How AI can Harmonize and Increase Efficiency with Industrial Design: A Case Study from Ai's Initial Exploration to its Professional Application

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Abstract. This study examines the current status and future mechanisms of human-intelligence collaboration in industrial design, highlighting the instability and efficiency issues of existing AI platforms (e.g., MJ and SD). While AI can generate numerous intention diagrams, designers must balance creative dispersion with focused direction. The study suggests developing a proprietary AI engine and underscores the designers' feedback role and the importance of intention maps. It concludes that two-way feedback mechanisms, instrumental reinforcement, and dataset specialization will optimize design efficiency and creative output in the future.

Keywords: Human-AI collaboration,Industrial design,AI platforms,Intention images, Creative output,Design efficiency.

1 Background

Since the early 1960s, digital platforms and tools have aided the design process through simulation and modeling. Recently, with the rapid growth of AI, exemplified by ChatGPT, there is widespread recognition of this irreversible trend. The focus on using AI to enhance industrial design efficiency has become a key research direction [1]. Understanding the functions of these AI tools is essential for boosting designers' creativity and productivity, allowing them to fully leverage technological innovations. This exploration begins with the initial use of AI and progresses to professional applications and case studies on harmonizing AI with industrial design efficiency [2].

2 The First Phase of AI Exploration

2.1 Hands-on Drills for the Initial Process

Here is an example of an innovative style study with a real live design, a portable ironing machine, to demonstrate the first attempts of human-intelligence collaboration.

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Chatgpt Role-Playing. Large-scale language models like ChatGPT have attracted attention for their text processing and generation capabilities. ChatGPT is effective in data tagging and knowledge transfer [3]. In design research, designers use GPT to explore positioning by querying various project roles. The responses are summarized, with expert designers involved in filtering and decision-making, leading to the identification of several innovative styles: 1. luxury style; 2. architectural style; 3. Chinese Zen; 4. technological style (see Fig.1).

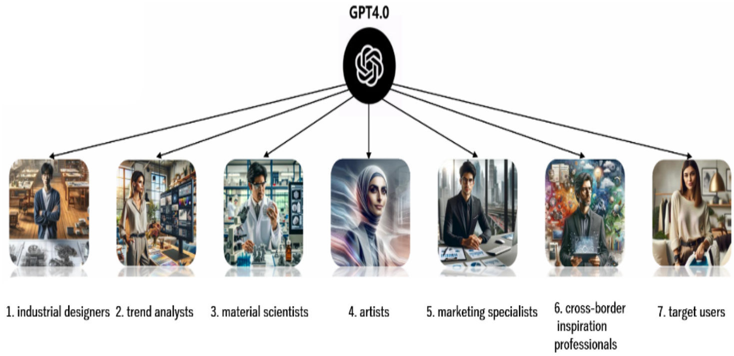

Fig. 1. Chagpt plays multiple roles

Production of Emotional Version. Using four main styles as input for MJ, we generate mood versions and supplement them with relevant online images. MJ produces around 100 unique images in about 10 minutes, allowing designers to freely extract elements, ideal for early product design inspiration [4]. However, its output is not fully controllable, requiring further screening to match the desired theme [5]. Ultimately, four mood versions are created, with the technological style selected for deeper exploration (see Fig. 2).

Fig. 2. Tech Mood Board

Cue Word and Product Mat Image. Sentiment versions are labeled with feelings and tonal styles. Researchers use these labels to create MJ text prompts. For matting, an abstract style picture and a figurative product picture are selected to output the first round of product target images in a picture + text format (see Fig. 3).

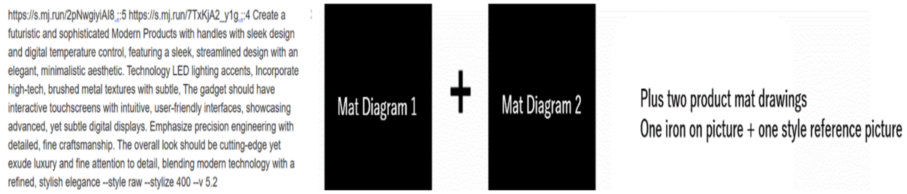

Fig. 3. Cue word and product mat image

Iterative Correction. The output is iteratively corrected by refining cue words and replacing the pad map. After multiple rounds of iterations, MJ generates a large number of raw images, gradually stabilizing the style, from which researchers conduct a final screening (see Fig. 4).

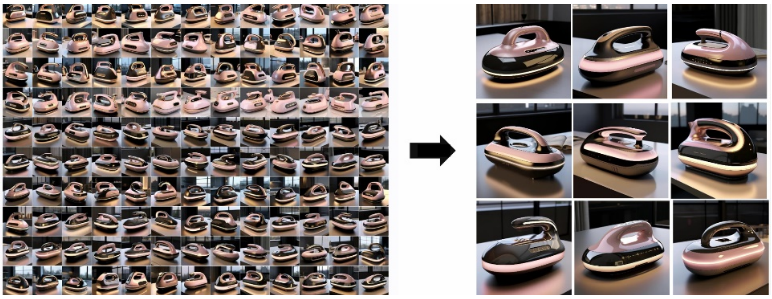

Fig. 4. Output image after iteration

Summarize Elements to Sketch. By the time the final results were selected, the researcher had a clear vision of the desired product. They summarized the characteristics from the first two rounds and the stable form from the third round to serve as a basis for sketching (see Fig. 5).

