.

Yuldashev, S., Akramov, M., Tursunova, F., Abdullaeva, K., Shakhmurodova, D., & Ubaydullayev, A. (2024). A development of AI connected system with adaptive assessments method for evaluation methods in education field. *2024 4th international conference on advance computing and innovative technologies in engineering (ICACITE)*. IEEE. https://doi.org/10.1109/ICACITE60783.2024.10616960

Zhan, F., Yu, Y., Wu, R., Zhang, J., Lu, S., Liu, L., Kortylewski, A., Theobalt, C., & Xing, E. (2023). Multimodal image synthesis and editing: The generative AI era. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 45*, 12. https://doi.org/10.1109/TPAMI.2023.3305243

Zhang, B. (2024). Innovative thinking for AI-based ceramic art design. *IEIE Transactions on Smart Processing & Computing, 13*(2), 167–175. https://doi.org/10.5573/IEIESPC.2024.13.2.167

Zhang, L., Rao, A., & Agrawala, M. (2023). Adding conditional control to text-to-image diffusion models. In *Proceedings of the IEEE/CVF international conference on computer vision*. https://arxiv.org/abs/2302.05543.

Zhao, T., Chen, C., Liu, Y., & Zhu, X. (2021). Guigan: Learning to generate gui designs using generative adversarial networks. In *2021 IEEE/ACM 43rd international conference on software engineering* (pp. 748–760). IEEE. https://doi.org/10.1109/ICSE43902.2021.00074.

Zou, Q. (2019). Thoughts on ceramic handicrafts in cultural and creative industries. *International Journal of Intelligent Information and Management Science, 8*(4), 313–315.