OwnDiffusion: A Design Pipeline Using Design Generative AI to preserve Sense Of Ownership

Yaokun Wu
Keio University Graduate School of Media Design
Yokohama, Japan
yaokun.wu@keio.jp

Kouta Minamizawa
Keio University Graduate School of Media Design
Yokohama, Japan
kouta@kmd.keio.ac.jp

Yun Suen Pai
Keio University Graduate School of Media Design
Yokohama, Japan
pai@kmd.keio.ac.jp

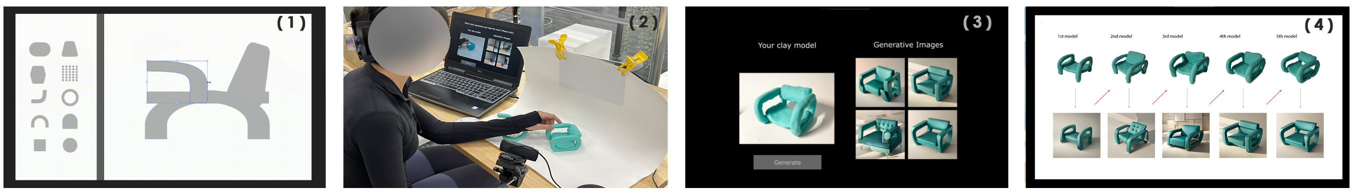

Figure 1: The user utilizes the (1) modular drawing tool for a design concept drawing that inspires physical prototyping ideation. (2) A real-time camera captures clay model photos, (3) input into Own-Diffusion Interface for AI-generated inspiration images,(4) Users iterate on models inspired by these generative images.

ABSTRACT

Generative Artificial Intelligence (AI) has been a fast-growing technology, well known for generating high-quality design drawings and images in seconds with a simple text input. However, users often feel uncertain about whether generative art should be considered created by AI or by themselves. Losing the sense of ownership of the outcome might impact the learning process and confidence of novice designers and design learners who seek to benefit from using Generative Design Tools. In this context, we propose OwnDiffusion, a design pipeline that utilizes Generative AI to assist in the physical prototype ideation process for novice product designers and industrial design learners while preserving their sense of ownership. The pipeline incorporates a prompt weight assessing tool, allowing designers to fine-tune the AI's input based on their sense of ownership. We envision this method as a solution for AI-assisted design, enabling designers to maintain confidence in their creativity and ownership of a design.

CCS CONCEPTS

• **Computing methodologies → Artificial intelligence**; • **Human-centered computing → Interface design prototyping**.

KEYWORDS

Virtual Reality, Journaling, Emotion Regulation, Avatar, Empathy, Mood, Reflection

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1 INTRODUCTION

Physical prototyping refers to creating tangible models or mock-ups as part of the design process to visualize and refine ideas, which has an impact on augmenting creative capacities among young learners[Indrasati et al. 2018]. Co-creative systems with artificial intelligence (AI) in the design process can fuel the creation of novel, diverse, and quality design solutions [Kim 2022]. However, with the integration of generative AI into mainstream design applications, there is an urgent need for guidance on designing these applications to be human-centered AI in order to facilitate a sense of ownership [Weisz et al. 2023]. The sense of ownership (SOO), in the context of ideas, refers to the psychological phenomenon where an individual feels that an idea is their own. People's feelings of ownership when they utilize AI to create something can be complex and multifaceted [Eshraghian 2020]. We believe that a design pipeline applying AI with guidelines can instil a strong SOO. We introduce OwnDiffusion, a design pipeline that helps novice designers conduct physical prototyping ideation from sketching and generate real-time ideation inspiration feedback with the help of Generative AI to improve SOO. The contributions of this work are twofold: 1) We propose OwnDiffusion, a generative design pipeline where designers can generate real-time inspiration image feedback from the physical models in the process of prototyping ideation. Furthermore, 2) we discuss the relationship between the Prompt Weight Number (PWN) and the SOO of the generated outcome in generative AI research and identify a suitable prompt weight range for high SOO.

2 DESIGN AND IMPLEMENTATION

The workflow of the design pipeline is as follows: 1) Using modular drawing to create a design concept drawing. 2) Using the drawing as inspiration to conduct physical prototyping ideation by making clay models. 3) Using the camera to capture the model's image as input to generate real-time AI image feedback to inspire the user's modeling process. 4) Continuously iterating and refining clay models with generative image feedback until satisfied.

