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Author	ウー, ヤオクン(Wu, Yaokun) 南澤, 孝太(Minamizawa, Kouta)
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Master's Thesis
Academic Year 2023

Own Diffusion: A Design Pipeline Using Design Generative AI While Preserving Sense of Ownership

Keio University
Graduate School of Media Design

Yaokun Wu

A Master's Thesis
submitted to Keio University Graduate School of Media Design
in partial fulfillment of the requirements for the degree of
Master of Media Design

Yaokun Wu

Master's Thesis Advisory Committee:

Professor Kouta Minamizawa	(Main Research Supervisor)
Professor Matthew Waldman	(Sub Research Supervisor)

Master's Thesis Review Committee:

Professor Kouta Minamizawa	(Chair)
Professor Matthew Waldman	(Co-Reviewer)
Project Senior Assistant Professor Yun Suen Pai	(Co-Reviewer)

Abstract of Master's Thesis of Academic Year 2023

Own Diffusion: A Design Pipeline Using Design Generative AI While Preserving Sense of Ownership

Category: Design

Summary

In recent years, Artificial Intelligence Image generator systems are rising fast, changing the perspective of how the worlds view new digital art and design industry. High-quality art and design can be done just in seconds with one click. On the other hand, this emerging technology scares people and put designers and artists' careers in threat. People are scared and overwhelmed by not being able to understand how to use this technology to benefit themselves.

In this thesis we explore a new design pipeline of Artificial Intelligent Image Generation (AIIG) that could cooperate with design ideation and improve sense of ownership (SOO) during the AI design creation process. We identify a suitable prompt weight range in AIIG that should be able to generate image results with a higher SOO level.

We introduce a new design pipeline of using AIIG in the design ideation process to help novice designers and design learner to build more confidence in design ability with a high sense of ownership called Own-Diffusion. By utilizing real-time camera capture during the design creation process (doodling, model making) to create new design references images to inspire and gain confidence for users.

This study investigated whether and how the Artificial generation results with specific prompt weight and cooperation with humans in the design process would affect one sense of ownership can help improve confidence and creativity in designing.

Keywords:

artificial intelligence, design process, creativity, sense of ownership, workshop, innovation

Keio University Graduate School of Media Design

Yaokun Wu

Contents

List of Figures

List of Tables

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Chapter 1
Introduction

1.1. Background

In the course of human history, art has consistently held a significant position even dating back to the earliest cave painting in the early human era [1]. Art has served as means to convey ideas, thoughts, and narratives. In the last decades, Artificial Intelligent (AI) has progressed remarkably.

Recent development in the text to image, image-to-image technology by Dall-E[1] from Open AI, Dream StudioE[2], Google Imagen[3], Mid Journey[4] has amazed the world. These AI systems generate high-quality and highly imaginative compositions of images. By assimilating large amounts of text and images, AI has acquired a natural language of understanding and enables the production of new images when paired with textual inputs, combining and aligning two separated things in a unique way [2]. Since the emergence of generative AI image systems, one of them stable diffusion[5] is open source, meaning the source code can be redistributed and used to create new models and products by others for free. With this generative AI-building environment, small businesses, organizations, schools, researchers, companies, and creators all come together to build new AI communities and develop more specific using cases for different needs, generating realistic renderings, art paintings, advertising commercial images, presentation images, AI

1 `https://openai.com/research/dall-e`

2 `https://beta.dreamstudio.ai/`

3 `https://imagen.research.google/`

4 `https://www.midjourney.com/home`

5 `https://stablediffusionweb.com/`

photography, movie, video art.

Many companies and people benefit from the AI models for business AI technology can significantly cut time and budget and resources for businesses by creating marketing and advertising materials [2]. With AI-generated content, even a small team could launch products and services in an entirely new way.

Artificial Intelligence (AI) has a huge influence on our daily life and potentially can replace many of our jobs. Some believe that machines are well built to do repetitive tasks, but humans will still be important for creative work. On the other hand, AI had created controversial discussions and even protests. In 2022, a digital art-sharing platform, Artstation [3] has thousands of Artists posting anti-ai image signs on the platform, causing traffic and loss of traffic in months. This is because of the Art Station AI scandal by allowing users to post AI-generated work on the sites. Many Artstation users in the community express their concerns and anger worried about their artwork being used by AI to generate art that could potentially take away their job opportunities without getting the credit and contribution of their original work [4].

Although companies are developing AIIO to help the design process such as Vizcom[6], Ando AI plug-in[7] but in general people do not take credit from AI images as part of their work because the results were assembled by images online created by other artists. However with the image-to-image feature on the stable diffusion, platform software like Vizcom allow users to freely draw like normally on a sketchbook and turn the drawing into realistic AI generative images that rendered the sketching into a product. This Image Image(ITI) feature is different from the text-to-image feature, allowing the users to feel participate in the generating process with the final results corresponding to the user's initial thoughts. Generative AI users would mostly think the final works are credited to the artwork's original author and the developer who created and modified the AI [5]. Even though people can participate and have results closer to their expectation, there are still not enough support for the users to learn from the AI tools in design ability other than generating good rendering images. Therefore it is important to

6 `https://www.vizcom.ai/`

7 `https://ando.studio/`

understand and explore and investigate what and how is the current AI not only helping users to get good results but to help people gain confidence and learning knowledge through the AI designing process. We want to go deep into digital design ideation tools and processes and AI modeling to figure out what is the next step for cooperating and designing with AI and what features in AI can help build mental strength confidence and creativity boost.

One feature of generative AI that increases the controls that users have in the AI image creation process is image-to images features provided by stable diffusion. One company that uses this model of features is called Vizcom. By allowing users to draw on the tablet and uses the sketches to generate image results. This has increasingly changed from the previous text to images feature because the AI is portraiting an image by tracing the image input and outputs very similar images with the composition, and components but will AI realistic details and realism. The Vizcom was designed for a designer to make rendering images from sketching efficient. Inside the image-to-image feature, there is a specific parameter called image prompt weight. It stands for how much the image input would affect the final result. The higher the number, the closer the final images would look like the image input. The smaller the number, the more the result will look closer to the text input. These features extend the ability of control for the users from the image-to-image feature even more. However, very little research has discussed deeply the potential of this image prompt weight, and image-to-image features could give a sense of control and ownership to the AI generative results. Therefore this has also become one main focus of this paper.

1.2. Problem Statement

The current AI models and generative AI tools cannot allow users to understand the process of how the images are being generated, therefore leaving the users has less sense of the ownership of the original [6]. Humans working with AI now create almost 20 million images per day. It is a huge amount of production and usage of generative AI. Even though people would not take credit and ownership of the images, because of the high details and realistic quality with only a single sentence as the text input allows people to be much more efficient to create art and designing images. Therefore this potentially created a problem for those young artists and designers who wish to learn about how to design and can now rely on AI to create results without thinking and learning, understanding the principles of creative thinking.

The second problem is that the current models of generation AI and image results are using algorithms to build new images from existing materials and data by combining and synthesizing existing works [7]. As a result, AI-generated art can be viewed as a transformer. If AI is helping designers be efficient in creating images, where before need to spend more than 50 hours learning software and 10 hours to craft each rendered image, can now be done in seconds. For example, AI artists are creating AI images that received multiple millions of views on Instagram[8], Twitter[9], Linkedin[10] , etc. The house was developed as a Nike sneakers (Figure1.1) and the Charles Eames Lounge Chair[11] made of Lego toy blocks (Figure 1.2). But because AI is generated from existing materials, there are potential need for the AI application to be human-centered AI, giving users more appropriate control of the generated results [8].

However, at the end there are still images created by AI, leaving the potential credit to those who came up with the interesting ideas and crafted the text input to AI models. The problem is that people do not feel confident using AI to generate images and claimed as their own idea unless they have used certain method of posting editing and methods to modify the AI results, for instance, using Photoshop to clean up the details and make adjustments and corrections. The current AI generative process does not obtain people a high sense of ownership of ideas thus people not feeling comfortable using it.

The third problem of Generative AI in the design industry is that the majority of AI design assistive tools on the market mainly focus on helping 2D or on-screen-related creating processes, sketching, ideation, UIUX app interfaces mock-up, movie animation simulation, etc. Researchers in the recent year working

8 `https://www.instagram.com/`

9 `https://twitter.com/`

10 `https://www.linkedin.com/`

11 `https://www.hermanmiller.com/`

(Source: MarkVonRama Instagram)

Figure 1.1 AI generated sneaker-themed houses *iiasTsukuba*

(Source: Vjeko Design Instagram)

Figure 1.2 AI generated Lego Charles Eames Lounge Chair *iiasTsukuba* on implementing generative AI in the design process. One interesting example is an exploration of Generative AIR by HU from the University of New South Wales, Australia [9]. Their prototype combining the system comprises software (two multimodal generative AI models) and hardware (three AR display devices), allowing the users to speak through microphone and connected clouds AI from speaking to text to images and finally displace at the AR devices. They are exploring the potential to use generative AI as a new methodology and pipeline that could help the design process. Their finding is positive that generative AI in AR is better than traditional on-screen AI generative process. However, how generative AI and what steps in the design process can be helpful have not been discussed further. The problem is the focus on helping the physical prototyping has not been discussed. Without understanding and researching from an end user (designer) perspective, it is difficult for the young rookie design learner to understand and feel comfortable using generative AI in the future.

1.3. Motivation

The importance of creating physical prototypes and the tangible objects creativity process is being discussed much less than on screen and two-dimensional methods design process. There should be a potential gap to fill in this area where generative AI technology can be implemented to benefit the physical brainstorming and prototyping process of industrial design.

Design thinking is a problem-solving methodology that prioritizes empathy, creativity, and iterative prototyping to tackle intricate and user-centric problems, which is important for creativity and problem-solving skill [10]. Prototyping is a huge step between ideas and results. It is a big step to transfer a concept into a tangible object that is closer to reality, giving more feedback and details to help shape the design concept and idea to reality. It also enhances the collaboration and communication of an idea between people in a team allowing design concept to be better developed [11].

This is similar to children play clay models to develop their creativity. Research has shown that playing clay models and allowing children to get a hand on experience and tangible objects [12]. By constantly checking, and adjusting clay,

(Source: Yaokun Wu Behance portofolio)

Figure 1.3 Product Design Prototyping process *iiasTsukuba*

allowing them to see the change and impact they make on their hands, giving children confidence and a creativity boost. This research is to explore how generative AI could benefit the design community but also transfer the importance of creative and design thinking that can be learned in industrial design to boader audiences such as children and college designer learners.

It is important to turn AI into a tool for designers or people to improve their confidence in creativity rather than a tool that people heavily rely on and lose the ability to creativity and design thinking skills. Therefore the problem and the motivation is to find out how we can design a new design pipeline that can help the creation process of prototyping and tangible object designing.

1.4. Research Question and Research Goals

Given that the topic of this research is to figure out how to enhance users' sense of ownership of their final generated image results in the Generative AI tools and improve their confidence in their creativity ability when using AI. Research Question

One (RQ1) is how the image prompt weight influence the sense of ownership of the ideas in the generated image results. The second research question (RQ2) is to what extent does a real-time generative AI help designers improve their confidence and creativity in the physical prototype-making process. These two big research question covers two smaller questions: RQ1(a)what is the ideal prompt weight range that prompt the best sense of ownership results? RQ2(b)Does gaining a higher sense of ownership has a relationship with confidence of their creativity ability when using generative AI tools?

The ultimate goal of this research is to improve the sense of ownership of the ideas when using Generative AI tools to help design communities and more. This is important to understand how can the users feel owning their ideas and having more control during the process and gaining positive mental feedback to help them become better well-being (improving confidence and creativity). In the future, AI would likely be developed into a daily used tool for everyone to use. The vision is to start talking about the impact that AI will bring to human ownership and creativity. Otherwise human would relies on AI to create ideas for too much to even start thinking and developing creative thinking and design problem solving skills. make designer learner to feel more comfortable to use generative AI and feel AI helpful in building their confidence in design creation, feel sense of ownership of the final results. To be more specific, the research goal can be described as:

- Find an new design pipeline to enhance people creativity and sense of ownership in generative AI tools.
- Find an proper parameter range number to make sure the AI tool is suit to individual.

1.5. Thesis Structure

This thesis is composed of five chapters, all related to two keywords, AI and sense of ownership. Below is the brief description of each chapter.

- Chapter 1: **Introduction** This chapter will mainly introduce the topic of the Generative AI design pipeline studies, Sense of Ownership, Prompt Weight, Creativity and Confidence, and the direction of this research.
- Chapter 2:**Literature Review** This chapter gives more scientific knowledge about and background information on the current generative AI products, the Psychology aspect of ownership, improving creativity and confidence related research, and the gap in these studies between other studies.
- Chapter 3:**Concept Design** These chapters elaborate on the concept and the design of the proposed design pipeline. Includes the survey, previous workshop, user studies, and experiment that lead to the current final prototype. It will also explain how the prototype was developed.
- Chapter 4:**Proof of Concept** We will mainly portray the final proposed design pipeline and procedure and assessment and evaluation of the prototypes with questionnaires and interviews. We also covered the user studies and, the outcome and the discussion of the results based on the experiments and feedback by participants.
- Chapter 5:**Conclusion** reiterates the research goal and summarizes and concludes what the findings mean and how they can contribute to the field of research and the future of design and AI.

