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Integrating image-generative AI into conceptual design in computer-aided design education: Exploring student perceptions, prompt behaviors, and artifact creativity

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ABSTRACT: Although image-generative AI (GAI) has sparked heated discussion among engineers and designers, its role in CAD (computer-aided design) education, particularly during the conceptual design phase, remains not sufficiently explored. To address this, we examined the integration of GAI into the early stages of design in a CAD class. Specifically, we conducted an in-class workshop introducing Midjourney for conceptual design and released a home assignment on mood board design for hands-on GAI design practice. Twenty students completed the workshop and assignment from a CAD class at a research-intensive university. We collected and analyzed data from surveys, students' prompts, and design artifacts to explore their perceptions of GAI, prompt behaviors, and design creativity and conducted a correlation analysis between these variables. After the workshop, students significantly rated GAI as more useful and user-friendly in design and found it more supportive in terms of design efficiency and aesthetics, while we did not find a significant difference in design creativity. By analyzing 365 prompts used for completing home tasks, we identified three types of prompt behaviors: generation, modification, and selection, as well as classified three types of workflows: exploration, two-step, and multi-step. The correlation analysis showed that design creativity changes significantly and positively correlated with their prompt behaviors. Students with more multi-step prompts produced more creative artifacts based on the instructors' evaluation. This exploratory study offered valuable insights into the integration of GAI in CAD education and suggested potential directions for future GAI curricula and tools in design education.

Keywords: Image-generative AI, Design education, Perceptions, Prompt behaviors, Creativity

1. Introduction

In contemporary educational landscapes, Generative AI (GAI) has significantly impacted the realm of Science, Technology, Engineering, and Mathematics (STEM) education (Cooper, 2023). Text-to-text models, such as ChatGPT, have been at the forefront of this technological integration (Lo, 2023). Moreover, GAI's influence extends to the domains of design and design education, where image-generative AI technologies such as Midjourney, DALL-E, and Stable Diffusion represent transformative advancements. These tools not only facilitate design processes but also democratize creative expression, enabling students to visually articulate their ideas and visions, irrespective of their inherent artistic skills (Hughes et al., 2021). Given this potential, it becomes imperative to conduct thorough research into the applications and effectiveness of integrating image-generative AI in design education.

In the academic realm, research on the application of image-generative AI lags behind that of text-generative AI, with a particular deficiency in comprehensive studies (Lee et al., 2023). In addition, most previous work on GAI tools focused on the acceleration of the content generation process, with few studies examining how GAI can be used to assist designers in the early stages of the design process to facilitate design thinking and complement the human creative process (Cai et al., 2023). Also, existing research primarily examines the use of these tools by designers in lab settings (Gmeiner et al., 2023) and focuses on aspects like structural efficiency and space layout in design. Attempts to integrate image-generative AI into real educational settings have been limited. One recent study (Lee et al., 2023) integrated GAI in classroom settings by running a workshop. However, taking the form of isolated workshops rather than fully integrated coursework overlooks two crucial aspects: first, the importance of integrated learning context for students to learn and use GAI naturally as a part of ongoing coursework; second, the necessity for students to engage in a thorough learning process with GAI tools by practicing on their own. Such learning context and process is crucial for students to fully comprehend and skillfully operate these technologies, which are factors largely absent in previous studies. Additionally, there is a significant gap in the depth of analysis regarding students' design process, such as prompt behaviors and design outcomes, such as creativity. Recent studies have shown that students' prompt behaviors are linked to their learning outcomes (e.g., Chen et al., 2024; Lee et al., 2023), and teaching prompt engineering techniques in design educational settings would improve their skills in creating more effective results (Hutson & Cotroneo, 2023). There is a lack of research that sufficiently explores the varied behaviors and workflows that emerge when students engage with image-generative AI and how these behaviors may affect design creativity, thus limiting our understanding of these tools' potential impact and utility in design educational settings. A more in-depth exploration of these student-tool interactions is essential for appreciating the role of image-generative AI in enhancing creativity and problem-solving within design educational settings.

The research gaps of GAI for conceptual design mentioned above could be summarized into two aspects: (1) lack of deep involvement in educational contexts; Most previous studies were in lab contexts or workshops without integrating into original curricula, lacking empirical studies in real educational settings that involved a course curriculum; (2) lacking sufficient analysis on behaviors, perceptions, and outcomes. There is insufficient evidence on how students use GAI for completing design coursework and a systematic analysis of student behaviors, perceptions, and outcomes of integrating GAI in art and design educational settings. To address these gaps, we undertook a field study involving 20 students in a Computer-Aided Design (CAD) class at a human-centered design department in a research-intensive university. The study's design started from a collaboration between the course instructor and researchers to design a workshop and a take-home task for a deep dive into using Midjourney (Midjourney, 2023), a prominent image-generative AI tool used in this study. The in-class workshop allowed students to learn GAI in a familiar context. The home task was assigned for further engagement with GAI outside the workshop as part of their course final projects. To understand students' perception of GAI, we conducted repeated surveys before and after the workshop, followed by the home task. We also analyzed student interactions with Midjourney, using content analysis (Elo & Kyngäs, 2008) to identify various behavioral and workflow patterns. In addition, we analyzed the artifacts produced by the students for the assignment using the Consensual Assessment Technique (CAT), comparing their creativity levels of similar projects they completed one month before the workshop without using GAI. The outcomes of this study led to a discussion on how to incorporate GAI into design education, which not only provides insights for educators but also suggests future directions for the design and development of GAI tools.

The unique contributions of this study include 1) we designed and provided an integrated learning environment, including a workshop and a home task to incorporate the GAI as part of the original curriculum; 2) we measured students' perceptions three times (before the workshop, after workshop, after home task) to understand how their perceptions about GAI have changed over time, which helped us better understand the effect of integrating GAI in the whole process; 3) we analyzed students' behaviors of using GAI in coursework via systematic coding and content analysis and the artifacts' creativity before and after using GAI; 4) we systematically explored the correlation between perceptions, behaviors, and creativity. More specifically, in this study, we aimed to understand student perceptions, behaviors, and outcomes of using GAI in conceptual design by answering the following research questions (RQs):

- RQ1: What are students' perceptions of GAI in design and artifacts' creativity change over time?
- RQ2: How do students use GAI in conceptual design work?
- RQ3: What are the correlations between perceptions, prompt behaviors, and creativity?