2.1 Modular Drawing Tool

We created the Modular Drawing Tool, a web-based drawing program using Figma[1], that helps users without a design background easily compose a design concept using various module shapes in a silhouette format. This concept can then inspire clay modeling and prototyping ideation.

2.2 Prompt Weight Assessing Tool

The PWAT helps users identify the most suitable PWN to generate a higher SOO of generative images. Users are asked to rate the performance of generative images in terms of matching their own image prompt on a scale of 1 to 10. Each rating influences the PWN, generating new images for voting until users click the "Finish" button, at which point the PWN is recorded.

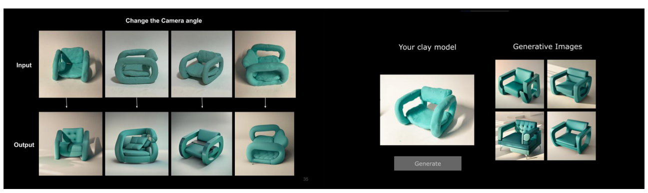

Figure 2: Different perspectives of Image input

2.3 Real-Time Modelling Feedback

We built OwnDiffusion using Touch Designer[2] and Stable Diffusion[3]. The web camera was set up and connected to Touch Designer to take photos of the clay models as image input into the generative AI. The users can generate images by clicking the "generate" button on the interfaces shown. Four reference generative images will appear on the interface window. The users can adjust the angles of the clay model to generate different perspective looks of the design. The generated results then work as references for future designs.

3 INITIAL STUDY

We conducted two initial studies for OwnDiffusion (Fig. 3). All participants were non-design background college students with a tendency to learn design, aged between 18 and 24 years old. The first study is a quantitative assessment of PWAT components in OwnDiffusion and the relationship between PWN and SOO. Sixteen participants (8 males and 8 females, mean age: 21.25, SD: 1) were recruited. We designed three different methods of controlling PWN (Slide-Bar Control, Voting Control, Random Control) to evaluate which one accurately assesses PWN with a high SOO. For the second study, we invited 6 participants (3 males and 3 females, mean age: 21.5, SD: 1) to be divided into three groups for a qualitative evaluation. The first group received no AI feedback. The second group received AI feedback after clay modeling ideation. The third group utilized the OwnDiffusion Design Pipeline. We assessed how the design pipeline affects the physical ideation process for novice designers. To evaluate SOO, creativity, and confidence during the experiment, we adapted the Creativity Support Index (CSI)[Carroll and Latulipe 2009], which was designed for evaluating creativity support tools to measure the concept of Ownership.

[1] https://www.figma.com/
[2] https://derivative.ca/
[3] https://stablediffusionweb.com/

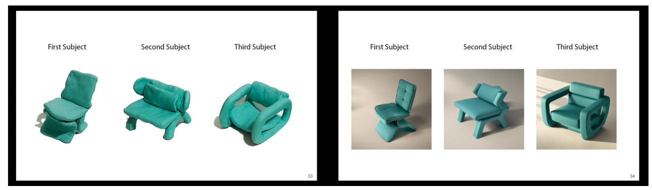

Figure 3: "Sort by emotion" feature in VR application.

4 RESULTS AND DISCUSSION

The Voting Control group has the highest SOO score (4.5), compared to the Slide-Bar control group (score: 3.75), and the Random Control group (score: 3). The results of the average PWN from the three different groups show: the Voting Control PWN is 52.9, which is closest to the overall average PWN of 53.8, compared to the Slide-Bar Control PWN of 48.2, and the Random Control PWN of 60.3. This indicates that the Voting Control method can generate the most accurate PWN and has the highest performance in generating high SOO compared to the other control methods. The results of the Second Study show: Modular Drawing helps design learners feel more comfortable starting to design from scratch with higher-quality ideation. The OwnDiffusion Design pipeline assists non-designers in gaining detailed and realistic information about the design subject, providing more constructive insights to help users refine their designs with a higher sense of ownership.

5 CONCLUSION AND FUTURE WORKS

OwnDiffusion's pipeline can potentially assist designers using AI while preserving ownership, and we plan to expand this to a variety of designs with an in-depth evaluation.

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