Chapter 2
Literature Review

2.1. Artificial Intelligence in Design

2.1.1 Generative Artificial Intelligence

Artificial intelligence (AI) refers to the development of computer systems that can perform tasks that typically require human intelligence, such as learning, problem-solving, and decision-making. One significant branch of AI is generative AI, which focuses on creating systems that generate new content, such as text, images, and music, without explicit human input. Generative AI algorithms, driven by large-scale neural networks, have made remarkable advancements in recent years, transforming various industries and impacting the world in profound ways [13]. These algorithms have revolutionized language translation, content generation, and data analysis, enabling faster and more accurate results. They have also found applications in fields like healthcare, finance, and autonomous vehicles, improving diagnosis, investment strategies, and driving efficiency. With the growing availability and accessibility of AI technologies, we are witnessing a transformative shift in how we live, work, and interact with technology, creating both new possibilities and challenges for society.

The infiltration of artificial intelligence into our daily routines has been steadily progressing since the early 21st century. This has led to AI applications spanning an assortment of sectors, user bases, and devices [14]. This broadening penetration of AI has instigated the emergence of new products, services, and systems. Notably, AI has become significant in the consumer market. The application of generative AI by firms to create content, a task previously considered the exclusive domain of humans, is a testament to this trend. Such examples emphasize how AI has quietly become integral to diverse services and products [2].

2.1.2 Generatve AI image generator

- **Open AI**[1]: OpenAI's Dall-E is an AI image generator that sets itself apart by creating images from textual descriptions. The distinguishing feature of this model is its ability to accurately render even the most fantastical and abstract text descriptions into detailed images. Dall-E's innovative approach to image synthesis can provide design communities with a tool to quickly and efficiently convert creative ideas into visual prototypes.

- **Stable Diffusion**[2]: Stable Diffusion, another AI-driven image generator, uses diffusion models in its image production process. [15] This process as a gradual denoising procedure that builds up an image in response to specific requirements. In comparison to Dall-E, Stable Diffusion allows for open sources implementation which creates opportunties for companies, businesses, creators, and developers to create a product around the model. [16]

- **Mid Journey**[3]: Mid Journey, unlike its counterparts, is designed to generate a series of intermediate images, rather than a singular final image. Dou et al. (2020) highlight the unique value of this system in contexts that require sequential demonstrations, thereby offering designers a valuable tool for visualizing and communicating processes.

- **Vizcom**[4]: Vizcom, another entrant in the AI image generation landscape, is specifically designed to support the design community. Although details about its specific algorithms or techniques are not widely available, the unique feature of Vizcom appears to be its focus on facilitating visual communication. By automating the generation of complex visuals based on textual inputs, Vizcom offers designers an efficient tool to express their ideas and engage with their audience visually. This particular aspect can greatly enhance the design process by providing quick visualizations and facilitating

1 https://openai.com/

2 https://stablediffusionweb.com/

3 https://www.midjourney.com/home/

4 https://www.vizcom.ai/

more effective communication.

To provide a comprehensive view, it's essential to note that the field of AI-driven image generation is vast, with each model incorporating unique techniques and offering distinctive features. However, it is the responsibility of designers and researchers to use these tools ethically and be aware of their limitations, as their effectiveness depends on the quality and variety of training data.

2.1.3 Copyright and AI fair use

Copyrighting AI art is a complex and contentious issue. Although AI generates the artwork, human creators who programmed and trained the AI algorithms usually claim ownership. Currently, AI-generated works, even if prompted by human input, are not protected by copyright according to the U.S. Copyright Office's stance on non-human creations [17].

Legally, AI systems cannot be considered the authors of the materials they produce, including AI image generators, ChatGPT [5], etc. However, AI art can still be copyrighted if it meets the criteria of originality and creativity with significant human input [18].

In cases like DALL.E2, the terms are structured to grant rights to the human creator who provided the original creative input. However, due to the nature of AI, similar results may be produced for other creators, leading to multiple owners of distinct outputs. The application of copyright law to AI-generated artwork remains an evolving area, and its resolution will depend on how courts and lawmakers address these issues in the future [19].

2.1.4 Image Prompt Weight

Currently, Mid Journey [6] and Stable diffusion [7] stands as a premier choice in the market for AI-driven image generation tools. The ' image-to-image generation '

5 https://chat.openai.com/

6 *Mid Journey* Prompte Guide book. `https://docs.midjourney.com/docs/image-prompts`

7 *Dream Studio* by stability.ai prompt guide `https://beta.dreamstudio.ai/prompt-guide`

Figure 2.1 A futuristic chair generated in Stable Diffusion

Figure 2.2 A futuristic chair generated in Vizcom

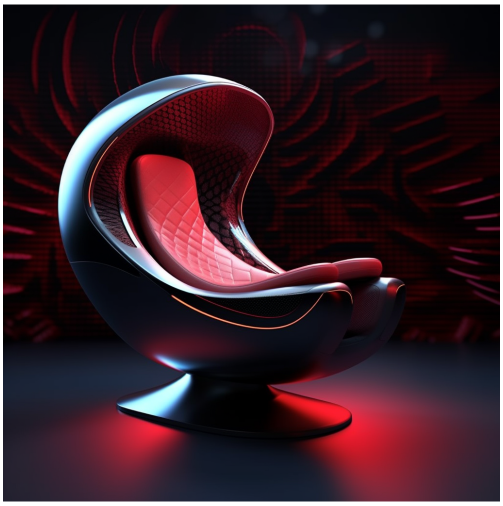


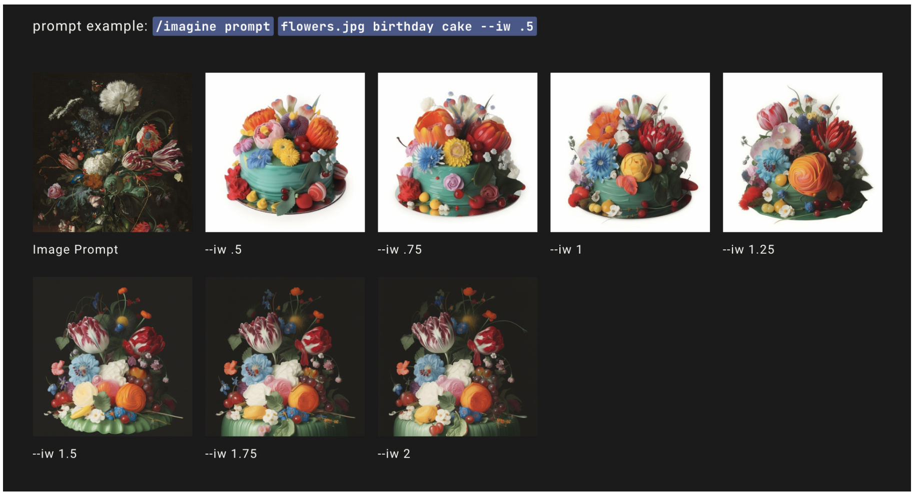
Figure 2.3 A futuristic chair generated in Mid Journey

Figure 2.4 A futuristic chair generated in DAll-E

is a prominent feature in the latest edition of Generative AI. This feature plays a significant role in the AI image generation landscape. It allows an image to function as a prompt, offering a point of reference for the resultant artwork. The integration of text and image inputs, alongside other command elements, enables users to achieve more innovative, detailed, and precise outputs.

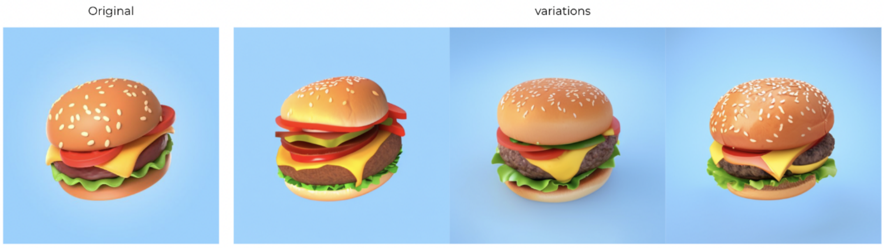
Within this 'image-to-image generation' capability, a specific parameter named 'image prompt weight', 'image strength', or 'image guidance' exists. This parameter essentially modifies the balance between the influence of the image input and the text input. The more the 'image prompt weight' or the greater the emphasis on the image input, the more the final output tends to resemble the image input.

In the process of image-to-image conversion in stable diffusion, noise is introduced to the base image. The diffusion process then continues, guided by the prompt. The degree of noise introduced is governed by the 'Strength of img2img' parameter, which ranges from 0 to 1. A value of 0 results in no noise addition, thereby replicating the original image, whereas a value of 1 replaces the entire image with noise, thus behaving similarly to a standard text-to-image (txt2img) operation rather than an image-to-image (img2img) operation.



(Source: MarkVonRama Instagram)

Figure 2.5 Mid Journey Images generated with different images weight *iiasT-sukuba*



(Source: MarkVonRama Instagram)

Figure 2.6 Stable Diffusion Images generated with different images weight *iiasT-sukuba*

2.1.5 Generative AI in Design Catogories

Generative artificial intelligence (AI) has been increasingly applied across various design fields, providing new insights and offering transformative capabilities. Among these fields, the generative text has been highlighted as a rich source of design inspiration [20]. In a study presented by Ideasquares, the authors propose how textual data, when processed through AI, can stimulate creative concepts and ideas, revolutionizing the design brainstorming process.

In the context of product design, there has been an ongoing discourse on the interplay between humans and AI. A paper by the Cambridge Journal author Tufarelli, emphasizes a shift towards a symbiotic balance between human intuition and machine-driven ideation in generative product design processes [21]. The study underscores the importance of maintaining an equilibrium that leverages the strengths of both entities to facilitate more comprehensive design outcomes.

The impact of generative AI extends to other more specific areas of design such as game and fashion design. Research on the role of AI in game design presents its capability in generating unique, engaging experiences for players, paving the way for more immersive and personalized gameplay [22]. Similarly, in the realm of fashion design, a study documented in IEEE illuminates how AI is being used to sketch and render fashion designs, enabling designers to create more innovative and efficient solutions [23].

In architecture, the use of generative AI, especially through deep learning, is reshaping the way structures are designed. A study in the Journal of Computational Design and Construction provides examples of how this technology has the potential to optimize the architectural design process by automating complex calculations and providing data-driven design variations [24].

Furthermore, the broader concept of generative design ideation is tackled in a chapter from Springer. It outlines how AI can be incorporated into the design thinking process, fostering creativity and accelerating innovation [25]. The framework discussed in the chapter presents a systematic approach to integrating AI into the design workflow.

Lastly, an academic paper from the Diva portal proposes a comprehensive design framework that encapsulates all stages of product design [26]. This framework signifies the growing role of AI, demonstrating how it can be integrated at various points of the product design process to yield more effective and efficient results.

2.1.6 Generative AI in Tool/Education

The recent advancements in artificial intelligence (AI) have spurred transformative applications in tool development. The use of generative design tools, as detailed in a study published in the ASME digital collection, brings forth an interesting symbiosis between designers and tools, facilitating the creation of more complex and efficient products [27]. The authors noted how the constraint-driven process enabled by these tools could refine the early stages of design, leading to a more thorough understanding of the design problem and solution space.

As we navigate the intricacies of AI, there is a growing emphasis on making it tangible and understandable. A research project presented in the ACM Digital Library introduces a series of concept cards designed to aid researchers' exploration of the graspable AI space [28]. Despite the challenge of making the interaction with AI tangible, the study found that creative exploration could foster new design perspectives and encourage the transition beyond anthropomorphic forms of AI.

Meanwhile, AI-generated content (AIGC) is being explored for its potential applications in augmented reality (AR). An exploratory study discusses the design space for employing AIGC, such as images and text, in AR displays [29]. Through a user-function-environment design thinking approach, the study highlights the potential of combining AIGC and AR to create unique user experiences.

The influence of generative AI also extends into the realm of craft education. In a study conducted with Finnish pre-service craft teachers and teacher educators, text-to-image generative AI was used to stimulate discourses and capture imaginaries concerning generative AI [30]. The study underscores the benefits and challenges of integrating AI into craft practices, addressing concerns related to data-driven design, algorithmic bias, and creativity.

Lastly, with AI's ubiquitous role in daily life, the need for AI literacy education has become more pronounced. A paper from the University of Malta library addresses this need through tangible game design, highlighting how digital games can be used to teach basic AI and machine learning concepts [22]. The paper demonstrates the potential of digital games as an engaging platform for enhancing AI literacy among the younger generation.

In conclusion, these studies collectively highlight the emerging importance of generative AI in tool development, making AI tangible, AR applications, craft education, and literacy education. This suggests a future where AI permeates various facets of society, providing innovative solutions and new ways of understanding and interacting with technology.

2.2. Sense of Ownership

The sense of ownership, in the context of ideas, refers to the psychological phenomenon where an individual feels that an idea is their own, often leading to an increased commitment to and valuing of that idea. This sense can be associated with increased feelings of self-efficacy, motivation, and pride, thereby affecting both personal and professional life, especially in collaborative environments [31].

The utilization of Artificial Intelligence (AI) has been investigated in various contexts, including the perceived sense of ownership when individuals use AI to generate outputs. People's feelings of ownership when they utilize AI to create something can be complex and multifaceted [32].