2. Literature review

2.1. Image-generative AI tools and mood board design

In this section, we reviewed the technological and instructional context of applying GAI to design education. For years, AI has been involved in the development of image-generation tools to help design. With the development of Deep Learning in the last decade, particularly generative models such as Generative Adversarial Networks (GAN), diffusion models (DM), and Contrastive Language-Image Pretraining (CLIP), the potential of AI for design has been expanded by its capability of generating realistic data of high quality and diversity. GANs have revolutionized the field of generative AI, where two neural networks, a generator and a discriminator, work in tandem to create highly realistic images (Aggarwal & Battineni, 2021). Building upon this, StyleGAN (Karras et al., 2020), an advanced variant of GAN, has gained acclaim for its ability to generate extremely high-quality and detailed images, particularly human faces, with fine control over the style features. Another groundbreaking development is DMs, which work by gradually transforming patterns of random noise into coherent images (Yang et al., 2023). In 2021, latent diffusion models implemented diffusion models within a compressed image representation instead of the image itself and then worked to reconstruct the image, which improved the model efficiency tremendously (Rombach et al., 2022). Another breakthrough is CLIP (Hafner et al., 2021), a multi-modal model. Given image and text descriptions, the model can predict the most relevant text description for that image without optimizing it for a particular task. CLIP was used for tokenization to allow users to have more control over the images generated.

Most current popular GAI tools, such as Stable Diffusion, DALL-E, and Midjourney, use the DM and CLIP technologies. Stable Diffusion is an open-sourced GAI tool based on CLIP and a diffusion-based deep learning model (Radford et al., 2021). It can be served on local computers or on the web. DALL-E3 is developed by open AI, uses CLIP and DMs, and is served in ChatGPT. Midjourney's mechanism is not disclosed, but it is believed to use similar techniques and is served via Discord. Even though the technologies behind these tools are similar, there are some important differences that influence their use in different contexts. In this study, we used Midjourney as the GAI tool, and the reasons for this are explained in the method section.

Mood boards are fundamental tools used in designing educational settings. The creation of mood boards involves cognitive processes in conceptual design and was used as not just a design tool but also a design research tool (Cassidy, 2011) for studying personal creativity (Mcdonagh & Storer, 2004; Lucero, 2012). Traditionally, creating mood boards has been a manual and skill-intensive process. It involves using basic tools like pen and paper, capturing images and textures through photography, and often employing software like Photoshop for editing and crafting something unique. This process demands significant time, effort, and thoughtful consideration. The graphical and visual competencies required are fundamental across various design disciplines, extending beyond graphic design to include areas like industrial, fashion, and product design.

Previous research has explored the use of GAI in mood board design, employing various tools like GANCollege (Wan & Lu, 2023), DesignAID (Cai et al., 2023), and Dream Studio (Lee et al., 2023). However, these studies were typically conducted in controlled settings like laboratories or workshops, which were not directly integrated with an academic curriculum. This raises questions about their effectiveness in addressing the practical applications of GAI in design education. In contrast, our study was embedded within a Computer-Aided Design (CAD) course. Here, students were tasked with creating mood boards using GAI as part of their process for conceptualizing and completing their final projects. In the next section, we will delve into the specifics of how we structured the curriculum to incorporate this innovative approach.

2.2. GAI for design perceptions, behaviors, and creativity

The use of GAI in design has primarily been investigated as a creativity support tool (CST). Creativity is seen as the ability to create something unique and innovative (Adam, 2005). It can involve generating new ideas (Sawyer & Henriksen, 2024) or combining existing knowledge in new ways (Massaro et al., 2012). Creativity is judged by both originality and usefulness (Oppenlaender, 2022). Recently, Ko et al. (2023) suggested that in text-to-image GAI projects, creativity should be measured, including prompts for generating images, which also reflect creative thinking. Creativity support involves helping with ideation by retrieving, analyzing, suggesting, and combining existing relevant materials (Wan & Lum, 2023). The influence of GAI on design has been explored across various fields, such as architecture (Zhao et al., 2023), fashion design (Särmäkari & Vänskä, 2022), interior design (Karadag et al., 2022), and user experience design (Houde et al., 2022).

In the context of CSTs, researchers commonly focus on understanding user perceptions of GAI, especially creativity support. This is often assessed through self-reported surveys, as seen in studies by Wan & Lu (2023) and Cai et al. (2023). These studies have found that GAI offers greater creativity support compared to traditional image search tools. Aesthetics, closely linked to creativity support, is another key area of focus. According to Oppenlaender (2022), aesthetics is typically evaluated through subjective assessments, and he suggests that GAI can produce works of high aesthetic quality. Efficiency is another important aspect often studied alongside creativity (Edwards, 2001). Efficiency in these studies is usually measured by the time taken to complete specific tasks, as explored in research by Cai et al. (2023) and Liu et al. (2023). As a relatively new tool, GAI's perceived usefulness and ease of use are also critical factors in understanding user acceptance of technology. The methods for measuring these constructs range from single-item questions (Cai et al., 2023) to more validated scales (such as Davis, 2001). One limitation of these studies is the lack of repeated measurements to understand how user perceptions were changed before and after using GAI, which is a key consideration in the educational technology field.

The study of user behaviors through their interaction with prompts has been another focus in recent research with limited amounts (Liu et al., 2023; Lee et al., 2023). For instance, Liu and colleagues (2023) categorized prompts into various types like text-only, text with images, variations, etc., and went further to visualize these prompt workflows and assess their complexity. Studies found prompt behaviors are linked to student perceptions and learning outcomes. For example, observing from the prompts complexity, Hutson and Cotroneo (2023) found students improved their understanding of GAI application with an increased understanding of the potential and limitations of generative AI tools and how to manipulate subject matter for more effective results. Lee et al. (2023) focused on analyzing the length and the number of subjects in a prompt, correlating these factors with patterns of convergent and divergent thinking, which were reflected in the design artifacts. Prompt analysis can enrich insights gathered from interviews or surveys (Bailey & Bailey, 2017). More recently, researchers applied a prompt-aided technique, namely the progressive prompts-based image-GAI approach, and found it could better promote students' learning achievement, extrinsic motivation, problem-solving awareness, critical thinking, and learning performance (Chen et al., 2024). Despite the potential of image-generative AI on student learning, its exploration in educational contexts has still not been enough (Lee et al., 2023).

