ProtoDreamer: A Mixed-prototype Tool Combining Physical Model and Generative AI to Support Conceptual Design

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Figure 1: A prototype process supported by ProtoDreamer. (a). A designer conceived and prototype the design of a *beach vehicle* through embodied interaction with tangible objects and physical materials. (b). The designer utilized ProtoDreamer to rapidly explore high-fidelity schemes. He captured a image of the physical model and inputted design requirements through voice: "*This is a Cyberpunk-style beach vehicle, the green part is the light and the blue part is a cockpit with transparent glass*". (c). Upon generating a satisfactory candidate scheme, the designer proceeded to mask local areas for refinement and optimization. (d). After the prototype has been realized through 3D modeling and printing as the first version, the designer further added physical materials on the first version model for rapid, on-site iteration via ProtoDreamer. (e). ProtoDreamer's user interface.

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ABSTRACT

Prototyping serves as a critical phase in the industrial conceptual design process, enabling exploration of problem space and identification of solutions. Recent advancements in large-scale generative models have enabled AI to become a co-creator in this process. However, designers often consider generative AI challenging due to the necessity to follow computer-centered interaction rules, diverging from their familiar design materials and languages. Physical prototype is a commonly used design method, offering unique benefits in prototype process, such as intuitive understanding and tangible testing. In this study, we propose ProtoDreamer, a mixed-prototype tool that synergizes generative AI with physical prototype to support conceptual design. ProtoDreamer allows designers to construct preliminary prototypes using physical materials, while AI recognizes these forms and vocal inputs to generate diverse design alternatives. This tool empowers designers to tangibly interact with prototypes, intuitively convey design intentions to AI, and continuously draw inspiration from the generated artifacts. An evaluation study confirms ProtoDreamer's utility and strengths in time efficiency, creativity support, defects exposure, and detailed thinking facilitation.

CCS CONCEPTS

• **Human-centered computing** → **Interactive systems and tools**; • **Applied computing** → **Computer-aided design**; • **Computing methodologies** → **Artificial intelligence**.

KEYWORDS

prototype, creativity support, generative AI, large-scale model

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1 INTRODUCTION

The conceptual design is a fundamental and essential stage in the industrial design process [24]. Designers embark on transforming vague notions into concrete ideas by delineating the product's overarching outline and layout in conceptual design [83]. Prototyping is critical in the industrial conceptual design process, offering designers a way to reduce mental loads and augment creativity through iterative representations that evolve over time [78]. This practice has proven beneficial for exploration of design space [17, 26], identification of design problem [28, 76], supplementation of designers' mental model [49, 68] and discovery of unexpected phenomena [31, 42, 48].

Enhancement of Artificial Intelligence (AI) in generative capabilities is transforming the paradigm of prototype and conceptual design. Large-scale text-to-image generative models such as Midjourney [13], Stable Diffusion [53], and DALL-E [51] have shown proficiency in applying common-sense knowledge and providing design schemes like human designers [71], enabling AI to be a co-creator in prototyping process [15, 22]. This AI involvement in prototyping expands human designers' logic and scale due to its generative variability [20, 72], thus showing potential in supporting creativity in conceptual design [56]. However, the challenge remains for AI to efficiently and accurately comprehend designers' intention while generating outputs that align with their expectations. Text-guided generative models necessitate clear text descriptions from designers to express their ideas, yet converting ambiguous design intentions into precise text remains difficult. Additionally, simple text prompts often fall short of capturing what designers imagines in their mind [12], underscoring the need for more natural communication modes. To overcome these challenges, AI research has explored various controlled conditions for generative models, including pose [69], semantic map [9, 80], bounding box [82], etc. These approaches offer more ways for designers to concretely communicate with AI, but most of them still require to conform computer-centered rules. For example, designers need to utilize semantic maps according to correspondence color rules. In this context, HCI research is increasingly focusing on designer-centered interactive AI. For example, in PromptPaint [12], the interaction between artists and their painting mediums is emulated through a graphic panel to assist in mixing prompts to express fuzzy concepts. Popblend [71] adheres the divergent and convergent thinking in generative process to achieve inspiration stimulation. The HCI community strives to enable designers to collaborate with AI using their familiar design material, language, and procedure, moving beyond computer-centered interaction rules.

Physical prototype is a universal and common design material used by designers in the industrial conceptual design stage [33]. It leverages tactile materials such as pasteboard and clay for rapid and tangible ideation, aiding designers in embodied sense-making and swift structuring [24]. Cognitive studies affirm that body movements are integral to thinking, with interactions with tangible models boosting creativity through body-based cognition [24, 73]. Additionally, design studies highlights the distinct advantages of physical prototype method in conceptual design: it offers richer sensory stimuli [6, 23], improves understanding of design problems [34, 47], and facilitates team communication [8]. The tangibility of physical prototype is especially valuable in function and structure testing, exposing defects and highlighting unrealistic prototype assumptions [29]. Given these inherent advantages of physical prototype, there is considerable interest in mixed tools that combine virtual and physical space, despite the growth of digital design support tools [5, 62]. These tools aim to integrate the intuition and tangibility of physical prototype with the high-precision simulation capabilities of digital prototyping, thereby harnessing their collective advantages of both domains [66].

This study introduces ProtoDreamer, a mixed-prototype tool integrating physical models with generative AI to support industrial conceptual design. Figure 1 presents a prototype process applying ProtoDreamer. Supported by the proposed tool, designers can engage with tangible materials for embodied ideation and concretely articulate design intention. Subsequently, design schemes aligning with given intention can be generated, which allows to be further regenerated and refined locally. On the one hand, ProtoDreamer supports designers to express design intentions to AI with familiar design language and intuitive interaction, enhancing the shared mental model between human designers and AI agents [22]. On the other hand, designers derive conceptual design inspiration not only from embodied interaction with physical models but also from the observation of incessant and random generated artifacts.

In this study, a formative study was constructed initially, and 20 designers was invited to conduct conceptual design tasks in a mixed-prototype environment. Their attitudes toward the integration of physical materials and generative AI were gathered. The findings served as essential guidance for the design and development of ProtoDreamer. An evaluation study with another 20 designers was also conducted, which proved the usability and creativity support of ProtoDreamer in industrial conceptual design. The results indicated that ProtoDreamer presented distinctive strengths including intuition, time efficiency, and strong expressiveness. This paper makes following contributions:

- Revealing designers' challenges in the mixed-prototype environment combining physical model and generative system, and proposing design goals for developing mixed-prototype tools through formative study.
- Building a novel mixed-prototype system supporting industrial conceptual design. ProtoDreamer allows designers to intuitively communicate with generative AI and concretely convey design intention in their familiar design language, fostering the shared mental models in co-creation system.
- Conducting evaluation study, verifying the effectiveness of ProtoDreamer in industrial conceptual design. Moreover, we discussed the influence of the mixed-prototype method combining physical model and generative AI on industrial conceptual design and its application space.

2 RELATED WORK

2.1 Generative AI in Conceptual Design

Generative AI refers to computational techniques that automately create new, plausible media [46]. Recently, generative AI is progressively becoming a collaborator with human across various creative design domains, including but not limited to industrial design [22, 38], graphic design [64], diagram design [50], UI design [55], urban design[14], and fashion Design [74]. Generative AI brings distinct advantages to industrial conceptual design process. Specifically, the participation of generative AI supports creativity in conceptual design [56]. As generative AI produces artifacts as output, rather than focusing on decisions, labels, classifications, or decision boundaries [72], generated outputs opens an imaginary space through the infinite generation, effectively expanding designer's creative exploration boundaries [20]. Kirsh [32] also indicated that the cognitive velocity and depth of the design process may be enhanced when designers shift their observational focus from their own actions to those executed by computational systems, which might transcend their inherent thinking logic and scale. In addition, as generative AI systematically produces candidate design schemes in real-time. [65], its participation enhances prototype efficiency. While generative AI has introduced subversive possibilities, designers often perceive it as a complex design medium due to challenges in communication with AI [16, 77]. In this context, enhancing the usability of AI-assisted design tools hinges on enabling designers to engage with generative AI both intuitively and efficiently in their familiar way.

2.2 Physical Prototype and Mixed-prototype in Conceptual Design

The physical prototype is a commonly used method in industrial conceptual design. It serves as an unambiguous representation of design concepts and is employed for various purposes like exploring shapes, communicating ideas, and verifying functional structures [29]. The physical prototype has distinct merits in supporting conceptual design. First, the tangibility promotes embodied sensemaking, reducing cognitive load and stimulating creativity. The embodied interaction utilizes interplay between mental and physical representations to facilitate the idea exploration and refinement [24, 67]. Second, the physical model increases the number of sensorial stimuli, such as touch, sight, and smell [6]. It makes the design environment more intuitive and interactive, promoting reasoning and facilitating the search for better solutions [24]. Third, the tangible quality of physical prototype supports function test and defect exposure. Prototype assembly and dissection is considered a deep-level interaction, providing broader visual cues, enhancing structure and mechanism understanding [63]. Owing to the irreplaceable benefits afforded by physical prototypes in conceptual design stage, there is a burgeoning exploration into mixed-prototype tools that integrate tangible models with digital technologies. The HCI community attempted to augment traditional physical prototype through integrating digital ability, such as version control, accurate editing, complex calculation, and digital simulation [29]. For example, Monteiro et al. [45] developed TeachableReality, prototyping tangible augmented reality with everyday objects. Suzuki et al. [60] presented RealitySketch, a sketching system which combined digital sketch with physical object in real world. Tao et al. [62] devised a novel mixed system that enables designers to prototype through a physical printing pen alongside fine guidance offered by tablet computers. In this paper, we endeavor to synergistically integrate the traditional physical prototype method with generative AI in a mixed-prototype tool, combining their collective strengths to support industrial conceptual design.