Initial research suggests that some people do feel a sense of ownership over the results produced by AI, especially when they were instrumental in providing the input or guidance (Kleszczynski, Rossmanith, 2019). This can be analogous to the "IKEA effect" mentioned earlier, in that people tend to place a higher value on the products that they partially created, even when that creation involved automated processes [33]. Moreover, this sense of ownership can also be leveraged to boost creativity and innovative thinking in organizational contexts [34].

In terms of creativity, AI has been demonstrated to augment human abilities, generate novel ideas, and foster creative problem-solving [35]. Users who interact with AI in creative processes may still retain a sense of ownership over the end product, as they've provided crucial creative direction.

In addition, there may be ethical and legal considerations concerning ownership when AI-generated outputs have significant economic or societal value (Abbott, 2018). As AI develops, the topic of whether and to whom he objects created by AI can belong has been discussed. The research looks at how laws could change to handle inventions made by AI, suggesting that, instead of focusing on the inventor, we should protect the investment behind these inventions [36].

2.2.1 Who gets credit for AI art?

Understanding the allocation of credit for AI-generated art is an increasingly pertinent issue, as highlighted by the sale of an AI-produced portrait for a significant sum. In their study, "Who Gets Credit for AI-Generated Art?", the researchers found that people's perceptions of AI anthropomorphism - the degree to which they view AI as humanlike - significantly affected how they assigned credit for the creation of such art. Interestingly, these perceptions could be influenced by the language used to describe AI, with more anthropomorphic descriptions leading to increased attribution of credit to the AI system itself. This finding is crucial because it reveals that how we talk about AI systems may shape our understanding of their role and the corresponding recognition they receive in creative endeavors [5].

Meanwhile, the study "Artificial Intelligence, Artists, and Art: Attitudes Toward Artwork Produced By Humans vs. Artificial Intelligence" delves into the comparative evaluation of artwork created by AI versus humans. Using an experimental approach, the researchers found that participants did not equate AI-created artworks with those created by humans in terms of their artistic value. Intriguingly, the knowledge of an artwork's origin (whether human or AI) did not significantly affect the evaluation of its artistic merit. However, individuals who strongly believed that AI cannot create art were more likely to negatively evaluate AI-generated pieces. This indicates that preconceptions about AI's creative abilities play a crucial role in our reception and valuation of AI-created art [37].

2.3. Creativity and Tools

Research discusses the application of clay play in fostering creativity among a group of children in a kindergarten called Islam Baitussalam [38]. It explores how involving children in this tactile form of artistic expression stimulates their creative abilities. This action research, leveraging the Kemmis and Taggart method (consisting of planning, action, observation, and reflection stages), confirms that the use of clay in a play indeed yields significant improvement in the creative development of the participants. It highlights the effectiveness of clay play as an interactive tool in augmenting creative capacities among young learners.

Another research revolves around the concept of co-creative systems with AI agents in the design process, particularly emphasizing the early phase of idea generation [39]. It investigates how a partnership between human designers and an AI agent can fuel the creation of novel, diverse, and quality design solutions. The paper introduces the Collaborative Ideation Partner (CIP), an AI-based system that supplies inspiring images based on their conceptual similarity to the task at hand while the designer is sketching. By stimulating the designer's creativity in real time, the CIP empowers users to explore a wider spectrum of design solutions during the initial phase of idea generation. The research result found that the AI's model of conceptual similarity significantly impacts the novelty, variety, and volume of ideas generated during the design process.

The gap we are filling is to explore the impact of co-creation with AI agents on people's sense of ownership during design ideation. We were inspired by the research [38] to further explore the possibility of implementing AI in the clay modeling ideation process in our final experiment.

2.3.1 Measure Creativity

The measurement of creativity, particularly in the context of design, presents a complex challenge due to the multifaceted nature of creativity itself. In their work, Shah, Vargas-Hernandez, and Smith [40], propose a novel method of assessing design creativity as a function of both novelty and usefulness. The researchers argue that to comprehensively gauge creativity, both these aspects must be considered. They develop and validate methods for assessing each aspect individually, and then blend these to construct an overall measure of creativity. This work provides a significant step towards directly measuring creativity in design outcomes, presenting new methods to assess novelty, usefulness, and overall creativity.

In contrast, Hokanson, argues for the value of specific training in fostering creativity among design students [41]. The research suggests that creativity can be significantly enhanced with targeted training. This assertion is supported by empirical data from a creative problem-solving class, where creativity, as measured by the verbal Torrance Test of Creative Thinking, exhibited a notable increase.

In a unique approach, Grace, Maher, Fisher, and Brady [42], offer an AI-based perspective on evaluating design creativity, combining three key criteria: novelty, value, and surprise. They suggest a common model that allows agents, whether artificial or human, to judge the creativity of their designs and those of others, thereby contributing to the computational modeling of creative design. This approach presents a relative measure of creativity, introducing a method to compare creativity across different systems and sources, fostering a common ground for evaluating creativity in human, computer, and collectively intelligent systems.

2.3.2 Accessing Design Tools

One research presents an exploration of AI's function in boosting creativity through the development of an AI-based Creative Support Tool (CST) in the context of fashion design. The tool, named FashionQ, incorporates three cognitive processes—extension, constraint, and blending—that are tied to divergent and convergent thinking. FashionQ's effectiveness in facilitating these types of thinking is confirmed through interviews and a user study with fashion design professionals. The research not only highlights the role of AI in these cognitive operations but also sheds light on the prospects and challenges of integrating AI into the ideation process [43]. The inspiration for our study was drawn from this research to create a support tool tailored for industrial design and the creativity involved in producing physical objects. We incorporated three cognitive activities - extension, restriction, and merging - that are associated with divergent and convergent thinking into our study. These elements were adapted into our survey and questionnaire that we used to engage participants in our final workshop experiment.

The other research is called Mixplorer: a design space exploration tool that inspired our research. The research centers around enhancing the problem-solving abilities of novice designers by expanding their awareness of the design space. It introduces Mixplorer, a system that facilitates the blending of initial designs with other designs, aiding designers in exploring gardening design concepts. Explorer stands out due to its focus on encouraging the exploration of ill-defined design spaces through social design. The efficacy of Mixplorer was validated through an interview study with design instructors, and a controlled experiment with novices. The results indicate that Mixplorer indeed enhances creativity and promotes the generation of more innovative designs [44]. Drawing from this research, we adopted their methodology to evaluate the efficacy of our tool in aiding the design process for novice designers. We appreciated their implementation of the Creative Support Index, which we incorporated into our final experiment as a measure of how strongly users felt ownership over the outputs generated by artificial intelligence.

2.3.3 How Digital Tools support creative activities

Before constructing our pipeline for AI design generation, we delved into existing literature to grasp how interactive tools aid the design ideation process. Here are three influential studies that informed our approach:

Firstly, a study compared the impact of analog and digital tools on the thinking patterns of design groups [45]. According to their results, digital ideation tools appear to bolster more convergent thinking, without noticeably affecting general productivity or divergent thinking. This comparison provided us with an understanding of the thought processes stimulated by various tools and the importance of balancing both divergent and convergent thinking in the design process.

Another study presented "Idea Bits" [46], a tangible design tool aimed to encourage broader exploration of tangible manipulations, which often pose challenges for tangible interaction design students. Idea Bits consists of interactive physical artifacts combined with digital examples and technical implementation guidance, facilitating idea generation for manipulation. This approach reinforced our understanding of the potential benefits of tangible and interactive tools in inspiring creativity, especially when paired with appropriate instructional resources.

Finally, a study introduced "MetaMap" [47], a tool designed to assist in creating visual metaphors - a crucial component of graphic design. MetaMap facilitates multi-dimensional, example-based exploration by using a mind-map-like structure. This tool not only provides sample images based on keyword association and color filtering but also tracks thinking paths and records ideas, enhancing both divergence and convergence in the ideation process. This study underscored the value of structured exploration and tracking mechanisms in fostering creativity.

These studies collectively inspired and informed our approach toward developing a novel design pipeline. They illuminated the potential of both digital and tangible tools in stimulating different types of thinking and promoting creative exploration, offering crucial insights for our research.

2.4. Conclusion

In conclusion, our literature review has underscored several key points. First, current Generative AI's role and its progress in helping the design process and fueling creativity. Second, a yet under-explored area is image prompt weight and its link to ownership over the resulting designs. Third, there are established methods to assess design tools and measure creativity.

In response to these findings, our research will create a new AI pipeline that improves designers' creativity, sense of idea ownership, and confidence via a tangible AI-co-creation ideation process. This approach aims to fill the research gap and bring forth a unique contribution to the field.

Chapter 3
Concept Design

3.1. Inspiration

The research of developing Generative AI designed tools has been started recently with the emerging of AI technology such as Open AI, Dall-E, Stable Diffusion, and Mid Journey. As the benefit and large amounts of text and images product and improvement of AI, the controversial sides of AI technology putting people in situations that feel threatened by AI could take the job of creativity designers. By conducting workshops and interviews we realized the current AI would be great to support the ideation process of design. However, it is challenging to allow users to feel a high sense of ownership when using AI to generate design ideas. On the other hand, it is still unclear whether AI helps build confidence in the creativity ability of users. Although research has been showing AI-assisted design tools in different design categories and design ideation processes, the gap between image prompt weight and sense of ownership is still there. Based on the understanding of AI has the potential to benefit designers, and the discovery of the problem that the users have experiencing AI creates results that are not matched their imagination. We want to follow up to discover to answer our research question; Is AI helping the design in design ideation? Does AI give confidence to non-designers or design learners in building up their confidence?

Furthermore, the current AI-assisted tools mainly was focusing on creating assistance to help designers digitally. Important ideation processes like prototyping, modeling ideation, and body brainstorming have not been researched to implement AI to help the design process. We believe it is a significant gap in the AI research field in discussing the parameter of image prompt weight in image-to-image generation technology and its relationship with creating a higher sense of ownership of the final result.

Therefore to combine these research gaps, we want to create a new design ideation pipeline implementing generative AI to help design rookies and design learners build creativity confidence. The key of the design pipeline focused on the sense of ownership of the idea from AI results and concentrate on tangible and physical modeling ideation, making clay models for chair design for instance. We hope with our proposed design pipeline, the contribution would be the following; 1) an AI design pipeline that generates a higher sense of ownership of the idea, therefore, building higher confidence in design. 2) A image prompt weight level range that corresponds with the sense of ownership can help the future generative AI tools to define a suitable image prompt weight level to prompt a sense of ownership and the possibility to generate ideal results.

3.2. Concept Design Analysis

Since this research focused on Generative AI design-assisted tools to help designers to increase creativity and confidence, several questions are necessary to be considered under this concept. These questions are:

- How to improve the current generative AI tools to improve the sense of ownership?
- What kind of design ideation method can help design learners can be confident in design with confidence and creativity?
- What is the relationship between the sense of ownership and image prompt weight level?

To answer the first question, it is necessary to understand how does people would feel about using the current generative AI on the market like Dall-E, stable diffusion, and mid-journey generate design ideation. To better understand the different situations of usage, we want to conduct an initial workshop and interview before any prototype construction. We narrowed down the users into two groups. The first group would be designers with professional design experiences in working in design fields. The second groups are design learners and novice designers who need to learn and build confidence in the design and improve creativity. In most cases, users would use generative AI tools with text prompt input, however, the image to image generation could allow more detailed controls and image input from sketches as input to increase the chances that the final results would be closer to the user's expectation. Therefore to answer this question, and conduct a workshop, we need to find an AI engine that allows image prompt input such as stable diffusion and Mid Journey. Considering the official interfaces created by stable diffusion called dream studio has more control settings and parameters which allows users to have a higher ability in controlling the graphic output. We decided to use Stable diffusion dream studio interfaces as the main experimental tool for the initial pre-workshop.

The second question involves the core principles of the design ideation method. There are many types of research on improving design ideation and tangible ideation. For example, (cited needed)... When comes to assessing the creativity and effectiveness of any ideation tool would be challenging. Although in the literature review, xxx and xxx review methods of measuring creativity, for the initial prototypes we would like to try to understand whether a modular drawing method can enhance the quality of design ideation. The reason why the prototype would be digital drawing software is that we believe with this method review the most basic and original way of creativity, sketching. It is a universal language for conveying ideas and creativity thought out to other people. However, considering people sketching ability is different and difficult to quantify. We developed a modular digital drawing software with initial prototypes with the following experiment and analysis of data to better answer this question.

The third question is the main discussion of the thesis paper. We believe the image to image generation technology has a great impact on the ability to affect how users view the generated results. One feature or parameter in the image to image generation most generative AI model is image prompt weight level or image guidance. It determines how an image input would weigh on the input end to guide AI results. By conducting an initial workshop, a prototype experiment, and second experiment, and a final experiment, we hope we can find a more confirm assumption of the relationship between AI image prompt weight and the sense of ownership of the idea in generative AI.

3.3. Initial prototype: Modular Doodling

3.3.1 Goal and Objectives

In this prototype, the goal and objective are to find out a way to do design ideation that can prompt higher confidence in creativity.

3.3.2 Concept Design

We designed a modular drawing system that allows people who do not have knowledge and confidence in sketching concepts to draw concepts out more. Also, we developed a creativity cue in the drawing systems, aiming to prompt the designer's creative thinking process during design ideation. Conducting experiments with participants using this initial prototype could help us understand better how modular drawing systems could potentially help design creativity boost. The creativity cues function works as a replacement in the early stage as a role similar to AI giving users references and inspiration during the design process.