Our study aims to fill these gaps by examining student perceptions, prompt behaviors, and artifacts' creativity in an educational setting. We mainly measure perceptions from creativity support perspectives, such as creativity support, aesthetic support, efficiency, and usability in relation to GAI tools for design. We utilized survey questionnaires to gauge these perceptions. We also analyzed student interactions with prompts to understand their behaviors and artifacts' creativity using the Consensual Assessment Technique (CAT), a commonly applied method that we will introduce in the methods section.

3. Methods

This study employed a case study research method as it provides the researchers with the opportunity to engage in in-depth data collection (Creswell et al., 2007) in a concrete, real-life environment (Yin, 2017) and is useful for formulating concepts (Mahoney, 2010). A single case study was utilized. In this section, we first introduce the study process, including tools, study context, participants, and procedures to give readers an overview. Next, we briefly describe how repeated perception surveys and Consensual Assessment Technique (CAT) were used to answer RQ1. After that, we described how prompt analysis was applied to answer RQ2 and how we utilized correlation analysis to answer RQ3.

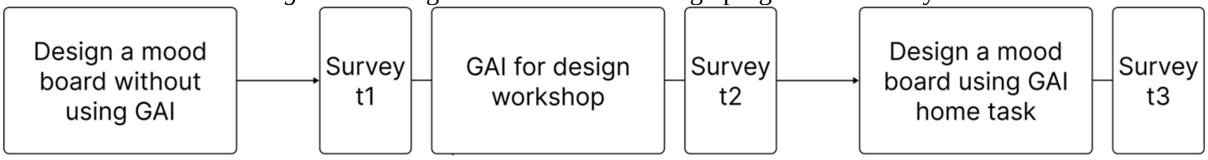
3.1. Study process

In this research, we used Midjourney via Discord as a GAI tool. Firstly, Midjourney is a Web-based tool with good user experience, especially for entry-level design students (Borji, 2022). Compared with another popular tool, Stable Diffusion, Midjourney is easy for a novice to learn and start. The features have been widely used by design students and professional designers (Caires et al., 2023). Compared to Dall-E, which aims for a highly realistic look, Midjourney focuses more on incorporating different art styles (Thoring et al., 2023). Another reason for choosing Midjourney is that it records every prompt in the server, which allows researchers to collect students' prompts. We created Discord accounts for students and subscribed them to the Midjourney one-month basic plan. Students were required to create their own server so that their prompts could be recorded (see Appendix A for the Midjourney interface).

Participants consisted of 20 college students (5 males, 15 females; mean age = 19; age range 18 – 22 years old) in a CAD course at a large U.S. university, who were informed of this research and gave us consent for participation. From the survey results before the study, 17 students had no experience of using GAI in design, while three students have tried GAI features in Adobe Photoshop Beta, Tiktok filters, or DALLE 2.0 but without much experience. Except for two students, the other 18 students used ChatGPT at least once a week for their general coursework. All students have learned CAD tools such as Adobe Photoshop, Illustrator, etc., for 10 weeks in this course and completed an assignment of mood board design about four weeks before we started this study.

The educational program included a workshop and a take-home task. As shown in Figure 1, the educational program was co-designed with the course instructor. One month before the workshop, students already completed a mood board design without using GAI. In the two-hour workshop, a range of commonly used features of Midjourney were taught from basic to advanced levels. Each part included a 15-minute lecture and followed by a 5-minute practice to complete a simple design task based on the lecture's content. After the workshop, every student was asked to complete a home task as a part of the course final project and submit it four days after the workshop. This home task required students to design a mood board for their final projects using at least eight images. At least four images must be generated via Midjourney. They are also encouraged to form their own workflows to complete the concept design via Midjourney (see Appendix B for the home task guidelines).

Figure 1. A diagram of the GAI for design program and surveys



3.2. Perception surveys

Participants completed five survey items measuring their subjective attitudes toward using the GAI in design using a 1 (strongly disagree) to 7 (strongly agree) scale. This study addressed user perceptions of CST, following the Technological Acceptance Modeling (TAM) framework (Davis, 1989), with three key elements: perceived ease of use, perceived usefulness, and attitude towards using, which, in our case, is the attitudes on creativity support. The TAM framework has been widely used to understand student experience and attitudes towards learning technologies in educational settings (Granić & Marangunić, 2019). Creativity is usually discussed with aesthetics (Cropley & Cropley, 2008) and efficiency (Redelinghuys & Bahill, 2006) in design, which are two constructs also related to GAI's capacity to rapidly create high-quality images (Xu & Jiang, 2022). Therefore, we measured subjective perceptions of usefulness (Davis, 1989), ease of use (Davis, 1989), creativity support (Isaksen & Lauer, 2001), efficiency support (Cai et al., 2023), and aesthetics support (Oppenlaender, 2022). We measured the attitudes three times: before the workshop, after the workshop, and after the home task. Using multiple surveys, we gained a detailed understanding of how students' perceptions changed over time and how different parts of the program (workshops and homework tasks) influenced them (Zhu et al., 2022; Zhu et al., 2024). We applied single-item scales to reduce mental workload (Drolet & Morrison, 2001), especially for these repeated measures. Please see Appendix C for the questions. All survey data was collected from Qualtrics (Qualtrics XM, 2023) and analyzed in R (Ihaka & Gentleman, 1996), with the tidyverse (Wickham et al., 2019) and rstatix packages (Kassambara, 2020).

We applied the Friedman test (Friedman, 1937) to analyze the repeated survey data. The Friedman test is a non-parametric alternative to the one-way repeated measures ANOVA test. It extends the Sign test in a situation where there are more than two groups to compare. Friedman test is used to assess whether there are any statistically significant differences between the distributions of three or more paired groups. It is recommended when the normality assumptions of the one-way repeated measures ANOVA test are not met or when the dependent variable is measured on an ordinal scale. We conducted pairwise Wilcoxon signed-rank tests (Woolson, 2007) to identify which groups are different. P-values are adjusted using the Bonferroni multiple-testing correction method. Kendall's W (Kendall & Smith, 1939) can be used as the measure of the Friedman test effect size. It is calculated as follows: $W = X2/N(K-1)$, where W is Kendall's W value; X2 is the Friedman test statistic value; N is the sample size. k is the number of measurements per subject (Tomczak & Tomczak, 2014). Kendall's W coefficient assumes the value from 0 (indicating no relationship) to 1 (indicating a perfect relationship).