2.3 Generative AI-assisted Design System Guidelines

With the development of large-scale models, HCI researchers have endeavored to formulate human-AI interaction guidelines aimed at mitigating the interaction complexities while concurrently enhancing their usability [2, 37, 72, 79]. Justin et al. [72] put forward six principles according to generative AI characteristics. They indicated that generative systems should enable to explore a space of possible outcomes based on users' query, provide version management to track outputs and corresponding parameters, and allow both users and AI to edit candidate artifacts, etc. Amershi et al. [2] also proposed 18 generally applicable design guidelines for human-AI interaction. They pointed out that it is essential for AI system to ignore undesired services, engage in disambiguation, and encourage granular feedback. Some studies also explored how to interact with generative AI effectively by prompting engineering. Liu and Chilton [37] presented design guidelines which can help users produce better outcomes from text-to-image models. Zamfirescu et al. [79] explored how to use natural language to steer generative AI and proposed prompting strategies. However, owing to the nascent nature of generative AI, limited endeavors have employed the suggested interaction principles within practical systems. In this paper, a generative system was designed and developed in accordance with the established guidelines. We concerned "How can designers better use AI" and "How can AI better understand designers", which includes helping designers to interact with AI through their habits while helping AI agent to comprehensively understand designers' creation intention, respectively.

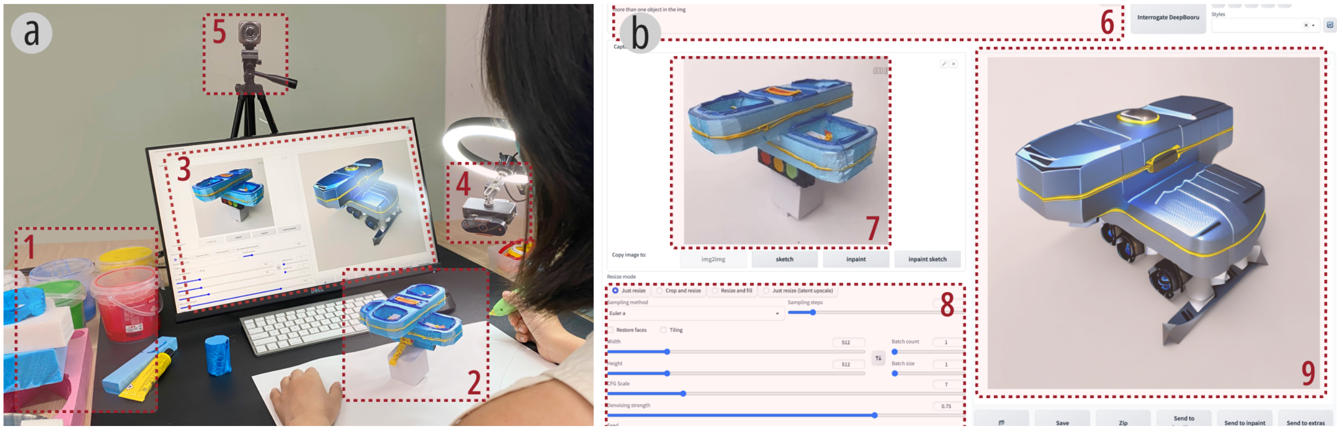

Figure 2: (a) The constructed mixed-environment for formative study. 1: provided physical materials and tools; 2: physical model made by participant; 3: UI of developed system for formative study; 4: a camera capturing the physical model during prototype process; 5: a video recorder recording the design process. (b) The developed system based on Stable Diffusion web UI for formative study. 6: prompts area; 7: captured image; 8: parameter area controlling the generation; 9: design scheme.

3 USER STUDY 1: A FORMATIVE STUDY

In this formative study, we constructed a mixed-prototype environment that integrates physical prototype and generative AI. We conducted an experiment with 20 designers to assess their attitudes and natural workflows in prototyping, aiming to identify challenges and requirements in such a mixed setting.

3.1 Participants

Twenty designers (12 female and 8 male, aged 25 to 30) with industrial design background were recruited. Eleven participants hold professional positions as designers, whereas nine are currently pursuing design education. All participants possess at least three years of practical experience in design. They are familiar with physical prototyping methods and generative AI tools, thus they can focus on design tasks rather than tool learning.

3.2 Experimental System and Environment

To conduct the formative study in a mixed-prototype setting, we established a laboratory environment (Figure 2a) and also built a system upon the open-source Stable Diffusion web UI [3] (Figure 2b). The Stable Diffusion v2.1 [58] was adopted in the system. Our setup included a computer and a camera within a controlled space stocked with diverse physical materials. During the prototype phase, designers could create and test appearance and structure of design concept through physical materials. They can also convey design intention to generative system through captured images and typed prompts to cooperate with the AI agent.

3.3 Task and Procedure

In the formative study, participants engaged in a 60-minute conceptual drone design task within a mixed-prototype environment. We provided a specific design theme to allow designers to have a similar ability to prototype as they usually conduct in real cases [35]. After the prototyping task, a semi-structured interview was conducted. We focused on two main questions: 1) *Can the mixed-prototype environment effectively facilitate conceptual design?* 2) *What are the challenges in conceptual design under support of the mixed-prototype environment?* Three researchers in this study analyzed all transcribed texts using afnity diagrams [44], extracting challenges and requirements.

3.4 Findings

Nearly all participants acknowledged the advantages of the mixed-prototype environment. Employing thematic analysis, three researchers aimed to gather positive perspectives and attitudes toward its implementation through a hybrid process of deductive and inductive coding [61]. After resolving disagreements through discussion, 10 codes related to the advantages of proposed mixed-environment were obtained: *Easy to prototype*, *Time-efficiency*, *High fidelity*, *High feasibility*, *Intuitive perception*, *Structured thinking*, *Detailed thinking*, *Defects exposure*, *Creativity support*, and *High accomplishment*. These findings corroborate the participants' favorable views on the mixed-prototype environment and system, thereby providing a foundation for further research. Moreover, we also summarized designers' challenges(C) during design process.

C1: ***I need more mobility and portability.*** Four participants (P2, P7, P11, P12) mentioned that the fixed camera limits the viewing angle of image capture. Four participants (P1, P7, P10, P19) indicated that the fixed environment with large equipment limits the spatial freedom of prototyping. Therefore, adopting portable and movable equipment to improve the mobility of the mixed-prototype system is essential to expand its application scope.

C2: ***I cannot convey my design intention in detail to AI.*** Participants mentioned challenges in conveying design intention in detail through physical models, especially the design details (P1, P13, P12). The accurate comprehension of a designer's intention by AI agent and subsequent controlled generation that aligns with this intention, are crucial in human-AI co-creation. Frequent misunderstandings from AI agent might reduce users' trust, patience,

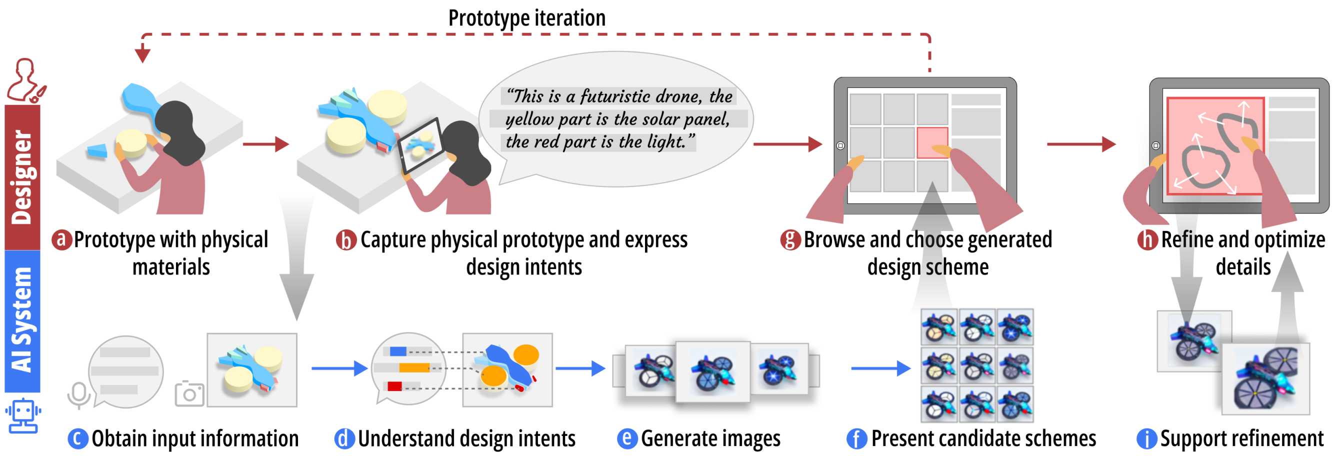

Figure 3: The flow chart using ProtoDreamer. Thin arrows indicate the flow sequence and thick arrows indicate the information transmission between designers and AI system.

and confidence of human-AI cooperation. For example, three participants (P6, P10, P12) indicated that they do not want to continue cooperation when AI tampers with their design many times.

C3: ***I face challenges in facing prompts and parameters.*** Participants complained that they spent a lot of time and energy on tool using rather than design. Specifically, Participants reported they are "*at a loss*" when facing complex parameters (P2) and "*don't know how each parameter affects design*" (P13). P7 mentioned challenges in writing prompts, especially prompts related to design quality and style. Participants emphasised that they "*care more about design outputs than the prompts and parameters*" (P8, P10, P13). It is crucial to reduce the difficulty of prompt writing and parameter adjustment through the interaction that designers are familiar with, which might enhance the AI usability.