3.3.3 Method

Participants

12 Participants from 18 to 25 years old participated in this experiment. 6 participants have no design knowledge and little design task experience before, and 6 participants have at least 1 year of learning design knowledge or working as professional designers. To avoid perception and cultural differences, all participants are Chinese and can speak Mandarin and English. No compensation was offered.

Prototype design

The design mission for the initial prototype is

- Able to help non-designers draw concepts easily without knowing how to sketch
- To understand to what extent modular drawing components help design ideation
- To understand if Creativity cues can boost creativity and ideation efficiency.

To correspond to these three missions, the prototype was made in an online open sources platform scratch 3.0 [1] , which is the world's largest coding language platform with a simple visual interface that allows young people to create digital stories, games, etc. By designing the prototypes in this way, it is convenient for the participants to participate in the experiment online and feel more comfortable creating the design because they are participating from their home or their familiar spaces while doing sketches. Below are the interfaces of the modular doodling prototype.

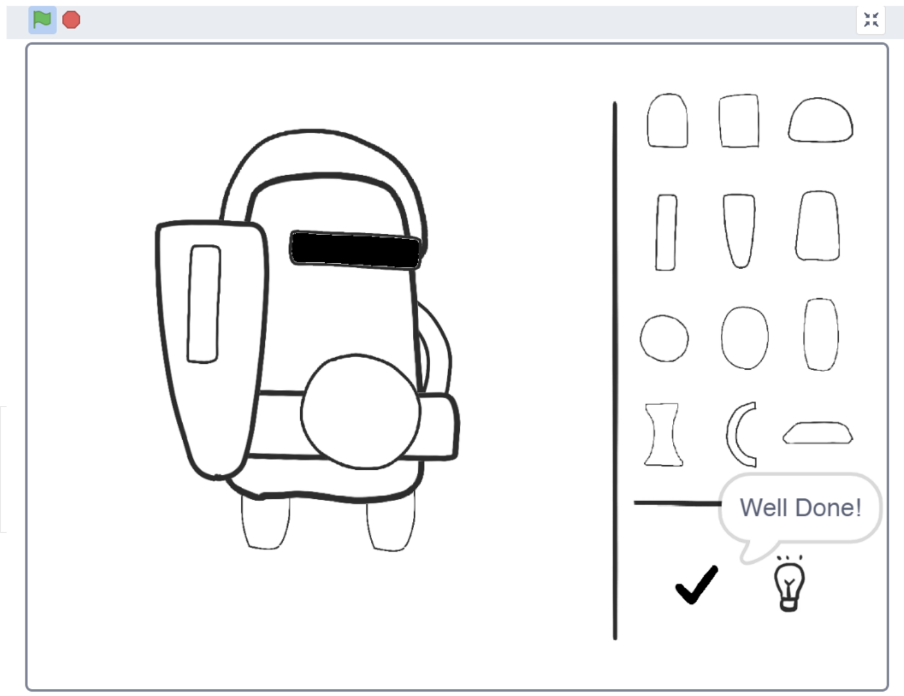


Figure 3.1 Modular Doodling with Robot Design Sketch

The interface includes a drawing board, tool selection section, creativity cue button, and finish button.

1 *scratch 3.0* `https://scratch.mit.edu/about`

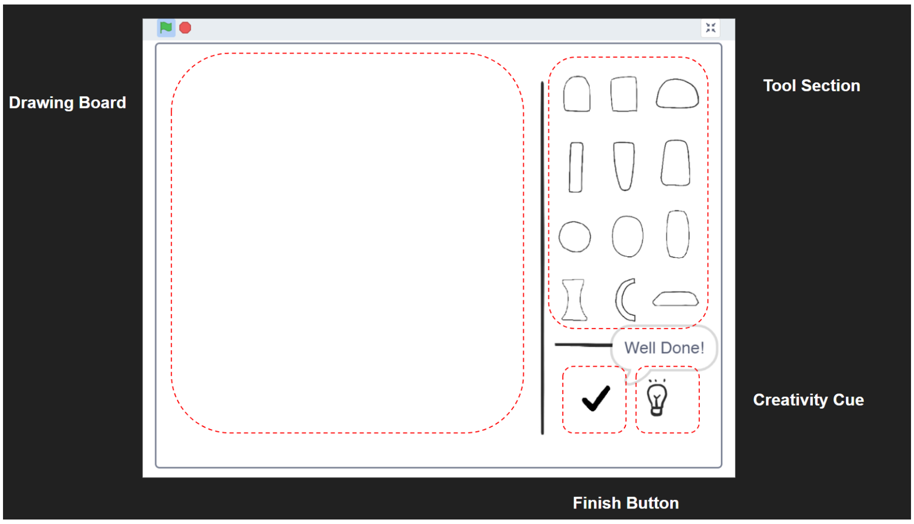


Figure 3.2 Modular Doodling Interfaces

- **drawing board**: the area for participant draw object. In this experiment, the object is a robot character design.
- **tool selection**: this section contains 12 different shape options available for the r participants to choose from and edit to draw the character design. Each shape can be rotated, scaled up and down, and move to different positions and layers to compose the drawing.
- **creativity cue**: A control experiment group feature that allows users to click and prompt creativity questions to boost creative thinking during the sketching of the characters. Creative cue questions often start with "what if", "How about", and "Why not try" to ask users to prompt their robot design creativity. Example: "What if the robots have four arms? What if the robot is floating?" "Try to use different sizes to contrast", etc

3.3.4 Procedure

Participants were divided into three groups to experiment. Each group has four participants (two novice designers, and two designers). All groups of participants participate in the same task: to use the modular drawing tool to design a robot character design. There are two rounds of design in total. In the first round, we asked the participant to draw as many robots as they want in 25 minutes. After that participants will choose one of their favorite robot designs and use it as a reference to draw a new robot character design in round two. Round two does not have time limits. After the second round of drawing. We will ask participants to write one sentence to describe the concept of their robot design.

There are three groups of participants corresponding to three different controlled groups. Group A has no creativity cues on both drawing rounds. Group B only has creativity cues in the second round of drawing. Group C has all accessibility to creativity cues on both rounds of drawing. The goal is to figure out how helpful and to what extent the creativity cue, a drawing references assistant affects people's creativity in a design ideation tool.

3.3.5 Evaluation

Two types of evaluation data will be collected. One is the time cost for each drawing and the number of drawings created in each round. After each round, a questionnaire will be handed to the participants. Both questionnaires will be compared for analysis. The questionnaires focus on finding out whether users have enjoyed the creation process, the overall experience, and an if they have built confidence in designing a creative robot character. The questionnaires would modify based on a creativity survey model called the Creativity Support Index (CSI), which is a standardized psychometric tool that evaluates the creativity support of a tool [48]. It includes seven factors: Enjoyment, Satisfaction, Creativity, Mental Effort, Physical Effort, Comfort, and Divergent Thinking.

3.3.6 Result

Creativity Support Index We found a significant difference among the three conditions on the overall CSI score. If we compare Group A and Group C, we can discover the difference in impact between with and without the creativity cues in the modular drawing tools. The tables 3.1 show an increase in enjoyment and satisfaction with their creation and divergent thinking with the creativity cues accessible. Although the mental effort has been increased with the creativity cues available, it shows the possibility that users have to put more effort into thinking and creating robot designs.

Table 3.1 Creativity Support Index

	Enjoyment	Satisfaction	Creativity	Mental	Physical	Comfort	Divergent
Group A	3	2	4	3.5	3	4	4
Group B	4	3	3	3	3	3.5	2.5
Group C	3.5	4.5	4	4.5	2.5	4	5

Comparing Group B with another group. It shows that the enjoyment increased when creativity cues were introduced in the second round of drawing and a slight decrease in mental effort, meaning it helps users to release the pressure to improve the robot design in the second round. However, satisfaction, creativity, and comfort have decreased compared to Group A and Group C. It shows the possibility that introducing creativity cues during the creation process could cause uncomfortable and effort to adjust to the new features. However, Group C data clearly show introducing Creativity Cue from the beginning has overall higher scores on the creativity support index than Group A and Group B.

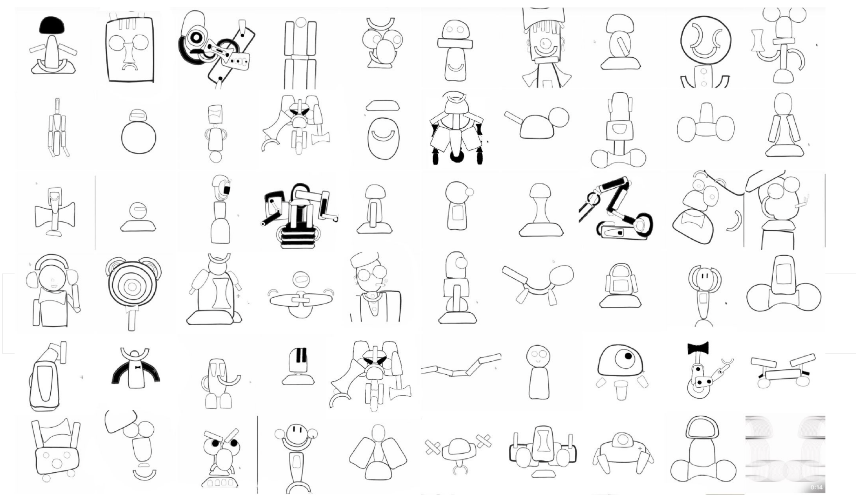


Figure 3.3 Participants robot drawings

Ideation Quality: To define the ideation quality and efficiency. One factor in this experiment is being considered, which is the number of ideation drawings within a controlled period. Although each participant may have different levels of design experience and drawing habits, also considering the experiment only has 12 participants which could not be considered a quantitative analysis, which may make this comparison less scientific, the comparison of the drawing numbers is still worth comparing and analysis needed.

Table 3.2 Number of drawing

/	Group A	Group B	Group C
drawing quantities	4.3	6.3	12

Table 3.2 data shows that the number of drawings has significantly increased with the creativity cues in Group C compared to Group A and Group B. This shows the efficiency of the design ideation has been improved with the creativity cues.

Table 3.3 Each Drawing Time Cost

/	1st drawing	2nd drawing	3rd drawing	rest drawing avg
Group A	2.5	2	4	5
Group B	3	2	3.5	6
Group C	1	1.5	4	3.5

The drawing time costs of each drawing in the first round of drawing can show how the creativity cues affect users' creative process. The more time taken to draw the more consideration and effort of thinking design concept. The first three drawing times and the rest of the drawing on average are being analyzed to be compared. Table 3.3 shows how Group C with creativity cues could help users do design ideation faster than without creativity cues.

3.3.7 Disccusion

After the experiment, participants were also asked to answer some interview questions to have a better understanding of how they think about the modular doodling tools and whether they feel positive about their creativity ability. We found that participants found positive about using these modular doodling tools. "I have never designed a robot before, so I didn't expect myself to draw 15 robot designs in 25 minutes.", "I tried to be creative to draw as many robots as I can, it turned out easier than I thought to start because the modular shapes allow me to know where to start", "It was fun like playing lego in 2d on a screen", "I think I did a pretty good job in sketching the robot design, I could imagine one of my cleaning robot design to be created in a Pixar movie." These quotes from the participants have given us more confidence that the modular sketching concepts could help people without design experience to have more confidence and fun to start making designs.

One participant who is an experienced industrial designer told us "It is interesting that you never really know what are you drawing at first, but it appears more and more interesting as you keep drawing and selecting shapes. I think this could be useful to teach children how to be creative in design." With this feedback, we became more confident that even without the creativity cues, the modular doodling has allowed users to be creative in the design ideation process. Therefore, we want to continue using and developing this modular concept in our later experiment.

The creativity cue in this prototype experiment worked as a creativity assistant. We want to see if the current AI image generator could be a potential creativity assistant that could give users and designers inspiration and references in their design ideation process. Based on this core thinking and findings about modular doodling. We moved to develop a second prototype that focused more on using Generative AI.

3.4. Pre-workshop

Continuing from the last prototype of modular doodling study, we wanted to continue moving forward with the studies of design ideation, but replacing the Creativity Cues with Generative AI as design assistant methods. Therefore to understand better the current generative AI system and sense of ownership. We decided to conduct a small workshop with interviews of users using stable diffusion image-to-image generation to create a design to find potential problems and directions for our next prototype.

3.4.1 Procedure

The workshop was conducted virtually online. Participants were instructed to install and how to stable the diffusion official service dream studio to participate in the workshop correctly before the workshop. There are two participants, both are novice designers. One is an industrial designer, the other is a character designer. Both have never used generative AI tools before and show strong interest in trying.

The workshop contains two parts. Two parts of the workshop were conducted separately. In the first part of the workshop, the participants only used the image to image generation method without accessing the image prompt weight level control. The participant, the character designer, drew a character design and used it as an image input with the text to generate different image results. The participants can generate as many as they want until they are happy with the results. In the second part of the workshop, the participant who is the industrial designer would draw a sneaker design concept and use it as an image input with text input to generate results. Different from the first workshop, the participant has access to the image prompt level control. Both participants were interviewed and briefly talk about their overall experience and the problems of using current generative tools as design ideation tools.