3.3. Creativity

To measure creativity, Consensual Assessment Techniques (CAT) have garnered significant attention in the realm of higher education for their efficacy in evaluating student learning outcomes, particularly in disciplines requiring qualitative assessment (Baer & McKool, 2009). First introduced by Amabile (1982), it involves a structured process wherein multiple expert raters independently evaluate student work and subsequently engage in a consensus-building discussion to arrive at a shared assessment. This technique has been applied across various domains, including writing assessment (Huot, 1990), creativity assessment (Treffinger et al., 2002), and critical thinking assessment (Halpern, 1998). CAT has been instrumental in evaluating the originality and novelty of student-generated ideas across disciplines (Treffinger et al., 2002). These applications highlight the versatility and robustness of CAT as a method for assessing complex constructs in higher education.

This study applied a quasi-experiment design to understand how GAI usage influenced artifacts' creativity. One month before the workshop, students already completed a mood board design without using GAI. Using the Consensual Assessment Technique (CAT), we engaged two experienced professors from the design department to assess the creativity of students' mood board designs with and without using GAI. They used a scale from 1.0 to 5.0, where 1 indicates a lack of creativity, and 5 signifies a high level of creativity. The instructions specified that they should rely on their professional judgment, developed over more than ten years of teaching design, to assess the creativity of each mood board compared to the others within the same group. It was important that they conducted their assessments independently, without being influenced by each other's ratings.

3.4. Prompt behaviors

We collected prompt data by downloading Midjourney prompts using DiscordChatExporter (Holub, 2023) and each server included the following fields: server name, time stamps, prompt content, and URL for generated images.

To analyze the prompt data, we used content analysis based on Elo and Kyngäs's (2008) framework. First, we developed the initial coding scheme with three categories: prompt behaviors, prompt task number (multiple prompts may be related to one task), and whether the task is selected for the final mood board. Here, the task means generating one image for the mood board. The prompt task number is just a series of numbers to distinguish whether this prompt belongs to the same task and always starts from 0 for a student. The prompt behaviors have a general subcategory such as "text prompt," "blend," "select," etc. Then, two PhD students openly coded the first 50 prompts and used the constant comparative method (Glaser & Strauss, 1967) to add more sub-constructs and codes that were not shown in the initial scheme but were present in our data to finalize the coding scheme. By constantly comparing each code with all others, further commonalities were found, which formed even broader codes. Glaser and Strauss (1967) described this method of continually comparing codes with each other as a "constant comparative method" as a process of clustering and merging (Zhu et al., 2024).

We identified nine categories and fourteen subcategories to operationalize different prompt behaviors, establishing concrete indicators. Table 1 presents the coding scheme exemplifying these prompt behaviors. Two students then independently coded the next 100 prompts, achieving inter-rater reliability of Cohen's Kappa 0.91 across all 150 codes, including the initial 50, which indicates desirable reliability (Landis & Koch, 1977). Subsequently, the students divided the remaining 215 prompts, coding approximately 108 each. To analyze students' workflows in completing tasks, we connected prompt behaviors to specific tasks and noted whether their final mood board designs included the selected task images. Similarly, in this coding process, two raters independently coded the same 150 prompts, yielding Cohen's Kappa scores of 0.98 and 0.99.

The prompt coding was implemented in Google Sheets and analyzed in R using tidyverse (Wickham et al., 2019) and ggplot2 (Wickham, 2011).

Table 1. Prompts coding scheme

Behavior	Sub behavior	Description	Example	Code
text	long	A text prompt with more than one word	frilly orange and blue ruffles swatch of fabric for formal wear	t-l
	short	A text prompt with one word	smoothy	t-s
blend	two	Blend two images	<image URL1> <image URL2>	b-2
	three	Blend three images	<image URL1> <image URL2> <image URL3>	b-3
	four	Blend four images	<image URL1> <image URL2> <image URL3> <image URL4>	b-4
text-image		A prompt with both texts and images	make clothes of this type of aesthetic but for men <image URL>	t-i
remix		Modify the generated image with new text	Original prompt-Remix	r
variation		Modify images by random	Original prompt-Variations (Strong)	v
zoom-out		Modify images by expansion	Original prompt-Zoom Out	z
selection		Select an image to improve quality	Original prompt-Image#2	s
upscaled	2x	Improve quality by two	Original prompt-Upscaled (2x)	u-2
	4x	Improve quality by 4	Original prompt-Upscaled (2x)	u-4
others	workshop	Prompts in workshop	NA	w
	error (prompt not going through)	Error prompts	Hi midjourney	er

3.5. Correlation analysis

To further answer RQ3, the relationship between perceptions, behaviors, and creativity, we only explore the correlation between perception and behavior, as well as behavior and creativity, due to the relatively small data size. Based on the previous studies' findings (Lee et al., 2023; Hutson & Cotroneo, 2023), we hypothesized that students' perception of GAI positively correlates with their behavior complexity and depth, and artifact creativity positively correlates with prompt depth. We calculated the Spearman rank correlation coefficient (De Winter et al., 2016) between each variable in self-reported perceptions after the home task, creativity scores of artifacts after using GAI, and representative prompt behavior variables to check these hypotheses.

4. Results

Following the analysis approach introduced, results detailing participants' perception toward GAI over time, as well as behaviors of conceptual design via GAI, are presented in this section. First, to address RQ1, quantitative analyses of each survey question on GAI's usefulness, ease of use, creativity, efficiency, and aesthetics were summarized and compared before the workshop, after the workshop, and after the home task; creativity scores for mood board without and with integrating GAI were compared. Second, to address RQ2, prompts were analyzed, and workflow patterns were identified using the coding scheme established in Table 2. Third, to address RQ3, correlations between variables of perceptions, behaviors, and creativity were calculated.

4.1. Response to RQ1

We first coded an answer to 7-point Likert-type questions to rank values (1-strongly disagree; 7-strongly agree). Then, we calculated the 25th, 50th, and 75th percentiles for each item at three-time points (before the workshop, after the workshop, and after the home task) to understand students' perceptions in summary. We conducted the Friedman test to understand whether the perceptions changed over time. In addition, we calculated Kendall's W to measure the effect size. We also did Paired Wilcox tests to further understand the difference between each two-time points to understand the effect of the workshop and home tasks. The results are presented in Table 2.