C4: ***I want to modify generated schemes further.*** Some participants (P7, P14, P19) expressed contentment with the overall quality of the output yet conveyed dissatisfaction with specific elements, expressing a desire for localized regeneration. P14 and P16 hoped to adjust the shape, angle, and proportion of the generated design scheme. P20 indicated that "*Local editing and regenerating is not an alternative to editing the generated results in Photoshop, but a data-driven detail optimization in my design*". By implementing localized constraints, the generated output can be more refined and comprehensive, and better aligned with the designer's anticipations [56].

3.5 Design Requirements

In response to the findings from the formative study, we summarized four design goals for developing a mixed-prototype tool. These goals not only address the specific needs identified by participants in the formative study but also correspond to established principles in human-AI interaction research [2, 37, 72, 79].

DR1: ***Integrating the mixed-prototype system on a mobile device to enhance portability.*** Improving mobility and portability by integrating the mixed-prototype system into mobile devices, thus enhancing the application scope of the prototype tool.

DR2: ***Enabling designers to convey design intention in detail based on physical materials.*** Enabling designers to correspond specified model details with local requirements or restraints, thus achieving detailed intention transmission and generation control.

DR3: ***Simplifying interaction and reducing the difficulty in adjusting prompts and parameters.*** Optimization of the human-AI interaction exempts designers from the minutiae of parameters and nebulous prompts, allowing them to concentrate on the conceptual design and selection of outputs that meet their approval.

DR4: ***Supporting local optimization and editing based on generated outputs.*** Supporting designers to continue to optimize the part of the generated scheme, including regenerating and adjusting the style, proportion, or angle.

4 PROTODREAMER

4.1 Interaction Flow

We provide a user journey to introduce the capabilities and interaction flow of ProtoDreamer (Figure 3). A designer conducted a conceptual design for the innovative drone. At first, the designer didn't have any ideas, so she built some rough physical materials casually, exploring the proportion and structure of the drone through embodied interaction with these materials (Figure 3a). She conveyed design intention to AI by designated colors and corresponding semantics (Figure 3b~c). After AI understood her intention and generated corresponding images (Figure 3d~f), she obtained and browsed several candidate schemes immediately and chose a satisfactory one (Figure 3g). Then she attempted to further refine the output for local amplification through adding anchors and arrowheads (Figure 3h~i). Under the support of ProtoDreamer, she explored the basic structure of the prototype by constructing and testing the tangible model, while concurrently drawing detailed inspiration from her interactions with the generative system.

4.2 Detailed Design

4.2.1 Implementing a Web Application Compatible with Mobile Devices (for DR1). ProtoDreamer is designed as a web application

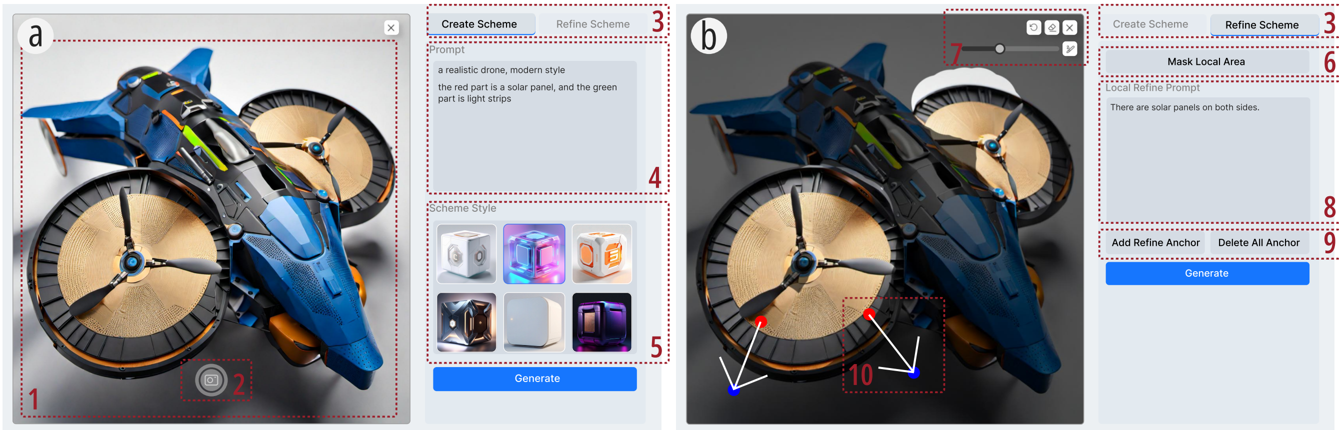

Figure 4: The user interface of ProtoDreamer. (a). The Create Scheme Page. 1: Prototyping Canvas; 2: Capturing Button; 3: Functional Navigation; 4: Text Prompt Area; 5: Scheme Style Folder. (b). The Refine Scheme Page. 6: Add Mask Button; 7: Brush Adjustment Tool; 8: Text Prompt for Local Mask Area; 9: Add or Delete Anchor; 10: Anchor and Arrowhead for Editing.

for accessibility on mobile devices such as tablet computers. The built-in rear cameras of these devices facilitate direct capture of physical models The user interface of ProtoDreamer is presented in Figure 4, containing two modes for global and local generation. In the "*create scheme*" mode (Figure 4a), there is a canvas to present captured image and show the design schemes generated by AI. Upon achieving an initial satisfactory scheme, users may opt to select "*refine scheme*" for further local refine (Figure 4b).

4.2.2 Enabling Detailed Generation Control via Colors of Physical Materials (for DR2). In the mixed-prototype setting, designers effectively convey the general form and structures via physical models and textual descriptions, but AI still faces challenges in comprehending these cues. For example, designers might use ad hoc paper cutouts to symbolize components like "charging ports" or "indicator light" during design. Current AI approaches process images and textual inputs separately, resulting in suboptimal localization and interpretation of specific design elements in physical models. ProtoDreamer addresses this by allowing the nuanced specification of design intention through color-based physical materials. Unlike the fixed color-content relationships in semantic mapping methods, ProtoDreamer lets designers freely associate colors with specific requirements, thereby enriching structured thinking and precise interpretation. We realized this via a two-step extraction of specified color regions and a sequential inpainting procedure (Figure 5).

Region Segmentation based on HSV Color Space. The extraction of designated color regions is performed within the Hue, Saturation, and Value (HSV) color space. Captured images of physical models are converted to HSV, facilitating color differentiation based on chromaticity and luminance. Following this conversion, predefined ranges for HSV are applied to segment the targeted color regions. This isolated specific color region becomes the foreground, while the remainder forms the background, yielding a binary mask that highlights the area of interest.

Morphological Dilation. The initial binary mask may present noise, manifesting as small gaps or holes. To address this problem and enhance the continuity of the segmented feature, morphological dilation is employed. Firstly, a structuring element, commonly a basic shape like a square or circle, is determined. The dimension and form of this element dictate the extent of the expansion. Secondly, the binary mask undergoes an expansion process using the predefined structural elements, enlarging the mask's white region.

Sequential Inpainting. Based on the obtained binary mask, regions designated by different colors are generated one-by-one using the inpainting model of ControlNet [81]. In addition, the text controlling the inpainting-generated content is extracted from the user-provided overarching prompt.

Algorithm 1: Iterative Sequential Inpainting to obtain Matrix-based Display of Generative Outcomes.

Input: Initial image x_t; color-designated regions m_1 and m_2; local descriptions d_1 and d_2 for m_1 and m_2 respectively; n control weight parameters $\{w^0, w^1, \cdots, w^{n-1}\}$.
Output: Candidate scheme matrix $\mathbf{A} \in \mathbb{R}^{n \times n}$.
for i ***from*** 0 *to* $n-1$ **do**
  $x_{t-1}^{w^i} \leftarrow Inpaint(x_t, m_1, d_1, w^i)$,where t denotes time step during diffusion process
  `// Inpaint the color-designated region` m_1 `based on the local description` d_1
  for j ***from*** 0 *to* $n-1$ **do**
    $x_{t-2}^{w^i w^j} \leftarrow Inpaint(x_t, m_2, d_2, w^j)$ `// Inpaint the color-designated region` m_2 `based on the local description` d_2
  end
  add $x_{t-2}^{w^i w^j}$ to $\mathbf{A}$
end
return candidate scheme matrix $\mathbf{A}$

4.2.3 Providing Matrix-based Generation to Present the Influence of Weighting Parameters (for DR3). Both prior research and our formative study reveal challenges faced by designers in predicting AI responses to parameters adjustments [22]. In response, we introduce a matrix-based generation and display mode. This method vividly illustrates generative outcomes under varying weight conditions,

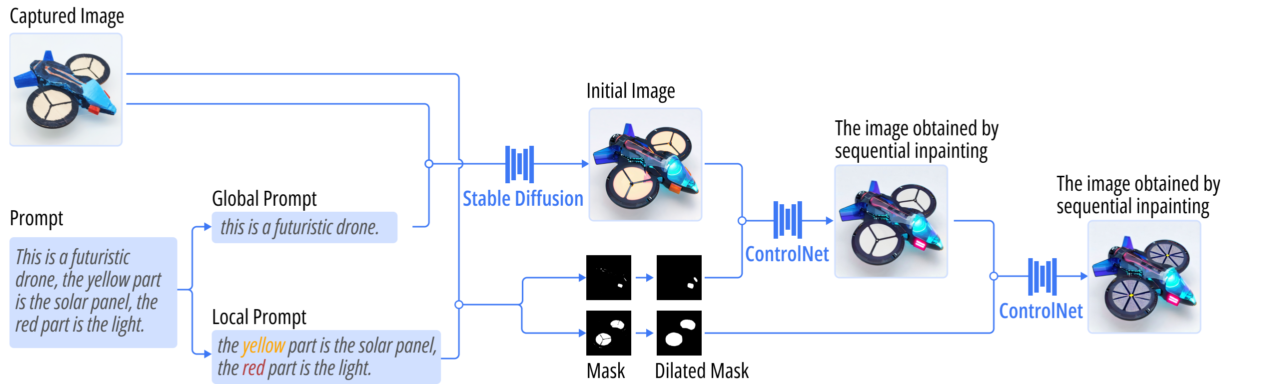

Figure 5: Technical architecture diagram of realizing detailed generation control via colors of physical materials, including a two-step extraction of specified color regions and a sequential inpainting procedure.