3.4.2 Discussion

Regarding the overall experience: Both participants found using generative AI tools helpful and over their expectations, surprised by the speed of the AI to create results. They found the tools useful and has the potential to use ideation tool to inspire the designer in the early stage. Both workshop participants agree that the AI results were rather helpful in early ideation rather than the later refinement process due to the details that have been removed and reconstructed from the image input the participants have completed.

Regarding the sense of ownership: "My sketch has contained a lot of details, for example, I drew a rifle on the waist of the character. However the AI did not understand and removed the rifle and turned it to something else."

said by the character design participant. This shows the outcome of the AI was not expected by the Artist's users and therefore the sense of ownership was not obvious. "I feel more like the AI created the result instead of me creating it." The second workshop participant has a different story. Showing in figure 3.5, the participants have tried to generate different results with the same image input but different prompt weights. The different generative images show a pattern of changing details of the shoes with the variation of prompt weight level. According to the participant feedback, as the image prompt level goes higher, the less the AI follows his prompt, the less he feels like the final results of the images belong to his design idea.

Based on these feedback from the workshop with the participants, we decided to continue the prototype with the focus of exploring the possibility of influencing the sense of ownership with prompt weight level controls, and tackling the problems that users feel AI created the results rather than themselves.

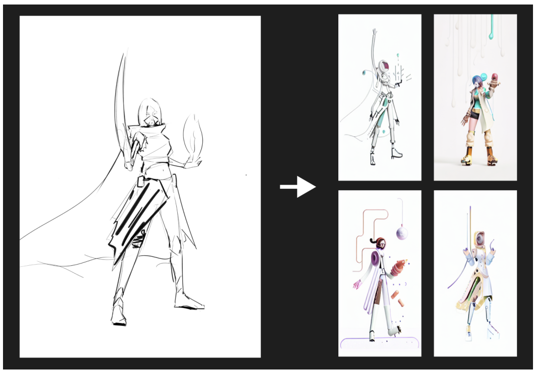


Figure 3.4 Pre-workshop part1 procedure.

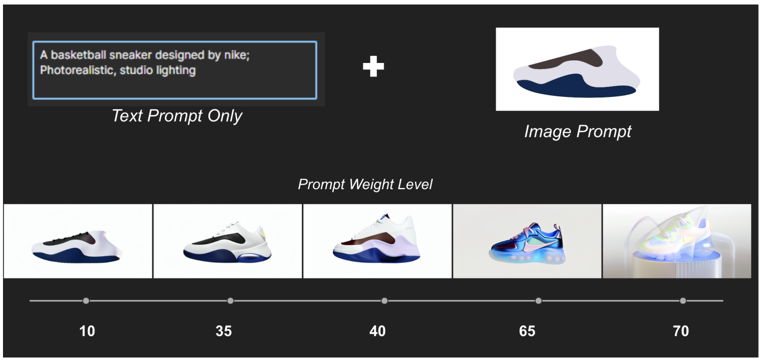


Figure 3.5 Pre-workshop part2 procedure

3.5. Second Prototype

3.5.1 Goal and Objectives

The second prototype would be built around the principle of using generative AI as assistive design tools, also with the implementation from the last prototype "modular doodling". With this prototype, the goal and objectives of the design is to find out the potential possibility to influence the sense of ownership of the results with image to image generative AI tools.

- How to influence the sense of ownership with image prompt weight level?
- What is the prompt weight range that can help artists create the most sense of ownership of the result?
- To understand to what extent people feel comfortable using co-created AI-generated work as their idea?

3.5.2 Concept Design

We designed design ideation drawing tools connected with generative AI, To further explore the potential to influence the sense of ownership (SOO) of AI results. We continued to use the concept of modular drawing from prototype 1, as the feedback from the experiment results proved it to be useful in creating confidence and creative thinking in the ideation process. In this prototype, we replaced the

Creativity Cues with Generative AI as an inspiration method to inspire the creating process. However, since the focus has shifted to exploring the prompt weight level and sense of ownership, the experiment and workshop will also be conducted differently.

We modified the Creative Support Index (CSI) questionnaire created by Erin Cherry and Celine Latulipe [48]. Upon the CSI, we also inplemented The Divergent Association Test (DAT): a quick measure of verbal creativity and divergent thinking, to the experiment. We designed a questionnaire called Prompt Weight Assessment Survey (PWS) to acquire the prompt weight level preferences from the participants.

3.5.3 Prototype Design

This prototype has these three main features:

- The modular drawing systems with refined interfaces with easier accessibility and contents of choices.
- Generative AI image to image generation: Generate images with 10 different prompt levels and saved the generation images
- Voting feature: Collect and shuffle the generation images and review images to participants for voting.

To correspond to these three functions, the prototype was built based on stable diffusion and Figma[2] to build the new drawing panel, while the drawing can be used and turned in the AI as image prompts. The generated images will be collected, and later input in the Google form as a platform for the participants to do voting regarding the generated results about their sense of ownership.

We picked stable diffusion as the main generative AI engine for our prototypes because it is open source and has been used by users widely, proving to be a popular AI tool. Furthermore, the image to image generation with image prompt weight level controls were first introduced by Stable diffusion. The switch from

2 https://www.figma.com/

scratch to Figma to build the drawing feature was because based on the user's feedback from the last experiment, the tools in scratch has limitations in operating and adjusting the shapes, and lack the features of undo. To maximize the user experience quality and reduce the physical effort of using the drawing tools, we decided to adopt one of the most well-known online design project tools, Figma. This has allowed the d us to build the prototype for our design pipeline, even more, quicker, and effortlessly. Figma allows us to create drawing panels with the ability to undo, change scales without keeping the ratio, change colors, etc.

3.5.4 Method

To understand how prompt weight level can influence the sense of ownership, this prototype was built specifically to find out the prompt weight level range.

Participants We searched for novice designers and people who have not yet experienced professionals design training before to participate in our workshop. 10 Participants from 18 to 25 years old participated in this experiment. 8 participants have no design knowledge and little design task experience before, and 2 participants have 1 year of learning design knowledge or working in design-related work. All participants participated remotely in the experiment using their remote controls and zoom video calls and screen sharing.

3.5.5 Procedure

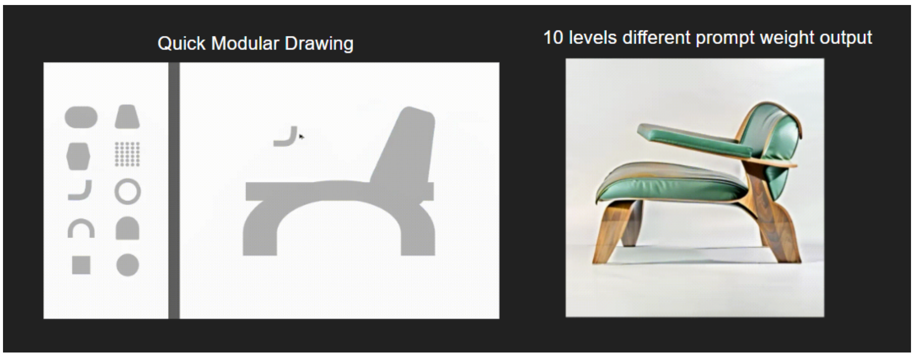


Figure 3.6 Pre-workshop part1 procedure.

All participants participated in the same experiment with the second prototype. Each participant participates individually online. The workshop contains three main sections. First drawing section: before the workshop began, the instruction on how to use the drawing panels was given, and allowed them to get used to the tool until they are comfortable enough to start the workshop. The first section is a free drawing section. The subject of the drawing is a chair design. Users have no time limits to finish three-chair designs and can edit however and as many times as they want. Once they finished the drawing, they will select one to be their favorite. Then a short break will be given. At the same time, the drawing is processed in generative AI stable diffusion to generate 30 image results with 10 different prompt weight levels. The range of the prompt weight level is from 0 - 100, categorized into 10 groups. They are 10,20,30,40,50,60,70,80,90,100. Each prompt weight level generates three different images and the prompt weight number will be tagged to each generated image accordingly. After the generation is completed, the second section is the voting images section. 30 images in total will be imported into a Google form to ask participants to vote for each image, "To what extend does the image represent your idea?" The prompt weight level would not be reviewed by the participant, the orders of the image shown to the participants were in random order, therefore participants would not notice the relationship between each image in terms of prompt weight level. Each prompt weight level are being rated on a scale of 1 to 5. The 5 means the higher sense of ownership Score (SOOS).

The DAT tests will be given twice, one each before and after the drawing section and the voting section. CSI test will be given once each section is completed. The PWS will be analyzed after the experiment.

3.5.6 Result

Creative Support Index: Comparing the Creative Support Index Score after the first second of drawing and the second section of AI image generation. Satisfaction, Creativity was increased in the AI generation section. Physical Effort and Comfort remain the same after both sections. The Enjoyment, Mental Effort, and Sense of Ownership were decreased after the section when the AI image generator involved.

Figure 3.7 10 different prompt weight levels.

Table 3.4 Creativity Support Index

	Enjoyment	Satisfaction	Creativity	Mental	Physical	Comfort	Ownership
1st Section	4	2	3	3	3	4	4.5
2nd Section	3	3	3.5	2	3	4	2.5

Divergent Association Test: To avoid of experimenter expectancy effect, participants were not informed about the score or how the Divergent Association Test functions. These test results helped us understand if the participant's creativity was increased after the involvement of generative AI. The DAT scores increased from 78.5 to 79.2 scores after the second section of the experiment, meaning the possibility that the participants have improved their creativity and divergent thinking ability after the experience of using the generative AI design tool. However the DAT only calculates the divergent thinking aspect of human creativity and verbal creativity, it could not represent every aspect of the creativity behaviors and characteristics. This at least gave us a little bit deeper understanding of the prototypes and creativity ability changes.

Sense of Ownership Assessment: This is the main focus of this prototype and experiment. Table 3.6 has shown 1)the distribution of prompt weight levels that has been voted the giving the highest sense of ownership in the experiment. 2)

Table 3.5 Divergent Association Test

/	Before	After
DAT Score	78.5	80.2

Each prompt weight level average Sense Of Ownership Score. 3) The satisfaction scores of each prompt weigh level.

The average of Sense of Ownership Scores reveals that 70 is the highest Sense Of Ownership prompt weight level, and 80 and 100 are the second. 90 are the third which is also above 4 points.

The highest sense of ownership scores distributes the most in the 70 -100 prompt weight level. 70 prompt weight level has voted the best sense of ownership prompt weight levels the most in all 10 different levels. 80 and 100 have the second most votes.

The satisfaction scores reveal which prompt levels can generate the highest satisfied image results. This could help us understand the relationship between the sense of ownership and the satisfaction of generative AI tools. The distribution of the satisfaction scores is different than the ownership scores. The highest satisfaction scores are the 50 prompt weight levels. On the other hands, 70-100 prompt weight levels which have the highest SOOS are contradictory lower in satisfaction scores.

Table 3.6 Sense of Ownership Assessment Tests

PW Level	10	20	30	40	50	60	70	80	90	100
Ownership Scores	2	2.5	3	2	3.5	3	5	4.5	4	4.5
Highest SOOS times	0	0	0	0	1	1	3	2	1	2
Satisfaction Scores	1	2.5	4	3	3.5	4	2	1	1.5	1.5

3.5.7 Discussion

Here are the main points we learned from the second prototype and experiment results.

- We have a brief understand of the range of prompt weight level and its relationship with a sense of ownership. The sense of ownership could be affected by the changes in the image input prompt weight levels. Currently, the prompt weight levels are only round numbers and only have a range. The limitation is that the prompt weight number is too rough, but it is a starting point for the exploration. Next step we will divine more specific and accurate prompt weight numbers.

- Higher Sense of Ownership does not represent higher satisfaction. The images that generated a higher sense of ownership scores were relatively low in satisfaction scores because the images look the same as the original image input. We discovered it is a limitation that could be the reason why they were the highest sense of ownership. Therefore with that in mind, we want to develop a better solution to avoid limitations like this in the final prototype. Also, the goal of our design pipeline is not only to increase the sense of ownership but also the confidence in building up creativity. Therefore the final prototypes need to represent a high sense of ownership scores that also offer high satisfaction scores. According to the data we have so far, the "50" prompt weight range has the potential to be the ideal prompt weight to reach the requirement for our goal, but further experiment is needed to confirm.

- Based on the data of the results, we realized that how people interpret a sense of ownership and what they think could represent their design idea varies. Therefore it is relatively difficult to have a fix prompt weight level number that could work for everyone. Based on this understanding, for our final prototype, We need to design a customized prompt weight number for individuals to produce their best sense of ownership images.

Figure 3.8 Images by 10 prompt weight levels.

Chapter 4
Proof Of Concept

4.1. Goal

This chapter talks about the final prototype and one quantitative experiment and one qualitative experiment we conducted. The main goals we want to achieve through this experiment:

- to understand what was the prompt weight level number that could generate the highest sense of ownership
- to understand what design pipeline method could generate the most accurate prompt weight number that generates a higher sense of ownership
- to understand the AI ownership tools' impact on real design ideation scenarios regarding ideation quality, sense of ownership, creativity, and confidence.