In general, students expressed higher levels of positive perception on each construct (median = 6 means agree with the statement of the GAI's role in design). The Friedman test showed differences in the perceived usefulness, ease of use, efficiency support, and aesthetics support of GAI across the 3 points in time. While no significance was found in perceived creativity support. This indicates that students' perceptions, except for perceived creativity support, were generally influenced by the GAI workshop.

Table 2. Students' perceptions of GAI over time

	Time	25th	50th	75th	Friedman	Wilcox
Useful	t1	5	6	6	F = 13.9**	t1 and t2*
	t2	6	6	7	W = 0.43	t1 and t3*
	t3	6	6	7		
Easy	t1	4	5	6	F = 10.0**	t1 and t2*
	t2	5.75	6	7	W = 0.31	
	t3	5	6	6.25		
Creative	t1	5	6	6	F= 5.8	ns
	t2	5.75	6	7	W = 0.18	
	t3	5	6	6		
Efficient	t1	5	6	6	F = 8.4*	t1 and t2*
	t2	6	6	7	W = 0.26	
	t3	5	6	7		
Aesthetics	t1	4.75	6	6	F = 14.3**	t1 and t2**
	t2	6	6	7	W = 0.45	
	t3	5.75	6	7		

Note. $^{**}p < .01$, $^{*}p < .05$, ns: not significant; Kendall's W uses Cohen's interpretation guidelines of 0.1 - 0.3 (small effect), 0.3 - 0.5 (moderate effect) and >= 0.5 (large effect); t1: before the workshop, t2: after the workshop; t3: after the home task.

Paired Wilcox tests further compared perceptions between each two time points. There is a significant improvement in perceived usefulness, ease of use, efficiency support, and aesthetics support after the workshop, while no significant difference after the home task. This indicates that the workshop had a positive effect on students' perceptions, but home tasks may not keep influencing their perceptions. We also calculated the effect size using Kendall's W and found the curriculum has a moderate effect on perceived usefulness, ease of use, and aesthetics support; it had a small effect on perceived efficiency support.

In contrast to most students' positive perceptions of using GAI in design, the design professor raters showed that Midjourney had no impact on design creativity. Rater A assigned lower average scores (mean = 3.0) to students' mood board designs following the Midjourney workshop compared to before (mean = 3.3). Only 4 out of the 20 students' works were identified as exhibiting improvements in design creativity facilitated by Midjourney. Rater B assigned similar scores both before and after the workshop (mean = 3.4), and 7 out of 20 students were recognized as showing enhanced creativity post-Midjourney training. In summary, no significant difference was found regarding artifacts' creativity before and after integrating GAI.

4.2. Response to RQ2

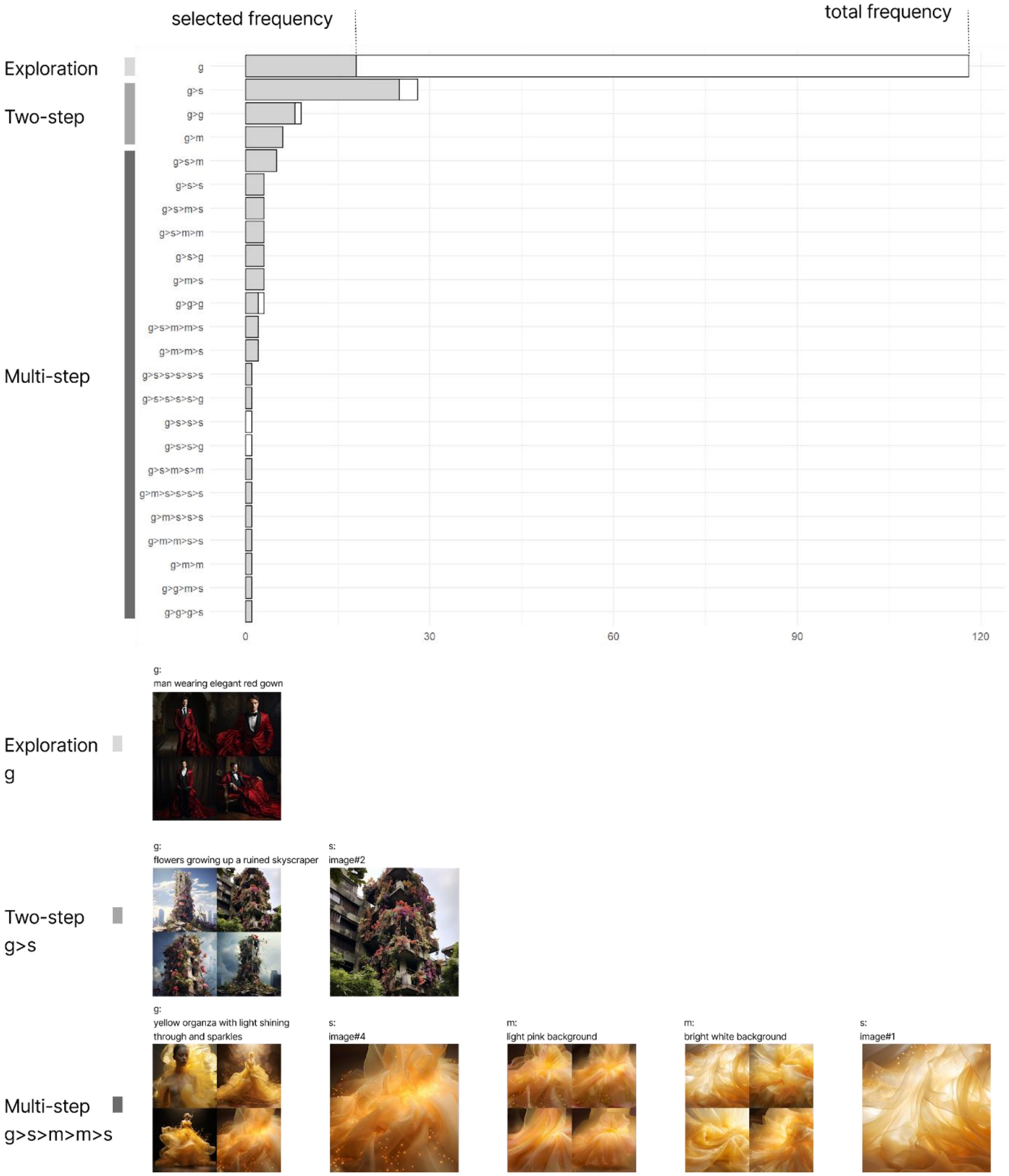
There are 18 students who completed the home task of using Midjourney for mood board design. They used 365 prompts to generate the images they wanted to use for their mood board. Figure 2 is an example of a student's mood board.