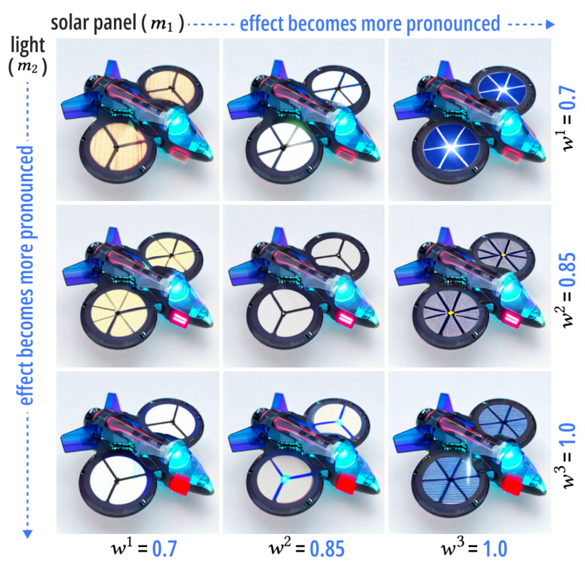

Figure 6: A matrix-based presentation example to demonstrate the influence of weight variation for two separate regions on the overall design schemes.

thereby offering designers with detailed control and immediate understanding of the effects of parameter changes. It aims to relieve designers from the burden of meticulously considering the specific meanings and influential scopes of diverse parameters during the prototyping process. Consequently, designers can redirect their focus entirely to the creative aspects of design. Specifically, we present results underscoring the varying impact of control weights across color-designated regions on overall design quality. This is achieved through iterative sequential inpainting, each iteration applying distinct control weights to designated regions (see Algo.1). In Figure 6, we show how weight variations in two distinct regions influence the design outcome. Control weights, represented as $\{w^1, w^2, w^3\}$ are adjusted in each iteration of ControlNet. As the weight value of increases, the inpainting effect intensifies, leading to an output more closely aligns with the local prompt within the masked area. For instance, the third image in the second row shows the result of generating a solar panel at m_1 with a control weight $w^3 = 1.0$ followed by the creation of a light at m_2 with $w^2 = 0.85$. Our system recommends employing two colors to signify different semantic intentions in a prototype. For designs requiring additional localized function modules, the method detailed in section 4.2.5 may be utilized.

4.2.4 Providing Prompts Style Folders (for DR3). Current text-to-image generation models necessitate designers to acquire specialized prompt engineering skills for obtaining high-quality design schemes. This often involves providing not only basic design descriptions but also various abstract terms and style references, such as "*pure background*", "*high quality*", or "*multi-details*", to enhance generation quality. In light of this, a plethora of guidelines and tips have been developed within the creative community, aimed at assisting designers and artists in crafting effective prompts that align with logic and rules of AI systems. Most guideline advocate for a structured approach to prompt input. However, a key element in improving human-AI cooperative systems is to align AI with the user's natural workflow, rather than adhering to a computer-centered logic. To address this, we design "scheme style folder" within ProtoDreamer (Figure 4 a5). This function offers an array of pre-selected prompts alongside stylistic images, akin to a range of camera filters. Designers can thus effortlessly produce stylistic accurate proposals with minimal input or even a single keyword. This designer-centered approach supports designers in goal-oriented exploration instead of opening the black-box aimlessly [22]. Examples of design schemes generated using the style folder are shown in Figure 7. The number and types of candidate styles can be continuously updated and customized by users.

4.2.5 Supporting Local Modification and Editing (for DR4). Through the aforementioned steps, designers obtain a series of candidate design schemes. Suitable options can be selected and subjected to localized modifications by clicking the "*refine scheme*" button (Figure 4b). These changes might encompass the incorporation of new

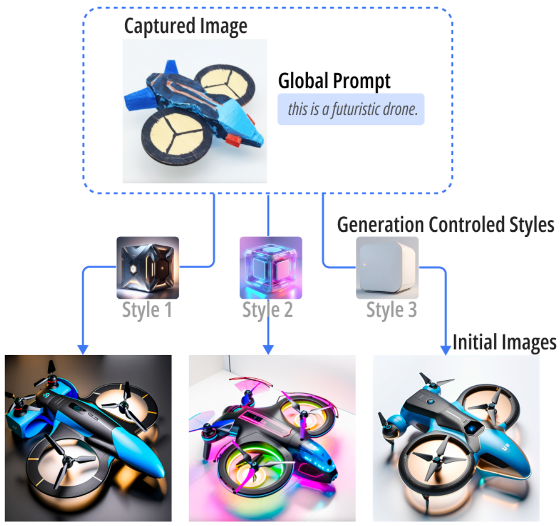

Figure 7: A drone design using the generation control of style folder for an example.

Figure 8: ProtoDreamer's refine ability.

design elements or the tweaking of existing geometries. We introduce two modification modes, local regeneration and local detail adjustment, supported by ControlNet [81] and DragDiffusion [57], respectively. The designer initiates adjustments by targeting a specific area and inputting local requirements or constraints, or by altering its dimensions and orientation via anchor points and movement arrows (Figure 8).

4.3 Design Iteration

We conducted a series of pilot tests to interactively enhance the system design. First, we integrate voice input functionality to simplify operation. Participants mentioned that voice interaction allowed for hands-free operation, thus enabling a more immersive interaction with physical materials. Second, we increase functional notes aligned with designers' cognition. We add intuitive notes to designers to clarify the functionality of each interactive component and how to respond after operation. Third, we enable designers to adjust the influence of physical models on generation results. We observed that designers expect AI to play varied roles throughout the conceptual design phase. Specifically, when a designer's creativity reaches an impasse, they look to AI to act as a creator for inspiration, generating schemes distinctly divergent from physical models. While when the designer has specific concepts, they expect AI as an executor to refine a scheme based on physical models. Consequently, we design an interactive component to enable designers to modulate the influence of physical models on generated schemes according to targeted needs.

4.4 Implementation

ProtoDreamer is developed based on Stable Diffusion Web UI [3], a Gradio library-based browser interface designed for Stable Diffusion [53]. The back-end server of ProtoDreamer invokes various diffusion models to generate images, which are then relayed back to the user interface. ProtoDreamer employs the pre-trained image-to-image diffusion model, Stable Diffusion XL 1.0 [59] to achieve initial image generation. For sequential inpainting and localized regeneration, the system utilizes the ControlNet inpaint model [39], which is compatible with Stable Diffusion v1.5. Furthermore, the system integrates DragDiffusion [57] for precise local detail adjustments. The developed ProtoDreamer is hosted on a local server equipped with a GTX 3090 GPU.

5 USER STUDY 2: AN EVALUATION STUDY

We address the following research questions in evaluation study.

RQ1: Is ProtoDreamer usable? How does ProtoDreamer support conceptual design?

RQ2: Does ProtoDreamer effectively enhance creative ideation during the prototyping phase?

RQ3: What advantages does ProtoDreamer offer over alternative prototyping tools?

5.1 Participants

We recruited another 20 designers (8 males and 12 females, average age is 28.8) with backgrounds in design. To ensure these individuals have enough insight in evaluation study, we mainly recruited professional designers and senior design students (MA and Phd) who had a minimum of three years experience. Participants in this study were recruited through online publicity and design forum. We also screened participants who familiar with prototyping skills and generative AI tools so that they could focus on exploring design rather than on tools learning. All participants signed a consent form approved by our institution. This study has no other ethical or privacy impacts.

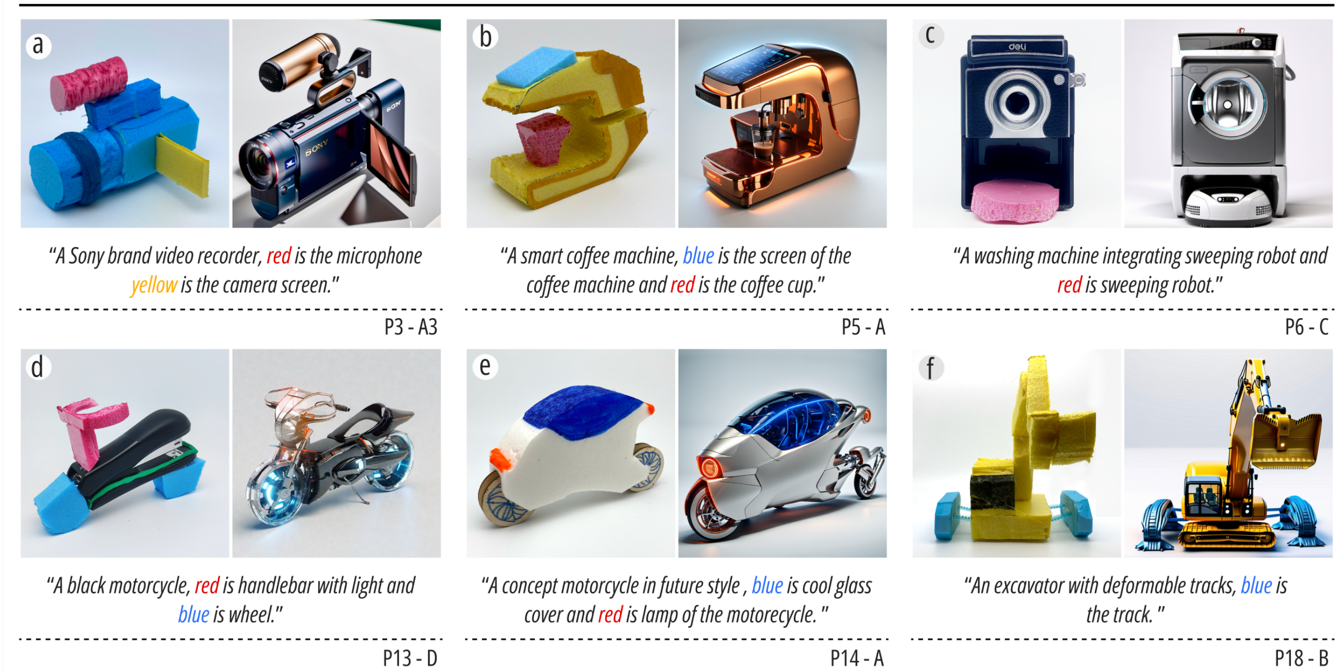

Figure 9: The presentation of the designer's satisfactory design outputs under the support of ProtoDreamer. The note P3-A3 meas that this is the 3rd iteration of the 1st design concept made by P3.