4.2. Overview

The final prototype was developed to understand about the prompt weight level number and its relationship with a sense of ownership of the ideas. The goal of the entire design pipeline is to help users enhance their sense of ownership, ideation quality, and creativity confidence. The design pipeline has two main phrases:

- Prompt Weight Learning phrase: These steps allow the models to understand individual preferences of prompt weight numbers that could be used to generate a higher sense of ownership images. By allowing users to go through a pre-design warm-up process, the prototype will learn and remember the prompt weight number(PWN) range of individual ua users and apply the customized PWN to the second phase of the design pipeline.

- Co-creation ideation phrase: This phrase is with the prototype already understanding the prompt weight number based on users' previous design thinking behaviors and decision-making from the first phrase. The users would start the clay modeling ideation process with the assistant with assistance from the Own Diffusion prototypes. By giving real-time generative image feedback and inspiration, the users could continuously refine and ideate the design.

4.3. Final Prototype

4.3.1 Quantitative study

To understand better the prompt weight number range and the desired pipeline interaction method that will be used in the first phase of the pipeline. We developed three different prompt weight control methods and conducted a quantitative experiment to find out the answer.

Prototype design

Here are the three prompt weight controls methods to control the prompt weight level:

- Voting Control: This control method is designed to study the user preference prompt weight number by letting users vote and provide feedback to generative images. This is our proposed method that aims to enhance the sense of ownership. There are 10 buttons of voting options showcasing a scale from 1 to 10 regarding how much does the image represent the participant's design idea?

- Slider bar Control: This control method offers a slider bar that users can adjust the prompt weight level to generate images. The slider bar was included in this prototypes study to simulate the controlling methods of the existing generative AI tools product, such as dream studio by stable diffusion.

- Random Generate Control: This control method is a single button that allows users to click and generate new images without having precise control of the prompt weight level of the next generation. This method simulates most of the existing generative AI tool products, such as Dall-E2 by Open AI, Mid Journey, etc. This method is the most commonly used in image generators, therefore we want to include this method in our study to compare and understand the existing methods with our proposed design pipeline PWN control method.

Method

Participants Sixteen Participants participated in this study. Two undergraduate students and twelve graduate students, two workers, ranging ranging from 20 to 35 years old participated in this study. 56.2 percent of participants identified as male, 43.8 percent as female. Same as in the previous prototype workshop, the participants were selected based on their experience in design, 50 percent of participants have never studied design professionally, and the other 50 percent of participants have experience in design from 1 year to 5 years of experience. their gender. There are three controlled subjects groups, Voting Control Subjects, Slider bar Subjects, Random Control Subjects, and one baseline subject: No-AI subject group. Participants were evenly assigned to each group based on their identity as designers or non-designers. Each subject group consists of two designers and two non-designers.

Procedure

In the baseline round (No AI involves) the subjects were asked to use Modular drawing tools to draw a chair design sketch, then followed by a CSI questionnaire that was used in the second prototype experiment (Fig 4.1).

In the other three control subjects, there are two main sections. Subjects were asked to draw a chair in modular drawing panels; Second section users would start generating images using the sketch as image input and control generation method (prompt weight number). Third section: Subjects would draw another design object (A Lamp Design) in modular drawing and generate a final round image. There are three controlled subjects groups. The differences between the subject were in the second section of the experiment:

- The first group, Voting Control Subjects: Participants were asked to answer the question "How well does this generation image represent your idea?" and by voting with 10 options to answer the question using the 10 buttons on the voting windows Fig 4.2). Each button represents a corresponding number of adjustments in the prompt weight number. The prompt weight number has a range from 0 to 100. The first generation image starts with a prompt weight number of 50. Once any voting button was clicked, a new image will be generated with a corresponding adjustment in prompt weight. The buttons on the left-hand side scale from “very undeveloped“ to the middle "well develop" to the right-hand side "highly overdeveloped". The generation will stop when the participants clicked the “Finished” button. The final prompt weight number will be recorded. 1: -9, 2:-7, 3:-5, 4,:-3, 5, -1, 6: +1, 7: +3, 8: +5,9: +7, 10:+9.

- The second group, Slider Bar subjects: Participants were asked to use a slider bar to control and adjust each generation of images. The first image starts with the prompt weight of 50, which is in the middle of the slider bar. The participants could adjust freely for the next generation until they clicked the finished button. The final prompt weight number will be recorded.

- The third group, the random Control subjects: The participant has only one button called “Generate” to generate images without having the ability to adjust the prompt weight. Each time the “Generate” button was clicked, a random prompt weight number will be assigned to the next generative image. The participants can continue generating until they clicked the “Finished” button to stop. The final prompt weight number will be recorded.

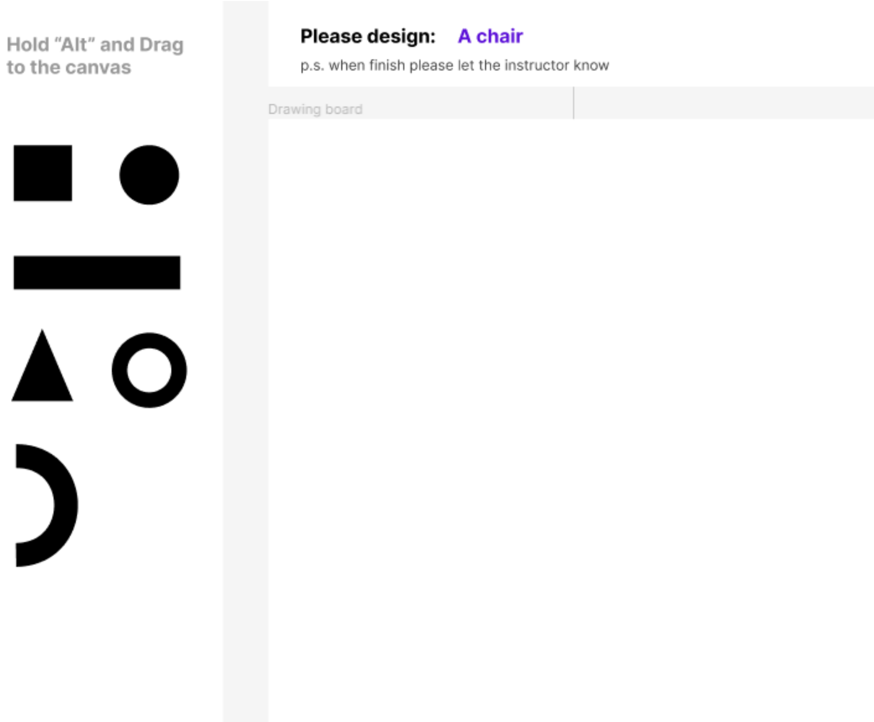


Figure 4.1 Modular Doodling Interface

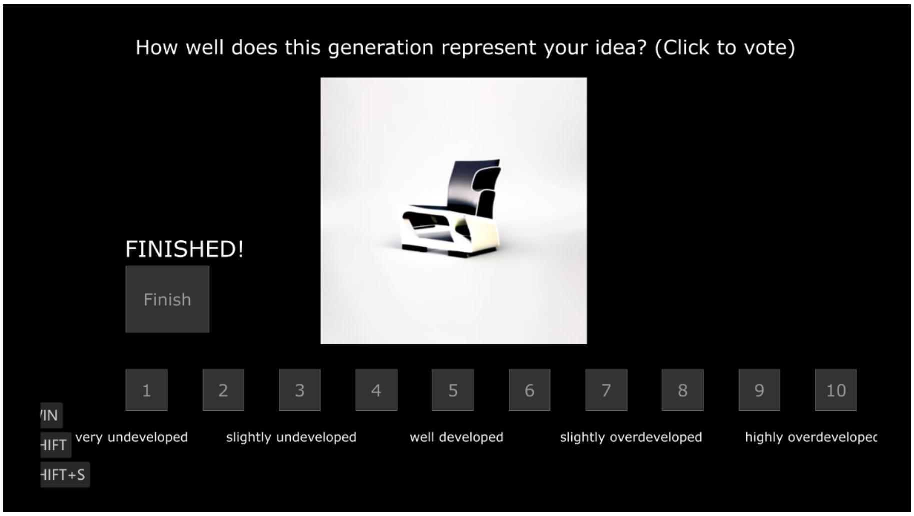


Figure 4.2 Voting Control Method Interface

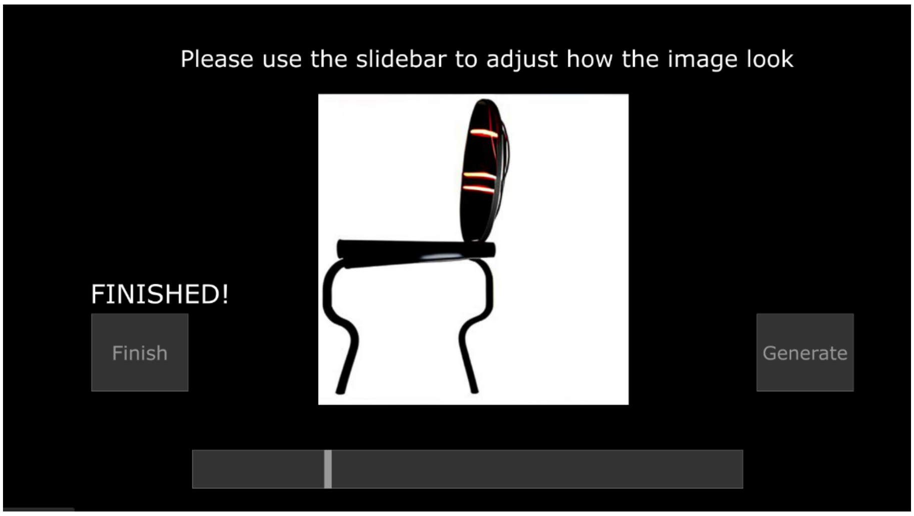


Figure 4.3 Sliderbar Control Method Interface

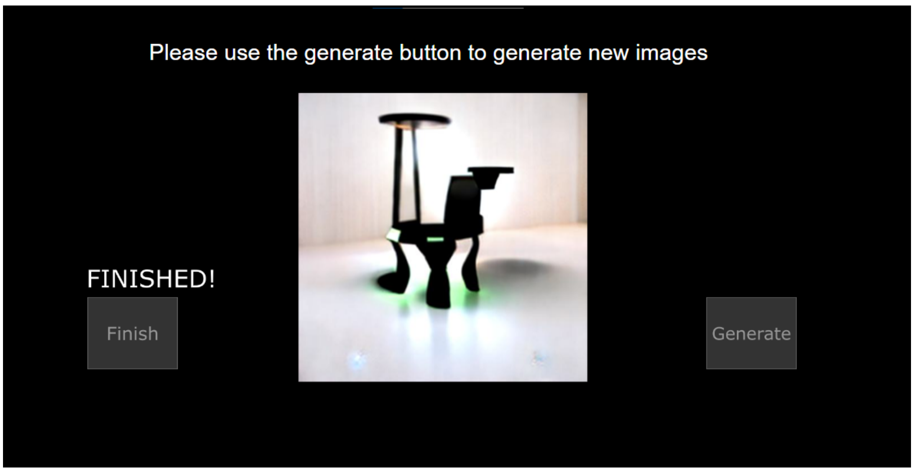


Figure 4.4 Random Generate Control Method Interface

Evaluation

Two types of evaluation data will be collected. One is the CSI questionnaire. Another is the prompt weight number by each participant in each subject.

4.3.2 Result

Creativity Support Index The main focus of this experiment was to compare the different impacts on the sense of ownership of the final idea. Based on Table 4.1, We found a significant difference among the four conditions on the overall CSI score. The ownership scores reflect that the baseline subjects have the highest ownership scores of 4.5. The voting control has the highest ownership scores among the three control subjects, higher than the Sliderbar subject (score: 3.75) and Random Subject (score: 3).

The other two indexes that we focus on are satisfaction and Creativity because we want the users to feel a sense of ownership, but also be satisfied with their work and feel promoted in creativity ability. Comparing the Satisfaction score among these four groups, the Baseline has the highest of 4.25, the Voting subject and the Sliderbar subject have the same score of 3.75 in the second place. The random is the lowest in satisfaction score with a score of 3.5. Comparing the "Creativity" index, the baseline and Voting and Sliderbar subject have the same score of 4, higher than the random subject.

The rest of the index, Enjoyment, Mental Effort, Physical Effort, and Comfort, were factors to understand how comfortable and easy to use the tools are. The lower the mental and physical effort indexes are, the less effort the participant feels during the tool-using experience. On the other hand, The higher the comfort and Enjoyment indexes are, the more enjoyable and comfortable the users would feel. Based on Table 4.1, Sliderbar is the most comfortable and easy-to-use method (Sum of Physical and Mental Effort: 5.5; Sum of Comfort and Enjoyment: 8). The Random subject rank in second place (Sum of Physical and Mental Effort: 6.25; Sum of Comfort and Enjoyment: 7.25). The Baseline subject rank at third place (Sum of Physical and Mental Effort: 6.5; Sum of Comfort and Enjoyment: 6). The Voting subject rank at fourth place (Sum of Physical and Mental Effort: 6.75; Sum of Comfort and Enjoyment: 6).