We merged all prompt behaviors into three main categories based on the goals of prompts: generation, modification, and selection. Generation behavior includes text prompts, image prompts, and prompts mixed with text and image. This behavior is the first step for a student to interact with Midjourney to create new images, and Midjourney would generate four images based on the student's prompt. modification behavior includes "remix," "random variation," and "Zoom out." This behavior can be achieved by explicitly typing in prompts or clicking specific buttons in Midjourney. It would modify the original images by a specified direction ("remix"), produce four new images by random ("random variation"), or extend the canvas of an upscaled image beyond its original boundaries without changing the content of the original image ("Zoom out"). Selection behavior is used to improve a specified image's resolution and size by adding more details. This behavior would lead to a single high-resolution image instead of four images, as generation and modification behaviors do. Among 365 prompt behaviors, about 60 percent of behaviors were generation behaviors, 10 percent for modification, and 30 percent for selection (Table 3).

Figure 2. A screenshot of a mood board submitted by a student. Most images were created by GAI; a few images were searched from internet resources.

By connecting prompt behaviors for the same task by time order, we were able to determine the workflow for each task. Figure 3 shows the workflow frequency. Students completed 204 tasks in total, and among them, 97 images from 97 tasks were selected and used for their final mood board design. Here, we classified three types of workflows. The first workflow is a one-step workflow used mainly for idea exploration. This workflow with the highest frequency uses one generation behavior for an image, while only 15 percent of the images generated from this workflow were finally selected and used in students' mood boards. This means this workflow is used mainly for exploration ideas, and students may get some inspiration from the results but not use the results directly. The second type of workflow has two steps: always starting from generation behaviors, then students may select one of the four images and let Midjourney generate the selected image with higher resolution (g>s). The second step can also be a new relevant generating prompt (g>g) or modifying the images by using the “remix,” “variation,” or “zoom out” feature (g>m). The third type of workflow needs more steps to create an image. Moreover, this type is diverse with 20 variations we found from students’ prompts. Among them, workflows ranged from 3 steps to 6 steps, and many workflows only appeared once. In Figure 3, we presented an example of this kind (g>s>m>m>s). We observed that the majority of second and third workflows resulted in students selecting the generated images in their final mood board designs.

Figure 3. Prompt workflow summary and examples. Selected frequency means the amount of these workflows that generated images that were selected and used in mood board design.



We also found most students (n = 17) used more than one step workflow, seven students tried multi-step workflows; while the remaining one student did not try much, only generating images from a single-step workflow which is writing text prompts.

Table 3. Prompt behaviors summary

Behavior	Description	Prompt	Code	Frequency
Generation	Generating new images by text prompt, blending multiple images, or prompts including text and images	Text	t-s, t-l	187
		Images	i	26
		Text and images	t-i	10
Modification	Modificating images by giving directions or by random	Remix	r	31
		Random variation	v	10
		Zoom out	z	2
Selection	Generating more details of a generated image	Enlarge	s	87
		Upscale	u-2, u-4	12

4.3. Response to RQ3

First, we selected variables to calculate the correlation between perception, behavior, and creativity. For self-reported perceptions after the home task, we selected all five variables: perceived usefulness (P-Use), perceived ease of use (P-Ease), perceived creativity support (P-Creativity), perceived efficiency support (P-Efficiency), and perceived aesthetics support (P-Aesthetics); for prompt behavior variables, we selected the amount of the three workflows for complete the mood board design: amount of one-step workflow (B-One), amount of two-step workflow (B-Two), and amount of multi-step workflow (B-Multi); The mean of two creativity ratings was used as the variable for measuring the artifacts' creativity. The reason for selecting the amount of each workflow for representing prompt behaviors is that the three types can reflect prompt complexity and interaction depth with GAI in design, which are the key aspects of prompt behaviors in our hypothesis.

The results (Table 4) show that all p-values are much larger than 0.05, except the correlation between creativity and B-Multi, with a p-value equaling 0.05, indicating a marginal significance. Its Spearman correlation coefficient value is 0.53, indicating a moderate effect size. As B-Multi is the amount of multi-step workflow measuring prompt behavior depth, we found a moderate positive correlation between prompt behavior depth and creativity, while we did not find a significant correlation between perception and creativity.

Table 4. Correlation coefficient value between behaviors, perceptions, and creativity

	P-Use	P-Ease	P-Creativity	P-Efficiency	P-Aesthetics	Creativity
B-One	-0.14	0.03	-0.26	-0.16	-0.16	0.19
B-Two	0.12	0.06	0.09	0.20	0.04	0.14
B-Multi	0.00	-0.08	-0.07	0.01	0.08	0.53*

Note. *Marginal significance: *p*-value equals .05.

5. Discussion

This study explored students' perceptions of GAI, behaviors using GAI, and design creativity in conceptual design in a CAD course. More specifically, we developed a workshop and home task that involved a GAI tool, the Midjourney, with CAD final projects to teach 20 students how to use GAI for mood board design. We measured students' perceptions of GAI usefulness, ease of use, creativity support, efficiency support, and aesthetics support before, after the workshop, and after the home task; we also evaluated the creativity of the mood board before and after using GAI. We found that students' perceptions of GAI were generally positive (median = 6, indicating agreement with statements) before the workshop, and their perceptions of usefulness, ease of use, efficiency support, and aesthetics support were significantly improved after the workshop with small to moderate effect size. While using GAI in home tasks did not further influence their perceptions. We also found that the creativity of students' mood board design before and after integrating GAI was not significantly different. In addition, we collected and analyzed students' prompts in Midjourney to understand their behaviors and workflows when using GAI. Content analysis results suggested that there were mainly three prompt behaviors: generation, modification, and selection. We further identified three types of workflows: One-step (exploration), two-step, and multi-step. Most students applied more than just a one-step workflow for creating the images for the mood boards. Correlation analysis indicated a moderate positive correlation between prompt behavior depth and creativity, while we did not find a significant correlation between perception and creativity.