5.2 Task and Procedure

Each participant underwent an individual orientation, beginning with a 5-min informed consent process and a subsequent 20-min demonstration. This preliminary phase aimed to acquaint them with ProtoDreamer and the Think-aloud method. This was followed by a one-week prototyping period. Participants had unrestricted access to ProtoDreamer, enabling them to explore various design concepts without limitation on time or the number of ideas pursued. The use of Think-aloud method was a requisite during the design process. Following the prototyping phase, participants reviewed their design schemes and prototyping video footage with the researchers. Then, they were asked to complete several questionnaires and engaged in interviews.

5.3 Data Collection and Analysis

Our study entailed a comprehensive collection of participants feedback, including video recordings of screen and workspace activity, execution logs, design outcomes, questionnaire, and interview. To evaluate the objective feedback, the System Usability Scale (SUS) [7] and Creativity Support Index (CSI) [19] were applied to measure the usability and creativity support of ProtoDreamer and Stable Diffusion WebUI. Specifically, CSI includes six factors: *Collaboration*, *Enjoyment*, *Exploration*, *Expressiveness*, *Immersion*, and *Results Worth Effort*. Similar to previous research methodologies [52], our *collaboration* index quantified the level of human-AI cooperation instead of human-human cooperation. All interviews in the evaluation were transcribed. Two researchers discussed the transcribed text together. Besides, to study the interaction process under the support of Protodreamer, two researchers reviewed the design process video with participants after the prototyping period, observed what they said when thinking and did while working. Researchers coded the design process and resolved differences through discussion. To analyze the design output of ProtoDreamer, we paid special attention to the captured physical model image and the generated scheme extracting from the execution log of the authoring process.

6 RESULTS AND FINDINGS

6.1 RQ1: ProtoDreamer Is Highly Usable in Supporting Industrial Conceptual Design.

6.1.1 Overall Design Outputs in the Evaluation Study. Participants learned the functions of ProtoDremer and applied them in the prototype process without difficulty. The accumulated total usage time was approximately 26 hours and 39 design concepts were produced. The average prototyping duration of each design concept and each iteration were 40 min. Figure 9 shows some prototypes that participants were satisfied with. Both physical materials (Figure 9 a, b, e, f), and commonplace objects from working surroundings (Figure 9 c, d) were used by designers to complete the prototyping processes, lowering the threshold of prototyping and bringing more possibilities for creation.

6.1.2 System Usability Scale (SUS) of ProtoDreamer. The SUS results are presented in Figure 10. The average total SUS score of ProtoDreamer was 82.50 (SD = 6.12). The acceptability of the SUS

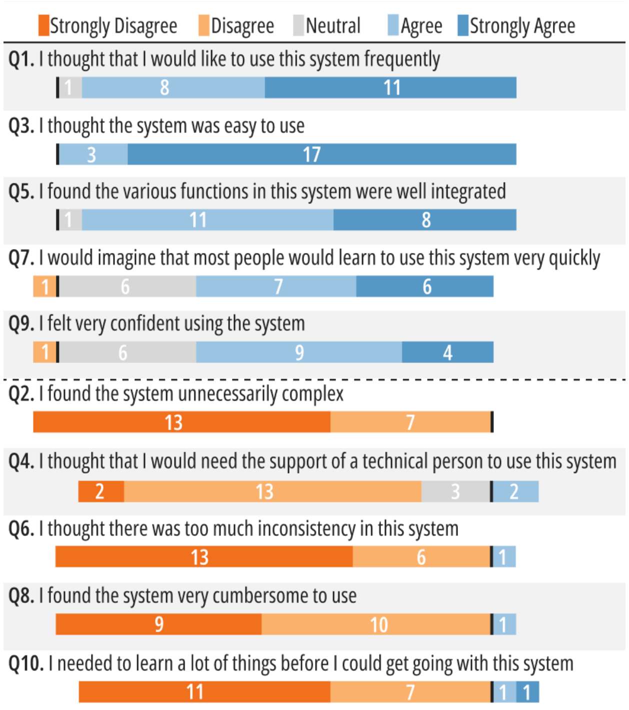

Figure 10: Results of the SUS questionnaire.

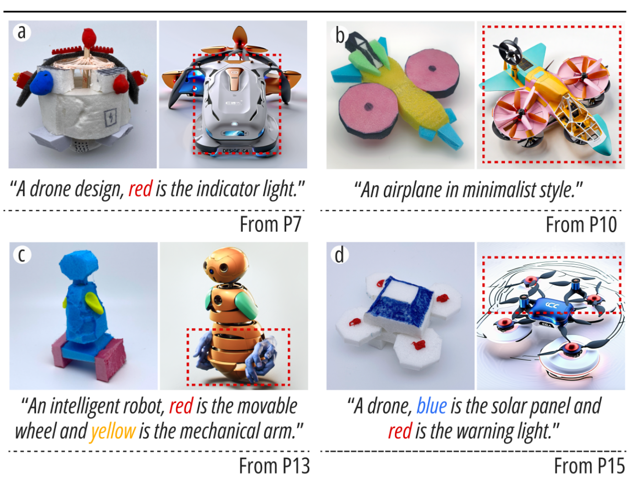

Figure 11: Dissatisfied outputs that are randomly selected from design process.

result was "*acceptable*" and its adjective rating was "*Good*" according to the standard proposed by Bangor [4]. Besides, the usability score and learnability score were 84.22 (SD = 6.13) and 75.63 (SD = 16.99) respectively. Specifically, most participants perceived the system to possess a significantly high level of availability and exhibited robust functional consistency, enabling them to accomplish conceptual design tasks efficiently.

Table 1: CSI results of ProtoDreamer in the evaluation study.

Factor	Avg. Factor Counts (SD)	Avg. Factor Score (SD)	Avg. Weighted Factor Score (SD)
Collaboration	2.50 (0.81)	17.40 (1.11)	43.50 (14.91)
Enjoyment	0.70 (0.46)	16.20 (1.33)	11.20 (7.41)
Exploration	3.20(0.75)	15.90 (1.97)	51.10 (15.32)
Expressiveness	4.10 (0.54)	17.90 (1.22)	73.60 (11.30)
Immersion	0.80 (0.75)	13.20 (1.47)	10.40 (9.28)
Results Worth Effort	3.70 (0.78)	18.60 (1.36)	68.80 (14.56)

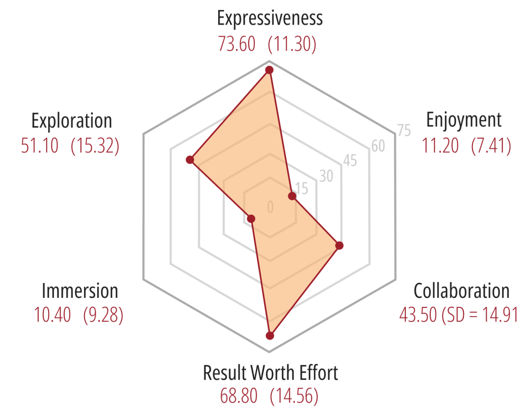

Figure 12: Average weighted factor score for each of six factors on CSI.

6.1.3 Dissatisfied Cases Presentation. To comprehensively demonstrate the design diversity of participants, we showcase some dissatisfied cases (Figure 11). We categorized the causes of dissatisfaction into three perspectives: AI's lack of structural knowledge, AI generation instability, and poor shooting quality. First, AI faces challenges in understanding the structural design in physical models and successfully converting it into digital solutions. For example, P7 designed a drone with a telescopic and lifting structure. P7 tried many times, but AI cannot comprehend and refine it successfully (Figure 11a). Second, due to the generation mechanism, the color information in the physical model may interfere with the results. For example, P10 built a colorful airplane with physical materials (Figure 11b), the designer failed to get a minimalist and realistic drone design after repeated attempts due to the complex color. The randomness and instability during the generation also occasionally lead to poor-quality outputs. Due to the prompt of "mechanical arm", AI mistakenly generated "human hand" in Figure 11c. Third, the interaction in the application of ProtoDreamer has an impact on the output results. For example, the poor shooting quality of physical models, including low background contrast, dark light, obvious shadow, inappropriate perspective angle, will reduce the co-creation satisfaction (Figure 11d).