Table 4.1 Creativity Support Index

	Enjoyment	Satisfaction	Creativity	Mental	Physical	Comfort	Ownership
Baseline	3	4.25	4	3.5	3	3	4.5
Voting	3	3.75	4	3.5	3.25	3	4
Sliderbar	4	3.75	4	3	2.5	4	3.75
Random	3.5	3.5	3.5	3.25	3	3.75	3

Prompt Weight Number: The prompt weight number determined by each method in the subjects group allows us to analyze the prompt weight range in the generative AI, which would be an ideal range to prompt the best sense of ownership. The baseline subject does not have Generative AI involved, therefore the baseline subject would not have a prompt weight number range to be compared in Table 4.2.

Table 4.2 Prompt Weigh Number

/	Voting	Sliderbar	Random	All
Prompt Weight	52.9	48.2	60.3	53.8

The prompt weight ranges allow us to understand what is the suitable prompt weight range that generates the highest sense of ownership. Based on Table 4.2, we collected the average final recorded prompt weight number of each group and analyzed the total average number of the prompt weight number.

The total average of the prompt weight range is 53.8. The voting has the closest prompt weight number with the total average. The slider bar has an average of 48.2 and the random subject has an average of 60.3 prompt weight number. The total average (prompt weight number: 53.8) is pretty close to the rough (prompt weight: 50) collected in the second prototype number in Table 3.6. This result has given us a more precise prompt weight number and further confirms the accuracy of our evaluation of the prompt weight number related to a high sense of ownership.

In summary, based on the Voting subject can generate the highest sense of ownership results, and create the same satisfaction and creativity improvement as the Sliderbar subject, while the Sliderbar subject has the highest comfortability. The prompt weight number range analysis shows that voting subjects can generate the most accurate prompt weight number than other subjects' methods.

Discussion

The results from the first quantitative experiment give us two main pieces of information. 1) the prompt weight number range is around 53.8 can generate a higher sense of ownership results in generative AI design tools. 2) The Voting method in generative AI is better than slider bar and random prompt weight control methods.

To highlight our focus on creating the highest sense of ownership and satisfaction and creativity for the users, we prioritize these factors over comfortability. Therefore we decided to use the Voting Control Methods for our final prototype design pipeline. The next step would be conducting a qualitative experiment with a real design scenario using the final prototype.

4.3.3 Qualitative Study

To understand the impact of our proposed design pipeline on the user's sense of ownership of the final results, satisfaction, and creativity confidence when using the generative AI tool, we conducted a qualitative experiment in a real design ideation scenario.

Prototype design

In this final prototype design, we focus on using the voting control method and our modular drawing to build a design pipeline to help users do physical design ideation to improve their sense of ownership of generative results, satisfaction with the design, and creativity confidence.

In this physical design ideation experiment, we focused on allowing the users to use clay models to build chair models with generative AI being the creativity reference. Here are the three main components of the final design pipeline.

- Modular Drawing: This component allows users to easily and quickly draw design concepts using the shape modular. This feature of prototypes has been proven from the previous workshop to be helpful and efficient in design ideation.

- Voting Control of prompt weight: This control method offer allows the generative AI tool to understand individual users' preferences of prompt weight numbers that can generate a high sense of ownership and apply the prompt weight number for each generative image.
- Camera Image capture input with generative AI: This component uses a camera to capture the clay models in real-time during the physical design ideation and use the captured image as input to the generative AI. The generated image results would be displayed as creativity references to inspire users to adjust the clay model during design ideation.

Method

Participants Three participants participated in this study. They are all non-designers or have design backgrounds or knowledge, ages range from 23 to 26 years old. 2 are male, and one is female. They were selected based on their nondesign background and interests in learning design and improving creativity.

Procedure

Prompt Weight Test Before Ideation

Before the real case tangible design ideation, participants were asked to use modular drawing to do design sketches and input into Generative AI with Voting Control prompt weight methods to understand and review their proper prompt weight level that reviews a high sense of ownership. In the Prompt Weight Test Before ideation, the participants were asked to draw a lamp design with no time limitation, once they finished their drawing will be sent to an AI Image generator to generate results. Every result and corresponding prompt weight number of each image can be adjusted with the voting system until the participants were happy with the results. The final prompt weight number that participants are satisfied with will be recorded.

Clay Model Making Design Ideation

This experiment focuses on physical prototyping in design ideation. Making models with clay is a common tangible ideation method in industrial design. To test out the impact of the own-diffusion design pipeline, we experimented with three participants in the clay model ideation process. Three participants were separated into three different subjects.

- First subject is the baseline group with no generative AI involved. The participant would use a modular drawing tool to design a chair, then make a clay model of the chair drawing.
- Second subject is the generative references group. The participant would go through the Prompt Weight Test before the ideation, then use the modular drawing tool to design a chair. Using the chair drawing, Participant would make a first clay model. Then the system would generate a reference image generated with the final prompt weight number recorded from the prompt weight test. Finally, the participant would make the second clay model from the AI resulted images as references.
- Third subject is the real-time feedback AI generation group. The participant would go through the Prompt Weight Test before the ideation, then use modular drawing to design a chair with the final prompt weight number from the PWT. Lastly, the participant would make clay models with real-time generative AI feedback as references by using a camera shoot of the clay model as the image input. Participants can constantly make new adjustments based on the generative images.

Set up

We set up a photo backdrop with studio lighting for the participant to put the clay models. The web camera was located to take photos of the clay models to use as image input into the generative AI stable diffusion that was built in Touch Designer on the laptop (Figure 4.6). The participant can generate images by clicking the "generate" button on the interfaces shown in Figure 4.7. Four reference generative images will appear on the interface window. The participant can adjust the angles of the clay model to input and generate different perspective looks of the chair design. The generative results would work as references to continue to inspire the users to keep modifying the models (Figure 4.5).

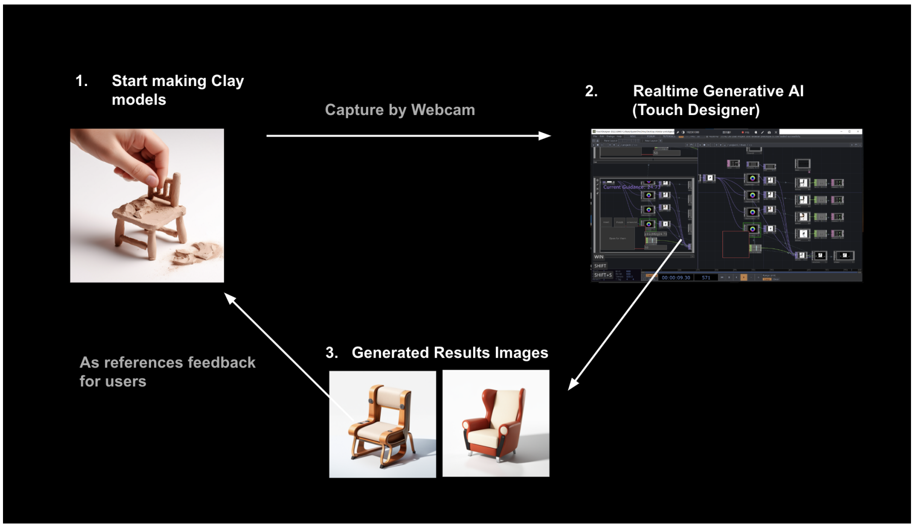


Figure 4.5 Real Time Generative Feedback Wireframe

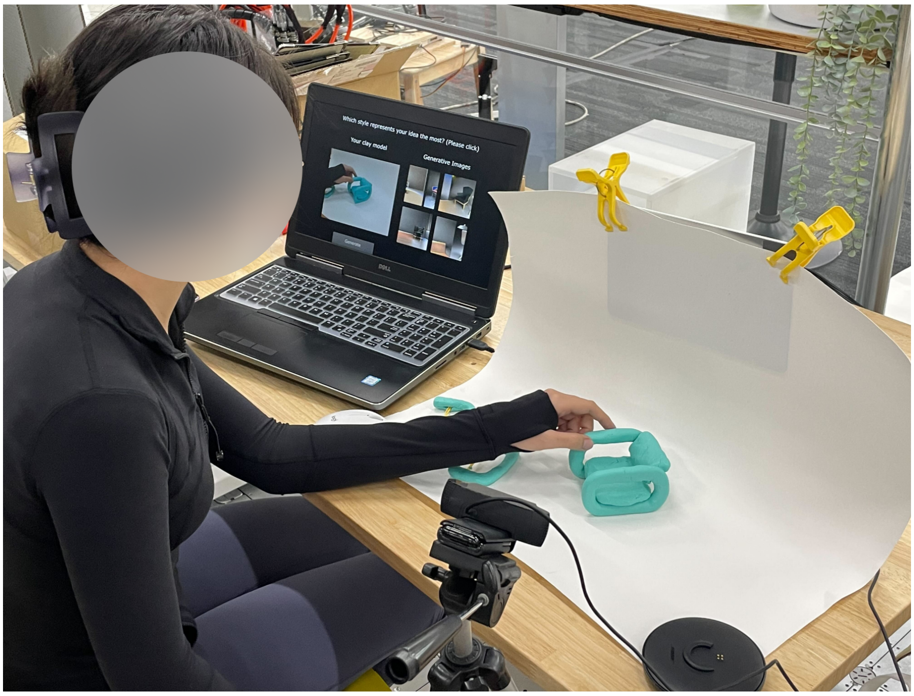


Figure 4.6 Participant trying out prototype

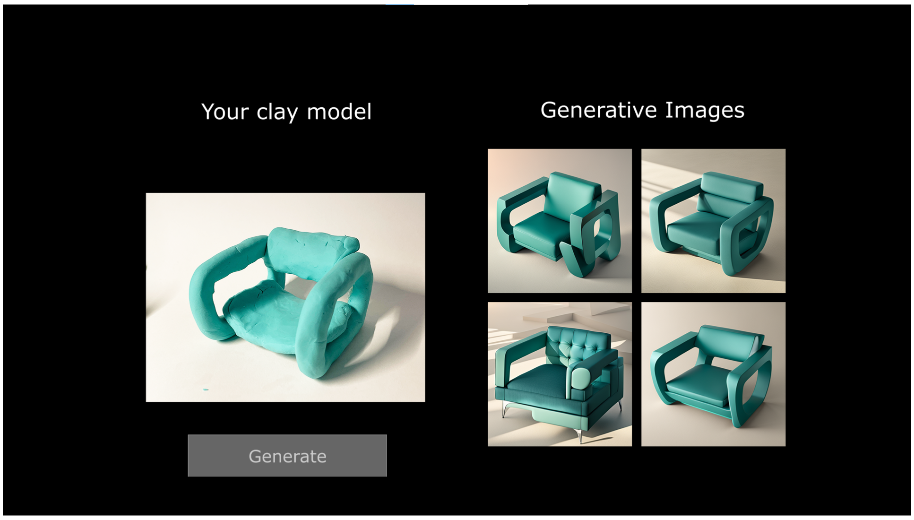


Figure 4.7 Final Prototype Interface

4.4. Result and Discussion

Three subject groups provide us feedback with on how the clay model of the chairs, and the design of the chair were developed during each condition. Through the development processes of each participant's concepts and the feedback from the participants, we have some insights regarding the own-diffusion design pipeline's impact on producing a high sense of ownership results and how it apply in real design ideation situation. The participants were interviewed and asked to provide feedback on the current design pipeline, their sense of ownership, and design confidence.

4.4.1 First Subject

The participant drew a chair with a modular doodling tool and took the sketches as references to make a clay model. Figure 4.9 showed that the chair model shared a high resemblance with the drawing. Based on the participant feedback, "The modular doodling tool allowed me to come up with the chair design quickly. I didn't struggle to pick the shape and think about how to construct the chair for too long. However, the clay modeling process was a little challenging for me. I struggled to make the curved legs for the chair with clay since it is soft and hard to support the weight of the chair's body. Even after the clay model was finished, I was not too surprised by how the clay model looked at the end. It did give me some more information about how the chair shape would look in a 3D world, but I think the chair looks less interesting in 3D. I wish I could add more details but I struggle to know how". The feedback provided us with the following information regarding the design pipeline:

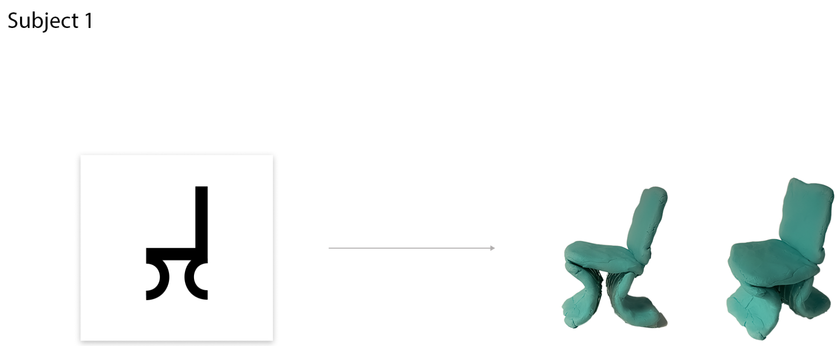


Figure 4.8 Subject 1 development process

Positive Feedback:

- The modular doodling helps quickly come up with design ideas without struggling to overthink.
- The clay model helps me get more information on the chair design in 3D.

Negative Feedback:

- The clay model was challenging and hard to be creative with at the same time
- The clay chair models lacked details and the participant struggled to know what and how to develop the design in the next step.