In this section, we further discussed three critical topics from these results. We first discussed how to better integrate GAI into design education. Then we addressed whether using GAI for design can be regarded as a design process. Finally, we discussed theoretical, instructional, and technological implications to enhance the integration of GAI within CAD courses and broader creative education.

5.1. Enhancing design education with GAI: Extended integration and deeper processes

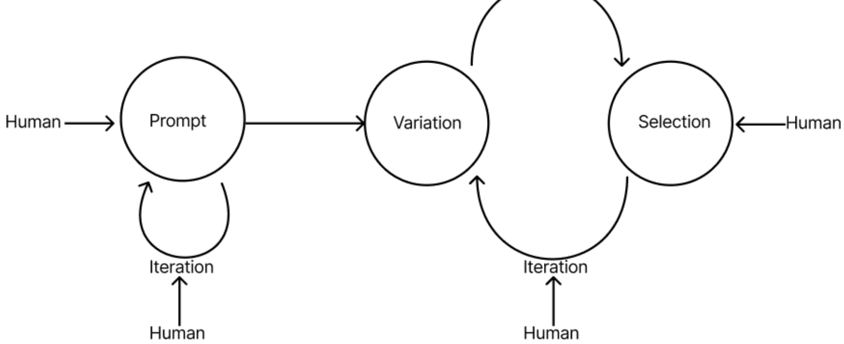
The answers to the RQ1 show the positive influence of integrating GAI in design education that improved students' positive perceptions of GAI. Students expressed more favor for using GAI regarding its support for design efficiency and design aesthetics, which is aligned with Dehouche and Dehouche (2023), suggesting that GAI can be used to teach design and art regarding its support for aesthetics and technique. However, despite these positive perceptions, the workshop and home tasks did not significantly enhance the one core objective of using GAI in design: to improve creativity. After learning GAI from the workshop and home task, we did not find a significant change in their perceptions of creativity support and artifact creativity. Another interesting finding is that students' perceptions did not change significantly after the home task, where they had more practice with GAI to complete their conceptual design mood board. On the contrary, without significance, some students even expressed lower perceptions of ease of use, creativity support, aesthetics support, and efficiency support. This finding shows that individuals' pre-adoption and post-adoption (continued use) beliefs and attitudes may change after using GAI for a longer period, suggesting that longitudinal studies may be needed for further investigating this relationship.

The need for a longer integration of GAI in design education was also expressed by Flechtner and Stankowski (2023) after practicing GAI education for years. They argued that there were mainly two teaching formats for integrating GAI in design: a) inspirational short workshops and b) semester-long supplementary courses. Workshops are much more common, and the focus of these formats is typically the experimental, creative exploration of a particular AI technology. While in semester-long formats, through the increased duration, a combination of practical hands-on exercises and theoretical topics could be achieved, students may finally have a more complete understanding of how to use GAI in their design. In this study, the workshop only lasted two hours, and the home tasks were submitted four days after the workshop. Further study of a month or even semester-long integration may lead to different results.

The responses to RQ2 proposed ways to classify students' prompt behaviors and workflows. We found most of the two- and multi-step workflows lead to selected images in final designs. In the responses to RQ3, we further found that the amount of multi-step workflows was marginally and positively significant with more creative design. These results may indicate that the depth of prompts may need to be guided and encouraged in the design process.

The result regarding the deeper design process of interacting with GAI can be extended to creative education. One of particular interest is the concept of evolutionary creativity (Simonton, 1999). It was further addressed by Thoring and Muller (2011) in design settings and integrated with GAI components more recently (Thoring et al., 2023). The concept of evolutionary creativity in design revolves around two main processes: "Variation" and "Selection." GAI can facilitate rapidly iterating "variation" and "selection" to achieve creativity. Figure 4 outlines the design process with GAI. It needs to be noted here that in the model, the variation process is completed by GAI, while prompt writing and selection are completed by humans. The variation process includes generation, modification, and selection behaviors that are found in our study. I added an interaction loop in the prompt to represent the commonly found process in which humans keep exploring different ideas by trying different prompts. This process also corresponds to divergent thinking, as addressed by Lee et al. (2023).

Figure 4. The process of design with GAI. Adapted from Thoring et al.'s (2023) diagram: I added a self-loop in the prompt corresponding to the process of exploration behaviors