6.2 RQ2: ProtoDreamer Supports Creativity Effectively during Prototyping.

6.2.1 Creativity Support Index of ProtoDreamer. The average CSI score for ProtoDreamer was 86.20 (SD = 4.83), which indicated excellent support for creative work. Table 1 and Figure 12 show the results of average factor counts, average factor score, and average

Mode	Design Lead	(Designer's) Time Distribution	Prototype Changes
Translator	👨‍🎨	mainly spent on building base shape of physical model	mainly physical changes
Stimulator	🤖	mainly spent on adjusting parameters and observing outputs	mainly virtual changes
Explorer	👨‍🎨 & 🤖	mainly spent on adjusting physical structures and generative inputs	physical and virtual changes occur alternately
Refiner	👨‍🎨	mainly spent on optimizing details virtually through AI	mainly virtual changes

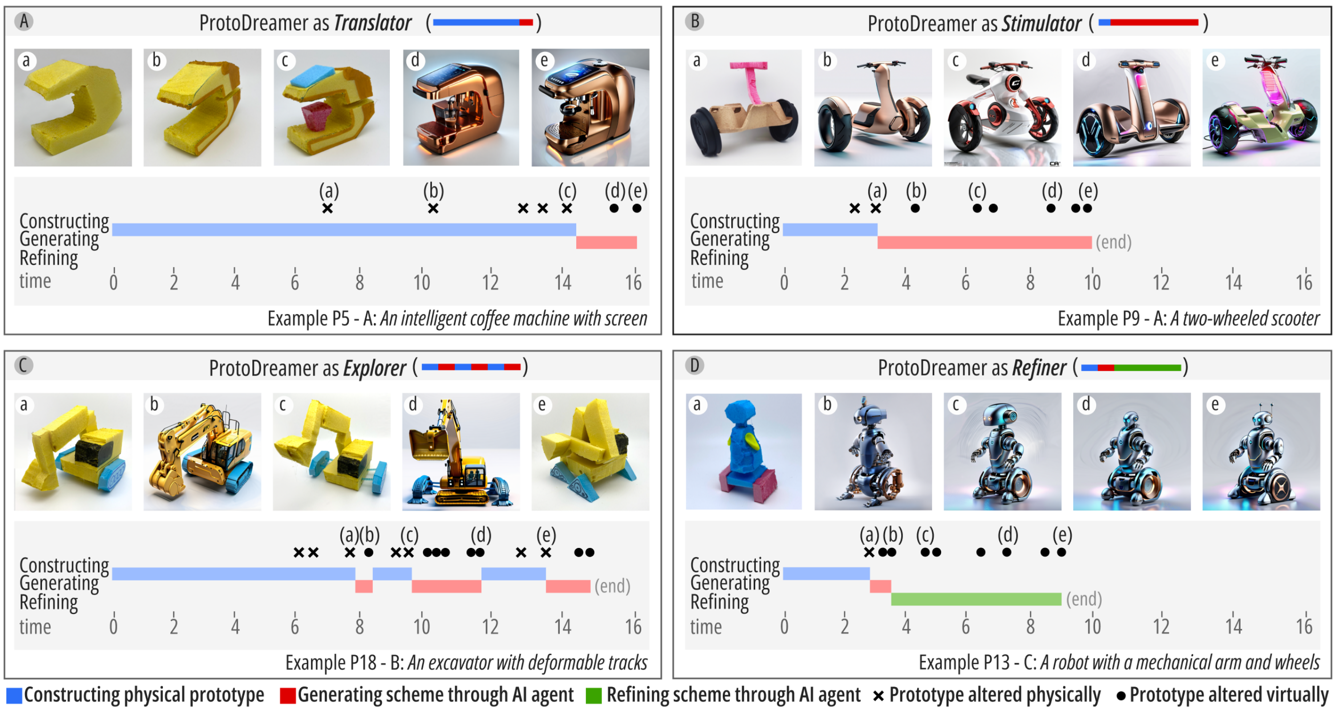

Figure 13: Extracted four support modes of PrtoDreamer during assisting ideation.

weighted factor scores for each of the six factors on the CSI. The CSI results highlighted ProtoDreamer's strengths in augmenting expressive capabilities and elevating overall satisfaction. Besides, the score of *collaboration* and *exploration* indicated that the collaborative engagement with ProtoDreamer during the conceptual design facilitates divergent thinking and creative expansion. However, the *immersion* and *enjoyment* factors were not significant with ProtoDreamer's usage. This phenomenon might be attributed to ProtoDreamer's reliance on unconventional design materials and cross-domain interactions. The incorporation of generative AI, an unfamiliar and challenging design material, alongside the unpredictability, demands a steep learning curve for designers [72]. This requirement for adapting to generative AI interfaces may lessen enjoyment associated with the design process. Moreover, the demand for designers to alternate between constructing physical models and virtual editing could reduce immersion due to frequent domain switching.

6.2.2 Support Modes of ProtoDreamer During Assisting Ideation. Through design process coding, especially paying attention to designers' behaviors and prototypes' changes, we extracted four modes of using ProtoDreamer to support conceptual design from the perspective of design lead, time distribution, and prototype changes and presented corresponding examples (Figure 13). Firstly, designers deploy ProtoDreamer as a *Translator*. In this mode, designers with clear concepts devote substantial time to develop physical prototypes and materialize their ideas, then use ProtoDreamer to translate captured images of prototypes into high-fidelity digital visuals. This phase chiefly involve physical prototype modification, with digital alteration limited to the final "adding skin" stage. Secondly, designers use ProtoDreamer as a *Stimulator*. Lacking initial inspiration, they quickly build a rough model, allowing AI to assume the design initiative and seeking further navigation through adjusting input parameters. In this mode, the prototype is mainly altered in the digital space. Thirdly, as an *Explorer*, ProtoDreamer aids in the entire conceptual design process. Here, designers continuously scrutinize, splice, and dissect the shape and function of current physical prototype, testing and verifying its structure. While AI contributes detailed inspiration for each physical state. This mode features sequential and alternate physical and digital changes of the prototype. Furthermore, designers employ ProtoDreamer as a

Refiner, using its "Refine Function" to optimize details on a relatively satisfactory output, with changes primarily in virtual local details. These four modes occur randomly in conceptual design, often in diverse combinations and multiple applications within a single design concept.

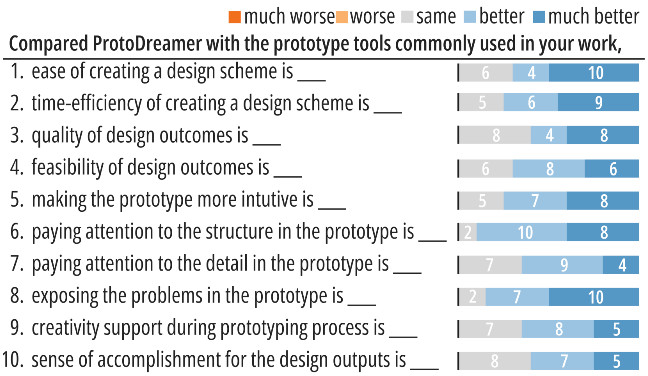

Figure 14: Advantages of ProtoDreamer compared with commonly used prototype tools

6.3 RQ3: ProtoDreamer Exhibits Distinctive Advantages in Comparison to Conventional Prototype Tools.

As ProtoDreamer represents a novel integration, it presents a challenge to identify comparable baselines or existing tools for comparative analysis. Therefore, we asked designers to compare their experience of ProtoDreamer with the prototype methods or tools commonly used in their design work, including sketching, modeling, traditional physical prototyping and so on. Specifically, 10 strengths of mixed-prototype system identified through thematic analysis in our formative study (Section 3.4) were used to construct a questionnaire to verify distinctive advantages of ProtoDreamer in a wider range (Figure 14). According to our results, we summarized the obvious advantages of ProtoDreamer in defect exposure, structure thinking, and detail thinking. For example, P3 reported that "*When designing and bonding the joints of physical components, I will consider the design of structural details more deeply. It will make me think about the influence of stability and balance of the product, avoiding some unrealistic ideas*". Besides, due to the ability to produce ample solutions within a design space of generative AI [65], the ease, time efficiency, and sense of accomplishment have been improved effectively. P18 mentioned that "*My sketching ability is not very strong. ProtoDreamer allows me to express my ideas in a simple manner, enhancing my sense of accomplishment and providing me with a better creative state*".

7 DISCUSSION

7.1 Design Support Offered by the Combination of Physical Model and Generative AI

7.1.1 The Combination of Physical Model and Generative AI Presents Distinctive Contribution. ProtoDreamer is the integration of physical prototype method and generative AI. We discuss the support of this combination behind the ProtoDreamer to the industrial design process through our results. First, when compared to other prototype tools, designers pointed out that the ProtoDreamer is good at providing schemes efficiently and accelerating the design iteration. As the long-time cost is the inherent disadvantages of physical prototype [29] while the AI owns the ability to offer a large number of schemes based on its generative variability [72], their combination can add data-driven details to low-fidelity physical models, accelerating the prototyping process. Second, the participation of generative AI in physical prototype enhances the design expressiveness , as well as promoting idea exploration. The CSI results indicated that the expressiveness provided by ProtoDreamer is significantly strong. Similarly, participant reported that "*ProtoDreamer can help me refine my physical model with high quality. It inspired me with many details based on my physical model scheme*". Besides, designers also consider the combination of physical model and AI provides a easier way to externalize ideas and express schemes, lowering the threshold of industrial conceptual design, which can be also proved by the *result worth effort* index in CSI. Third, the tangibility and AI participation jointly promotes the mixed-modality prototyping methods and tools. Designers can perceive different modalities of design information in ProtoDreamer. In contrast to mere visual prototypes like sketches, tangibility of physical model offers a more accurate sense of scale and texture, allowing for continuous examination, verification, and manipulation, thereby promoting structural thinking and highlighting incorrect assumptions. [24, 63]. The randomness of AI helps designers capitalize on the outcome as probabilistic and offers generated schemes based on each physical configuration [21]. Therefore, ProtoDreamer provides the potential implementation path for multimodal prototype tools.