Regarding Sense of Ownership:

The participant feel a high sense of ownership of the idea because he said "I came up with the chair design by myself without taking references of other people's ideas nor copying anyone's design. Therefore I am confident to say I design this chair." This baseline subject does not have AI involved, and based on the participant's feedback, the sense of ownership of this process is high.

Regarding improving confidence in design: "I did feel comfortable designing if I can use the modular design tool because it is easier than drawing the chair with a pen. I am not sure about how my confidence in design has changed overall, but I think It is a good start for me to be creative and learn design." The participant was not clear about the confidence improvement, but he feels comfortable using the tools to design a chair as it is easier compared to drawing ideas on paper.

4.4.2 Second subject

In this subject, the participant drew a chair design and made a first clay model based on the drawing, then the drawing was input into a generative AI model to generate AI reference images to inspire the participant to adjust and make the second clay model. We compared the differences between the first clay model chair and the second clay model chair and also interviewed the participant regarding the feedback on the design pipeline.

The participant interview key sentences: "I feel comfortable using modular doodling to design chairs, I didn't expect it to be that easy, because I never design a chair before. I was excited to see what I designed." "The clay modeling-making process is fun to me. I did spend some effort in making the clay model structure to support the weight, but It turned out better than I thought." "However it was hard to change the proportion of the chair component, I realized I made the seat too big than my drawing, but I couldn't make it too small because it has to hold the legs of the chair." "I guess the clay modeling ideation process gives me ideas about things that might need to consider if making the chair in reality with material which I would never think about if only making a design on screen or paper." "The generated results of my drawing are helpful. They allowed me to see more details of a real chair with the shape of my design." "I took inspiration from the AI images and make some adjustments to the first model" "I tried to add more details, for example, the headrest on the back of the chair. I added cushion support on the back because the references reminded me that the chair needs to look comfortable as well." "Regarding the final generated images based on my clay model, it is very exciting to see the AI can follow my clay model and design shape to generate a realistic chair image. However, I still think it was not a hundred percent exactly how I pictured the chair to look in reality. But it did give me more information and push my chair design concept a little further."

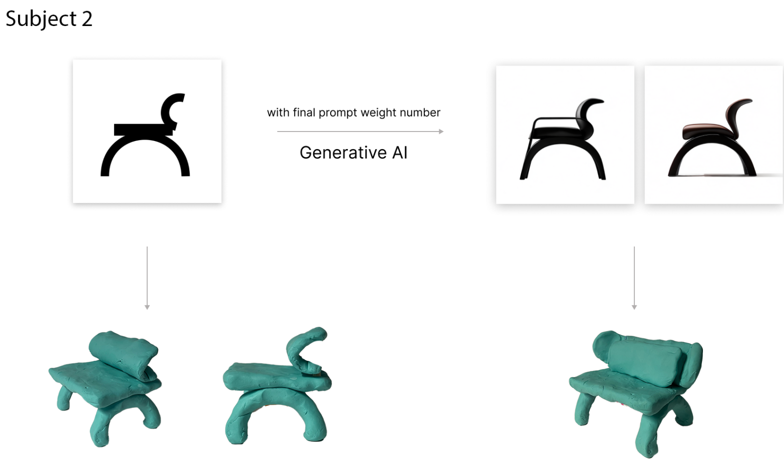


Figure 4.9 Subject 2 development process

Positive Feedback:

- Modular doodling tool helps users feel comfortable to begin designing objects.
- The clay modeling process helps users to think more about how the drawing of the chair would look in reality, because the chair has to support weight in reality.
- The generative images inspired me to add more details.
- The generative images give more information for users to learn how to create a design that can be potentially made in reality.

Negative Feedback:

- The clay model was hard to change the proportion of the design object because considering the function of the weight support, in reality, is necessary.
- AI image result was not the same as the users expected.

Regarding Sense of Ownership:
"I think the final images generated by AI were taken from the design idea from me, even though it was not hundred percent the same as I expected, but I think the overall design elements were picked up from my clay model and modular drawing. However some of the design elements on the images were not designed by me, so there is a loss of sense of ownership when I saw those irreverent elements." The participant feels some extent of a sense of ownership of the idea with the final results of the image. It could be improved if the users feel more control of the details in the image.

Regarding improving confidence in design: "I was not expected myself to come up with a chair design. So I think using this design pipeline or tool would help me be more confident to create a design concept. However, I was not sure if my confidence in my design ability will increase if without the help of the tool and AI still." The participants said. It helps the user to be confident with the tool and design pipeline but unsure about the impact of the confidence without the design tools.

4.4.3 Third subject

In this subject, the participant drew a chair in modular design and start making clay models based on the drawing. The camera was capturing the model in real-time and used as image input into the AI model, the participant can generate AI images based on the current clay model to help make progress in this ideation process. Each generation's images would provide new feedback and inspiration.

The participant interview key sentences:
The participant said: "The modular doodling tool helped me to draw the chair quickly, but I was not exactly sure how it will look in 3D form." "Making clay model was a great process for me to learn to understand how a 2D flat image

would turn into 3D." "Making clay models is challenging because it requires me to know 3D." "With the real-time AI generative images help, even though it is a little scary because I was worried if I made a bad looking chair, the AI images would inspire me and work as a reference for me to work on the model." "Each generation's images were different, I was always looking for some elements that were new to me and thinking about if I can use them to adjust my clay model." "For example, I saw an image with a circular shape armrests and I made changes based on it to look the same." "It is the s easy to refine the chair and know where to start because the image was based on my clay model with the exact position and proportion." "The final generative images still were not exactly how I imagine the chair to be like in reality." "I think it was because the clay model I made has a much thicker arm, while I was imagining the real chair to have thinner metal tubes as the chair arms."

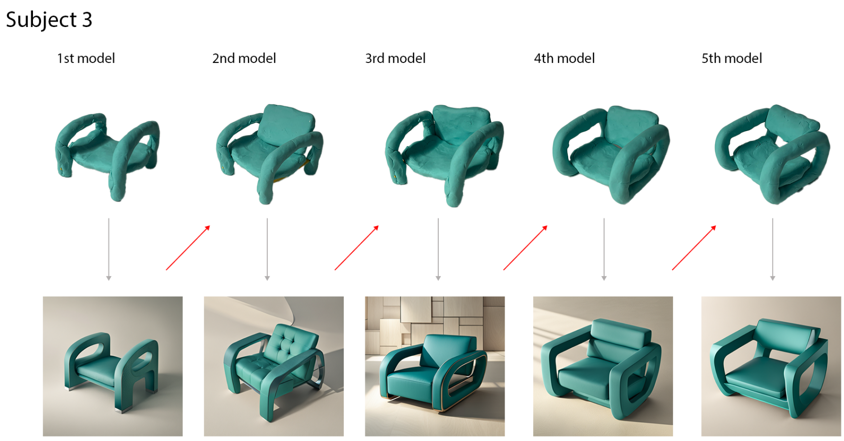


Figure 4.10 Subject 3 development process

Positive Feedback:

- Modular doodling tool helps non-designers easy to start designing.
- The clay modeling process is a great opportunity for users to learn and think about the relation between a 2D drawing and a 3D form.

Figure 4.11 Three subjects clay models comparison

- The real time generative AI with a camera helps me feel less scared to make a clay model from a 2D drawing because it is constantly providing me feedback on how to make the shape.
- The generative images would provide new and different elements that can inspire me to make changes and improvements to the clay model.
- The real time AI feedback make it easy to adjust models with more details because it follows the exact same proportion and position of the clay model.

Negative Feedback:

- The modular design tool only depicts a 3D design object in 2D.
- AI image followed the clay model's shape instead of the user's imagination of the chair design proportion in reality, which caused the final generative results slightly off the user's expectation.

Regarding Sense of Ownership:
"I think I will say I designed the ca hair by myself, so I think I own the ownership of the design idea or concept of the chair. Making adjustments and iteration gave me more control of the details and overall design elements of the chair concept."

The participant feel a sense of ownership of the chair design because of the steps of refinement and iteration during the process she made offered control of the details.

Regarding improving confidence in des pieces of ign: "I think the design pipeline and process helped me feel less scared to start design ideation from scratch. The feedback from AI provided me with enough realism and details for me to start and make adjustments to the clay model of my chair design. I think it improves my confidence if someone asked me again to make a chair design drawing or clay model." The participant's confidence has been improved with the experience of using the design pipeline.

4.4.4 Discussion

The results show that the overall design pipeline with the modular doodling and real-time generative AI feedback received positive feedback that it helps users feel more comfortable to start designing, increasing their sense of ownership of the generative results. The camera capturing the models and generated AI images would help users gain detailed and realistic information about the design while keeping the same proportion, position, and angles of the clay model, making the generative images receive a higher sense of ownership and providing more constructive information to help users refine their design.

However, there remains some problem regarding the design prototypes and how they could be used in real design situations. Firstly, even though modular doodling has been provided with the previous experiment of our research that helps people with design ideation and improves confidence, there are still some difficulties for users to learn how to design 3D objects in only 2d media form. secondly, the generative AI results retain the potential for improvement in the sense of ownership for users, because the AI models closely followed the image input which contains information like position, proportion, angles, shape, colors, lighting, etc. This is information that helps the results look close to the user's input while the materials and the color can only be whatever the color of the image input (input), making the final results less realistic like a chair in terms of materials and colors. This could potentially influence ta the sense of ownership of the ideas. We found that users want the AI to generate images that follow the image input so it looks like they have control of the element instead of generating images by combining images online, but the users also hope the AI would be smart enough to figure out what elements they do not want the AI to follow, such as the color, materials, sometimes a proportion of specific elements, for example, the arm thickness in the subject 2. (Feedback provided by Participant 2.) Therefore in our next prototype, we want to provide options that could help users gain more precise control of AI generation.

Considering this experiment only from d three participants participated, and the feedback was collected in the interviews which might cause bias in the result. In the next step, we want to focus on conducting a quantitative experiment of the own-diffusion design pipeline that could give us more precise data about the experiences and their impact on people's sense of ownership.

Chapter 5
Conclusion

This research was intended to explore a new generative AI design ideation pipeline that can help raise the sense of ownership, and improve creativity and confidence for novice designers and design learners. With the background of up-growing generative AI technology, we tried to solve the problem and fill the gap of the design-related generative AI by creating a design pipeline to improve the sense of ownership of the generative results. With the current AI tools, anyone can easily generate beautiful drawings or renderings by writing a sentence input and combine with a simple 2D drawing image input from the users. However, the results and the idea of the drawing would be treated as created by AI, making the users feel less participated in the creation process and has less relationship with the final results even though the idea of the drawing and the sentences were coming from the users. The users of image generators need to feel ownership of the idea from the collaboration with AI in the image to image generation technique to create comfortability to use AI to benefit the design community in design processes.

The image prompt weight in generative AI is a factor that researchers have been less discussed, which we have found effective in influencing users' sense of ownership of the generative images. By conducting multiple workshops and experiments, we have identified a specific prompt weight range from the result that could generate a higher sense of ownership image results to help design learners feel confident and intuitive to using generative AI as a design ideation tool. We design our Own-Diffusion design pipeline to include a voting method to personalize and further precisely understand the prompt weight range for different individual users.

We also conducted quantitative and qualitative experiments to test the main components of our design pipeline and prototypes. Modular doodling is a modular drawing feature that was shown to help non-designers to come up with design ideation efficiently with more quantity of design and in less time. We experimented in real design ideation cases with our design pipeline to help design learners create clay model design ideation. The results and the feedback from the users were positive that the design pipeline with modular doodling, prompt weight voting control methods, and real-time generative feedback using a camera could benefit users to develop high-quality and intuitive design ideation.

Aside from the limitations on the amount of data, other works regarding the design pipeline and experiment content can be improved for future studies. For the current prototypes, we still need to give users more control of the image input to generate a higher sense of ownership of image results. Such as the materials and colors in the AI models would still follow only the images. For the experiment content, we still need to further explore and conduct quantitative experiments to identify the impact of the prototype of the design pipeline that would affect tangible clay model design ideation and how a non-designer would gain more confidence in design ability without the tools and pipeline.

To sum up, this research attempted to explore the possibility to solve the problem of owning the design idea of the AI generative images and fill the gap of the design pipeline using controlling the prompt weight range to affect the sense of ownership of Generative AI in design ideation. We even explore the potential area to use the camera and generative AI to benefit the physical modeling ideation for non-designers. The result suggested that the sense of ownership of a generative image could be affected by controlling the prompt weight range and a specific prompt weight range that could maximize the sense of ownership.

As the capabilities of generative AI technologies continue to expand, their integration into various fields is becoming more widespread. Applications utilizing generative models need to focus more on creating human-centered AI that can provide users with more control of the application to improve the sense of ownership of the outcome and efficiency as the technologies of AI are being developed so fast. More guidelines and attention are needed for research and developer to tackle this problem Otherwise there might be harm to humans from AI very soon in the future. Questions like Will we be replaced by AI? The answer now is probably that We will not be replaced by AI but instead, we will be replaced by the people who used AI. However, people who learned how to use AI as a tool to improve their efficiency do not gain personal and inner growth in creativity, design thinking, and problem-solving skills. The AI technologies would be over-relied upon, which can become really dangerous. Therefore our research aims to focus on how the future AI application could possibly be more human-centered to allow users to gain control of AI and a sense of ownership of the outcome.

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