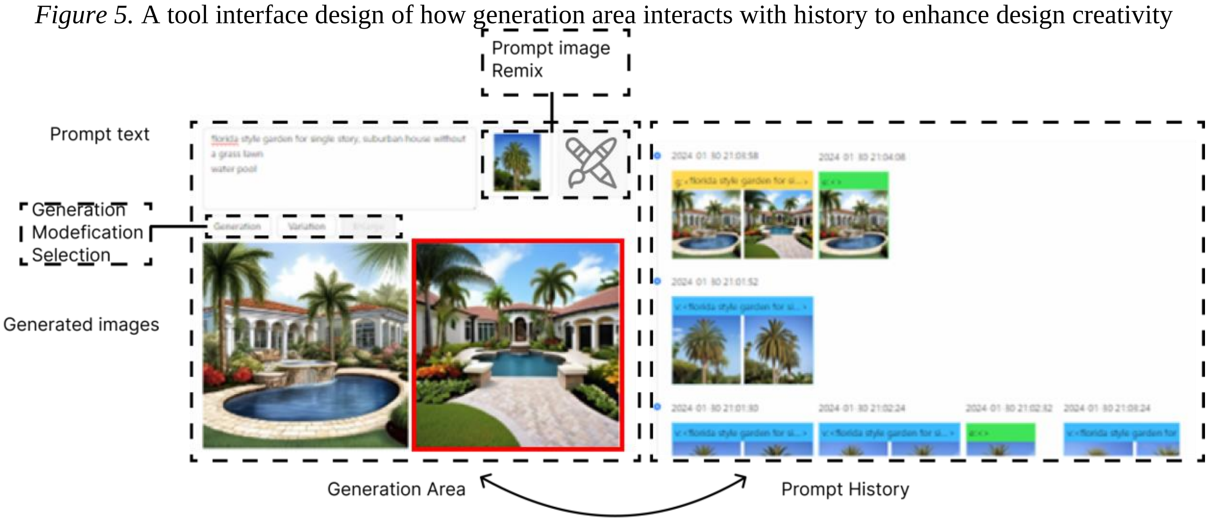


5.2. Instructional and technological implications

This study proposes enhancements in instructional design to better integrate GAI into design and creative education. Firstly, instead of short-term workshops, longer-term integration may improve design creativity. This approach suggests restructuring workshop curricula to introduce GAI features gradually, starting from basics and advancing to more complex functionalities. One way to organize the curriculum could be around key behaviors such as generation, modification, and selection, and integrating these into cohesive workflows can facilitate a more structured learning experience and enhance the practical application of GAI in design creativity (Zhu et al., 2024). In addition, in the longer-term curricula, addressing ethical concerns identified by Bartlett and Camba (2024), such as bias and copyright issues, could also be possible. Secondly, integrating teaching of the design process alongside GAI is crucial. This study emphasizes the importance of guiding students through the design process, as deeper interactions with GAI may lead to more creative artifacts, which is essential for fostering creativity in design and creative education (Atman, 2019). Future instructional designs should emphasize effective guidance of student interactions with GAI in educational settings, particularly in studio-based curricula.

Our study proposes a new GAI tool aimed at enhancing creativity in design education. Existing GAI applications, such as Midjourney examined in this study, typically offer a basic interface where users input prompts in text, images, or both and adjust settings to generate multiple images (e.g., Midjourney produces four images per prompt). However, these tools often lack a dedicated space for organizing and managing prompts and their generated images, which is crucial for visualizing and interacting with the design process to foster creativity. Our proposed interface, illustrated in Figure 5, introduces a generation area and a prompt history area to improve organization and tracking. The generation area enables easy access to frequently used prompts for generating, modifying, and selecting images, while the history area records and displays both prompts and their corresponding images for reuse in subsequent iterations. This setup facilitates an iterative approach for refining and developing design concepts, providing a platform for instructors and students to engage in design critique and collaborative learning.

Figure 5. A tool interface design of how generation area interacts with history to enhance design creativity



6. Conclusion and limitations

In this study, we developed a two-hour workshop and home task for integrating GAI into a CAD course. We found that the students have positive perceptions of GAI's usefulness, ease of use, creativity support, efficiency support, and aesthetics support. Their ratings, except for creativity support, were significantly higher after participating in the workshop. However, artifact creativity was not significantly different after integrating GAI. We also classified three behavior prompts: generation, modification, and selection, as well as three types of workflows: exploration, two-step, and multi-step. The amount of multi-step workflows was positively significant with more creative design. In the discussion section, we addressed the need to develop a longer period of GAI curriculum in design education and deeper interactions with GAI to achieve creativity. We further proposed instructional and technological implications for better integrating GAI into design and creative education.

This study has several limitations that must be considered when interpreting the results. These limitations stem from the exploratory nature of the research, the sample size, and the variables examined in the study. First, the exploratory approach employed in this research indicates that the results are preliminary and may require more accurate exploration and recursive processes. While the approach is valuable for an initial understanding of the problem and identifying potential relationships among variables, future research should employ more robust research designs, such as experimental or quasi-experimental designs, to confirm the findings and better understand the causal relationships among variables. The sample size of 20 students may be another concern, and more evidence would need to be collected in future studies. Lastly, we have just applied content analysis to summarize common behavior patterns and workflows; future data analysis on behavioral dynamics (e.g., Xing et al., 2024), relationships between behaviors and perceptions or design outcomes (e.g., Li et al., 2024) may also be of great importance and interest.

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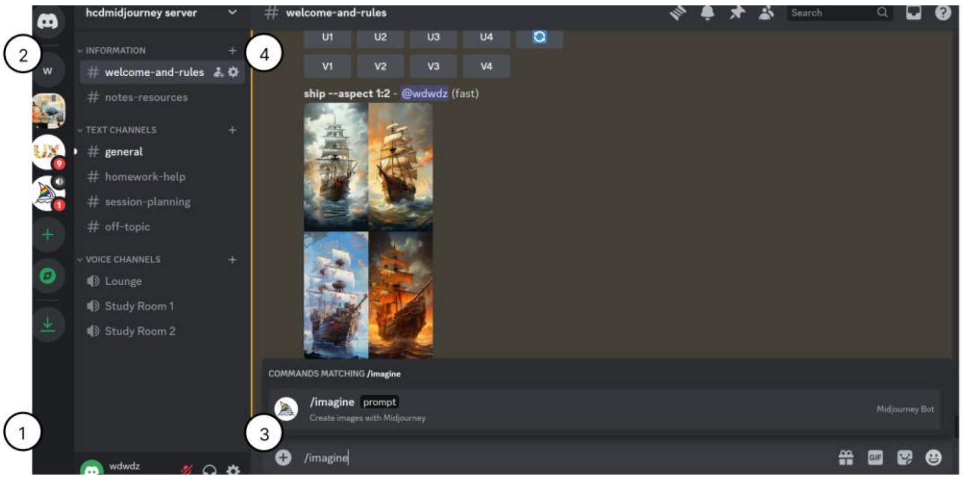
Appendix A

A screenshot of the Midjourney user interface. 1. Discord account; 2. Separate server; 3. Prompts input area; 4. Specific buttons.



Appendix B

Create a Mood Board for Your Final Project Using Midjourney
DDL
Submit your Mood Board on Miro by Monday's class (11/20).

Task
Create a Mood Board using Midjourney in an 11 X 17 size document at 300 dpi for your final project based on your group theme.

Requirements
- The mood board should be based on your group's theme.
- Use a minimum of 8 different images.
- At least 4 images must be created or adapted by Midjourney.
- Combination of the 8 images may use photoshop, or just Miro.
- Include the name of your mood board and a brief description.
- Use of other Adobe tools is optional.
- Try to form your own workflows using Midjourney in design.

Grading Rubric
The mood board should clearly convey the style and design concept based on your group's theme.

This figure is just for reference, it does not meet the requirements

Appendix C

The following 5 questions will ask your attitudes on using Generative AI (GAI) in design:
Q1 GAI is useful in design.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree

Q2 GAI is easy to use in design.
The answers are the same as Q1.
Q3 GAI can improve my design creativity.
The answers are the same as Q1.
Q4 GAI can improve my design efficiency.
The answers are the same as Q1.
Q5 GAI can improve my design ethnicity.
The answers are the same as Q1.