7.1.2 Newly Challenges Introduced in Combination of Physical Model and Generative AI. Although ProtoDreamer received positive responses from designers in the evaluation study, we engaged in a critical discussion regarding the newly introduced challenges, in order to give potential users or industrial designers a more extensive application guidance. On the one hand, the randomness and unpredictability of AI might lead distraction in the conceptual design. During the evaluation study, designers occasionally got unsatisfactory AI output, which may be due to poor input information (such as poor shooting quality, unclear prompts, etc.). Once designers encountered unexpected feedback, they became confused because they didn't know what happened in the black box and felt difficult in maintaining focus on the creative process. This distraction might contribute to lower *enjoyment* and *immersion* score in CSI results. On the other hand, the generation of a high-fidelity scheme during the preliminary conceptual design phase might potentially result in creativity fixation, as it discourages the ongoing exploration of alternative solutions [10]. For example, in the *Refiner* mode of ProtoDreamer (e.g., Figure 13D), designers spent more time perfecting details instead of engaging in the exploration of diverse possibilities, which might limit their ideas to a narrow space prematurely. Therefore, we suggest designers alter their prototype in the physical world and the virtual world repeatedly to explore more possibilities when applying ProtoDreamer or this kind of mixed-prototype method. It is also recommended that designers constantly adjust capturing angle and input parameters, and generative more times in order to alleviate design distraction and fixation caused by generation randomness and similar schemes.

In addition to concerns in generation, our mixed interaction mode might add limitations related to designers' manual labor. In participants' feedback, excellent high-fidelity schemes were mostly produced based on well-made and detailed physical models, which requires designers to pay more labor and time. Therefore, although the embodied interaction with physical materials can promote embodied thinking, structural ideation, and verification test, ProtoDreamer might be more inefficient than the pure digital generative systems from the production efficiency perspective.

7.2 Designer-AI Co-creation in ProtoDreamer

7.2.1 Tangible Interaction Supports Concrete Communication in Designer-AI Co-creation. The design process is not only result-oriented but also process-oriented. The goal of conceptual design is not to generate high-quality design schemes but to constantly refine ideas and find better solutions. Therefore, HCI studies extend beyond merely facilitating creative processes via generative results. It encompasses an ongoing cycle of refinement and iteration of ideas through dynamic interaction with generative AI [11, 75]. From our process observation and user interview, we found that tangible interaction in ProtoDreamer supports concrete communication with AI. In ProtoDreamer, the physical model serves as an anchor point and shared base for AI agent, expressing design intention more intuitively and concretely to AI, while enabling AI follow the designer's original intention by understanding the rich details on physical models. Few designers mentioned challenges related to detailed intention share in the evaluation study. P5 indicated that "*Physical prototype contains abundant information including shape, scale, and color, which supports me to communicate with AI intuitively and efficiently*". P8 also reported that "*Color materials can bind position and semantic information, expressing requirements to AI in detail, without the help of coordinates and directions*". Previous study demonstrated that multi-modal and non-verbal communication could support AI partners in developing better shared understanding of design goals [22], which also proved the effectiveness of applying tangible models in ProtoDreamer to promote human-AI communication.

7.2.2 Generative AI Participation Promotes Design Creativity. We discuss the AI-enhancing-creativity beyond ProtoDreamer system. First, generative AI can promote design ideation and enrich design reasoning. Designers are presented with the opportunity to continuously obtain a diverse range of outputs by adjusting prompts simply, providing designers with an infinite number of design schemes for design reasoning and concept exploration. Second, generative AI can take over tedious and laborious expression tasks [56], enabling designers to focus on the most important thing in conceptual design, the "exploration"[27]. For example, in the refine mode of ProtoDreamer, designers can control the AI generation to change the scheme scale and shape by simply placing anchors and arrows. This delegation not only saves time but also reduces the cognitive load on designers, allowing them to think more freely and innovatively. Third, generative AI might offer insights escaping designers' relevance sense and awareness through providing data-enabled understandings [20]. Participants reported many times that AI supplemented the surprising details based on physical models. This data-enabled random addition might surpass designers' subjective logic and opinions and bring unexpected design concepts and inspiration.

7.2.3 Human-AI Co-prototyping Experience Influenced by Designers' Understanding of Scope, Limitations, and Applicable Scenarios of AI Agent. In observation of our study, designers sometimes harbored unrealistic expectations towards AI agent, leading to a gradual erosion of confidence and trust. For example, P3 only provided a simple keyword with the expectation that the AI agent would yield intricate details in return. P10 wants a generated scheme in minimalist style based on a colorful physical model (Figure 11b). Therefore, effective human-AI co-prototyping necessitates not only user-friendly system designs but also the incorporation of educational and guiding measures for designers, ensuring that designers understand the capacity scope and boundaries of AI partner [2]. We summarized some directions to effectuate this objective after practice. First, face to target end-designers and reduce using professional technical vocabulary. P5 reported that "*I am a little at a loss when faced with 'Prompt', but when it is changed to 'Design requirements and restrictions', I can better understand it*". Second, make clear how to interact with component in user interface and what they can do. Sufficient annotations need be provided for interactive components to effectively communicate the implications and impacts of user interactions. Third, instructional guidance phase plays a pivotal role in enhancing users' comprehension and grasp of capacity of AI.

7.2.4 Ever-changing Role of AI Agent Confuses Designers and Disrupts Design Rhythm. Through the observation of human-AI co-creation in this study, we found that ProtoDreamer can assume a variety of cooperative roles according to AI's contribution, such as "create new", "extend", and "refine" [52]. However, due to the uncertainty inherent in the generation technology, the ever-changing AI role will cause problems for designers. P9 reported that "*when I am in the final process of fine adjustment of the candidate scheme, AI will still change the color matching and basic functions of the design, which disrupts my control and thinking of the design rhythm*". Someone also indicated that "*I hope AI can clarify its role and execute corresponding endeavors in accordance with my intended trajectory, rather than embarking upon a random and unpredictable course*". Although we provided interactive components to adjust the influence weight of physical model control generation in ProtoDreamer, it still remains insufficient for designers to comprehend AI's ability and contribution. As comprehending the scope, background, and knowledge of collaborators holds pivotal significance in co-creation [18, 54], it is necessary to clarify and present designers with a range of distinct AI roles, defining the role types, cooperation modes, and contribution forms in human-AI co-prototyping system. For example, we can provide specific AI roles, such as *Translator*, *Stimulator*, *Explorer*, and *Refiner*, to end users directly, improving the specific ability and usability of each AI role through prompt engineering or fine-tuning, instead of letting users face an unknown and changeable AI.

Figure 15: Application space in lowering threshold of design. (a) An ordinary user applies ProtoDreamer to change LEGO model shapes and styles. (b) Utilizing ProtoDreamer to improve the efficient communication of customer's intention in the process of customized jewelry design. (c) A prototype process of Intelligent Motion Capture Gloves designed by an engineer independently under the support of ProtoDreamer.

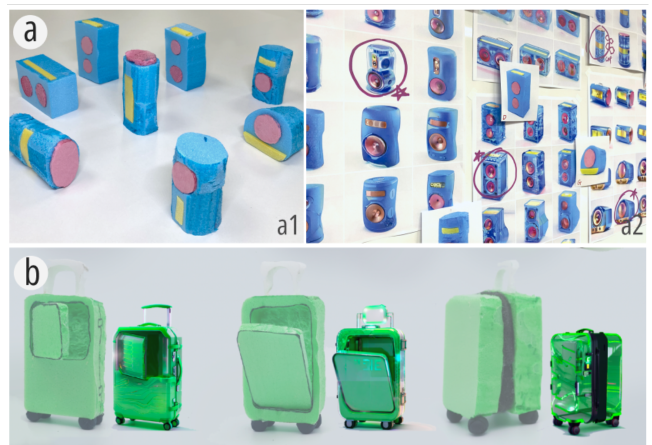

Figure 16: Application space in facilitating design exploration. (a). Exploring the shape design of an intelligent speaker based on various combinations of rough physical models under the support of ProtoDreamer. (b). Exploring and expressing various configurations and states of a luggage structure under the support of ProtoDreamer.

7.3 Potential Application Space of ProtoDreamer

7.3.1 Lowering Threshold of Design: "Everyone is a designer". ProtoDreamer offers a user-friendly and low-barrier approach for prototyping, enabling individuals without specialized painting or modeling skills to materialize their ideas into prototypes. For example, ordinary users can use ProtoDreamer to innovate LEGO gameplay, unleashing more potential for imaginative ideation and creativity space (Figure 15a). Customers can also participate in customized design process through ProtoDreamer, conveying their visions to designers effectively, thereby enhancing both communication efficiency and overall satisfaction (Figure 15b). Besides, engineers and technicians can independently undertake modeling design tasks based on technical principles (Figure 15c).

7.3.2 Facilitating Design Exploration and Deliberation: "Unleashing possibilities for prototyping". During the design process, prototyping serves not only as a mean to express schemes but also as a tool to navigate design problem space and solution space through imagining, discussing, and shaping potential states [25, 41]. ProtoDreamer presents a unique platform for professional designers to engage in swift and comprehensive exploration during the conceptual design phase. This is illustrated in Figure 16a1, where designers use physical materials to create and modify diverse preliminary shapes. These shapes can then be quickly transformed by AI (Figure 16a2), uncovering a multitude of possibilities in a short time. Moreover, ProtoDreamer supports testing different product configurations. For example, in Figure 16b, designers can experiment with different states and configurations of a suitcase by rearranging tangible materials, fostering in-depth consideration of structure and details through interactive, physical engagement.

7.3.3 Supporting On-site Testing and Iteration: "Fostering situation-based action and thinking". The mobility of ProtoDreamer allows for prototype iteration process to transcend traditional design studio boundaries, supporting on-site design activities. With ProtoDreamer, designers can effectively conduct prototype testing and iteration in actual settings and environments (Figure 17a), utilizing materials present in these real-world contexts. This on-site application of ProtoDreamer not only circumvents the spatial dimension compression and conversion typically associated with prototyping [1], but also promotes context-specific action and thinking by enabling direct design iteration with the real scenarios and configurations of the targeted product [40].

7.3.4 Enhancing Team Communication and Design Collaboration: "Empowering collaboration for seamless design". Tangible object facilitates spatial reasoning and reduce cognitive load during collaborative design [24, 30, 43]. With ProtoDreamer, tangible prototypes enable design team members to constantly create, test, explain, or negotiate schemes, endowing them with new meanings [36]. Besides, given the often interdisciplinary nature of design process [70], ProtoDreamer supports team members to intuitively and freely adjust the prototype through physical materials. Engineers and even clients without any design skills can also actively participate in

Figure 17: (a). Application space in supporting on-site design. Designers used ProtoDreamer to test and explore the design of Head-mounted Night Light based on existing helmet products. (b). Application space in enhancing design collaboration. The interdisciplinary design team applied ProtoDreamer to enhance design communication with a Fruit Picking Manipulator in the meeting room.

creating and testing activities, contributing to reaching team consensus for design goals (Figure 17b). Design team members are able to directly articulate their requirements and swiftly access generated design schemes aligned with the current iteration, thus facilitating efficient communication and decision-making.

8 LIMITATIONS

We discuss the limitations of our study that need to be addressed in future research.

First, the way to capture the information of physical model is single. We only achieve intention share through capturing the image of the physical model by camera. It might not only reduce the dimension of information, but also be affected by shooting quality, such as clarity, shooting angle, shooting environment and background. In future research, we plan to capture the 3D data of the physical model directly through the tangible user interface or 3D reconstruction technology.

Second, more comprehensive quantitative research is needed to fully explore the underlying factors that contribute to the facilitation and augmentation prototype process. The comparative analysis against existing tools, as a benchmark, can be conducted to discern the effectiveness of ProtoDreamer, bolstered by robust statistical analysis. Experiments with strictly controlled conditions (such as design tasks and design time) should also be carried out to provide a more complete and in-depth efficiency report.

Third, the research duration scale and participant sample are relatively limited. A more realistic evaluation could apply ProtoDreamer in actual design workflows, involving large-scale design teams over extended periods. We intend to release ProtoDreamer to the wild for a broader understanding of usability and utility.

9 CONCLUSION

We propose ProtoDreamer, a mixed-prototype tool combining physical model and generative AI to support industrial conceptual design. ProtoDreamer allows designers to construct preliminary prototypes using physical materials, while AI recognizes these forms and vocal inputs to generate diverse design alternatives. In an evaluation study, designers were able to create a satisfactory design scheme under the support of ProtoDreamer. In addition to the usability and learnability of the system being verified, the creativity support in prototyping process had been confirmed, especially in perspectives of improving expressiveness and worth of effort. Designers showed a strong preference for the mixed-prototype modes and indicated its distinct strengths in time efficiency, defects exposure, and structured and detailed thinking. Our work and findings provide effective AI-assisted tools to support design and offer important insights and suggestions for human-AI co-creation based on large-scale models.

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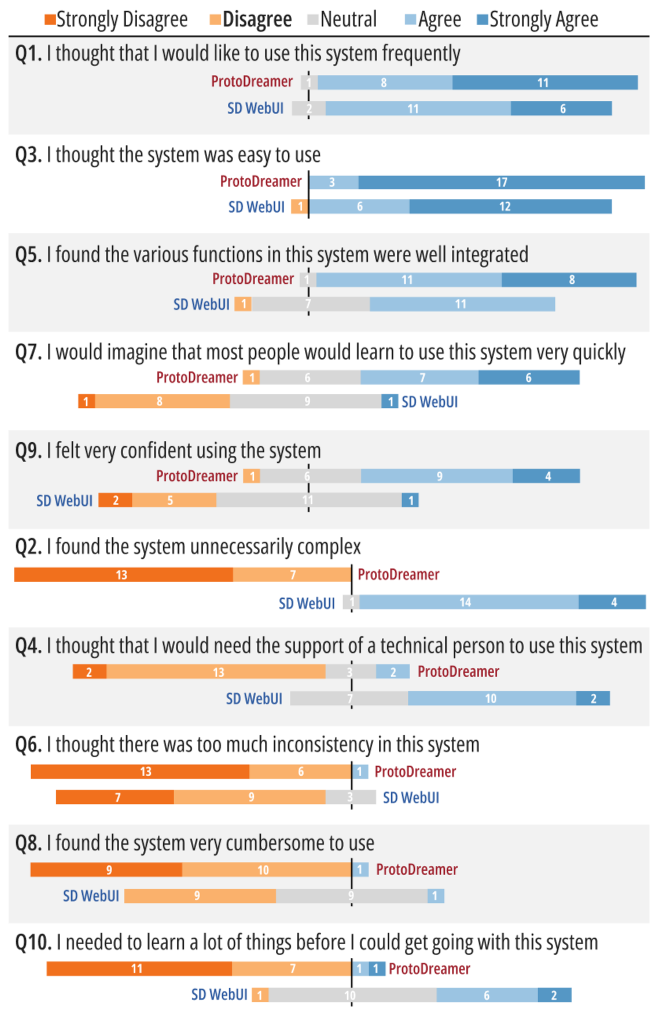

Figure 18: SUS Results of ProtoDreamer and SD WebUI.

APPENDIX1. PARTICIPANT INFORMATION

The participant information in the evaluation study is showed in Table2.

APPENDIX2. A SUPPLEMENTED ANALYSIS

During the rebuttal stage, we supplemented a comparative experiment. We contacted 19/20 participants in User Study 2 and invited them to use the StableDiffusion WebUI interface to complete design task. All back-end server implementation is same to ProtoDreamer to ensure fairness. Aiming to ensure participants to complete similar design tasks, we summarized all product categories they created in User Study 2 as text, and they were asked to choose one or more as design tasks. After design, they completed SUS and CSI questionnaires. For the data analysis, the Shapiro-Wilk test was run at a significance level of 0.05 for normality test. The t-test for normal distribution while Mann-Whitney U test for non-normal distribution.

Table 2: Overview of participants in the evaluation study.

ID	Age	Gender	Domain	Occupation
P1	27	F	Industrial Design	Student / Phd
P2	25	M	Computational Design	Designer
P3	26	M	Industrial Design	Designer
P4	24	M	Industrial Design	Student / MA
P5	27	M	Industrial Design	Designer
P6	23	F	Industrial Design	Student / MA
P7	35	F	Mechanical Engineering	Designer
P8	24	F	Industrial Design	Student / MA
P9	24	F	Industrial Design	Student / MA
P10	26	F	Industrial Design	Student / MA
P11	26	M	Industrial Design	Student / MA
P12	24	F	Industrial Design	Student /MA
P13	26	F	Industrial Design	Student / Phd
P14	24	F	Industrial Design	Student / MA
P15	24	F	Industrial Design	Student / Phd
P16	27	M	Mechanical Engineering	Engineer
P17	26	F	Industrial Design	Student / Phd
P18	25	M	Mechanical Engineering	Engineer
P19	25	M	Industrial Design	Designer
P20	26	F	Computational Design	Student / Phd

The SUS results are presented in Figure 18. The average total SUS score of ProtoDreamer and baseline was 82.50 ($SD = 6.12$) and 50.92 ($SD = 6.08$), in which there was a significant difference ($t(37) = 15.869, p < 0.001$). Besides, the usability score was 84.22 ($SD = 6.13$) for ProtoDreamer while 54.93 ($SD = 5.94$)for baseline, in which there was a significant difference ($U = 380.0, p < 0.001$). The learnability score was 75.63 ($SD = 16.99$) for ProtoDreamer while 34.87 ($SD = 11.88$) for baseline, in which there was a significant difference ($U = 364.5, p < 0.001$).

The average CSI score of ProtoDreamer and baseline was 86.20 ($SD = 4.83$) and 69.90 ($SD = 4.87$), in which there was a significant difference ($t(37) = -10.357, p < 0.001$). Figure 19 show the average weighted factor scores for each of the six factors on the CSI. Specifically, ProtoDreamer presented significant higher performance in *collaboration* ($U = 98.0, p = 0.009$), *exploration* ($U = 39.0, p < 0.001$), and *expressiveness* ($U = 54.0, p < 0.001$) than the baseline.

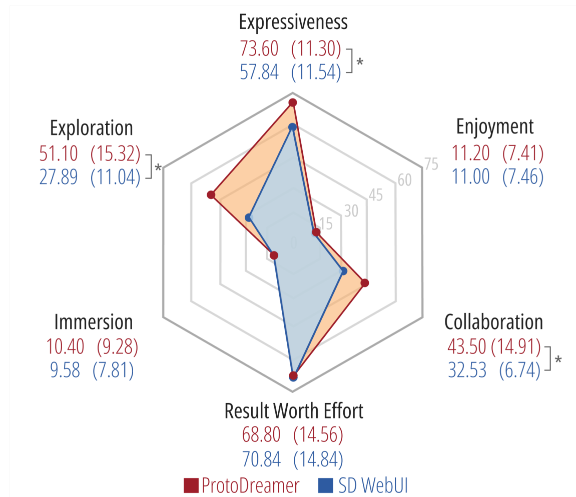

Figure 19: Average weighted factor score for CSI. *indicates the significant difference.