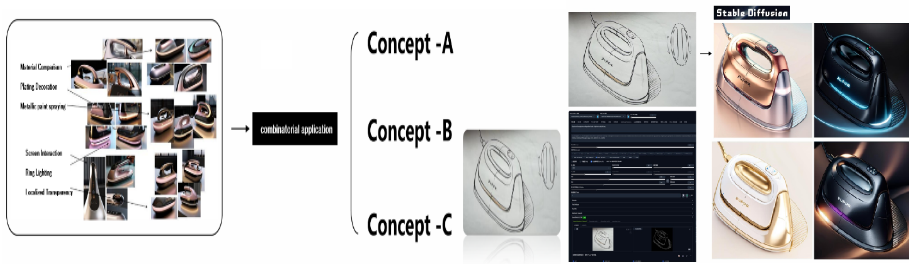

Fig. 5. Summarize elements to sketch and Sd output of the effect graph

Sd is Used for Detail Deployment. SD facilitates creative dispersion due to its uncontrollability. Once sketches are generated, its high controllability enables precise outputs (see Fig. 5). This marks the end of human-intelligence collaboration in design, leading to 3D optimization by experienced designers who refine any incorrect human-machine details.

2.2 Summary of Initial Process Pain Points

After some time of practice, researchers generally feel "exhausted," mainly reflected in the following points:

Unstable MJ Outputs. The results from AI platforms like MJ are unpredictable, requiring researchers to repeatedly adjust prompts and find reference images, leading to low efficiency. Currently, there are almost no AI models tailored specifically for industrial design in the market.

SD Suppresses Inspiration. When using Stable Diffusion to generate product images, designers need to provide clear prompts, which can ensure direction but limit creative divergence, potentially leading to homogenized design outcomes.

Lack of Commercial Value . From a commercialization perspective, clients are willing to pay for precise solutions rather than relying on trial-and-error methods. The current high trial-and-error probability collaboration is hard to accept in the market.

2.3 Initial Process Advantage Summary

Due to issues like instability and low commercial value, the initial human-AI collaboration process is gradually being abandoned in the internal industrial design field, though still used in some small projects. This exploration has clarified the core logic and main advantages of AI software:

Core Behavior Remains Unchanged. The act of finding reference images persists, but these images are now used to communicate with AI, generating more reference images. In the AI context, reference images serve as a medium for human-machine communication.

Main Advantage: Increased Output Quantity. Previously, finding reference images was time-consuming; now, communicating with AI using a single image can yield many new reference images, termed "explosive secondary reference images." This approach significantly enhances the chances of inspiration, as designers, while interacting with AI, can visualize a vague target image, increasing the likelihood of creative insights.

3 The Second Phase of AI Exploration

3.1 Initiating the Development of an Industrial Design + AI Engine Platform

The design company moves to the second phase, building on initial explorations that clarified AI software's core logic in industrial design, particularly the importance of reference images and strong output capabilities. However, the lack of specialized design images has led to distorted connections and increased workload for designers. Consequently, researchers are developing an AI design engine platform based on Stable Diffusion, using ComfyUI to break the process into nodes for improved workflow customization and reproducibility.

3.2 Practical Process of Building a Proprietary Model-based Industrial Design + AI Engine Platform

In the model construction phase, engineers manage technical aspects while expert designers lead development. Experts collect, evaluate, and optimize design images, infusing their aesthetic and industry experience into the AI platform for high-standard outputs. Model testing is cyclical, involving real design practice and designer feedback. Below is a summary of the sofa testing case:

1.Sketch Divergence.Initial sketches combined with reference images revealed that cluttered backgrounds affect divergence, and data for hollow and organic forms is insufficient.2.Sketch Coloring.Color output shows that large areas of hollow structures are difficult to recognize, resulting in poor style and quality.3.Style Reformation.No issues found in style shaping.4.Detail Adjustment.Insufficient capture of detail features, needing improved integration.5.CMF Transfer.Auto-generated scenes during CMF transfer should be avoided; wood material recognition is good, but hard hollow effects are poor.6.Scene Creation.Scene output lacks quality, appearing unrealistic.

3.3 Current State of Model Output after Round Robin Testing

After testing and optimization, the model's performance has significantly improved. Designer feedback has enhanced sketch divergence, coloring, and detail adjustment. In CMF transfer and scene creation, the model better understands prompts and generates high-quality design images that align with industry standards. Below are examples of the output quality from the self-developed industrial design and AI collaboration platform (see Figs. 6 and 7).

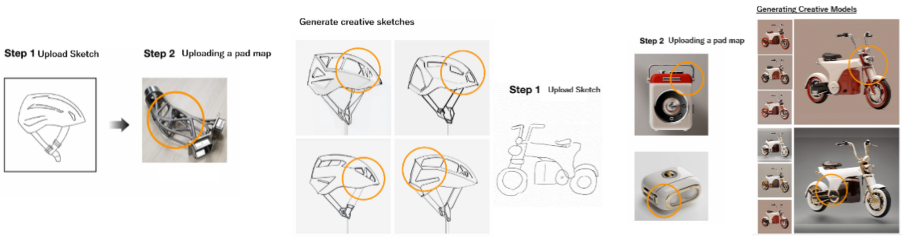

Fig. 6. Sketch and model output performance

Fig. 7. Style migration and cmf migration

4 Conclusion

4.1 Dilemma Intervention Points and Opportunity Intervention Points

Dilemma Intervention Points.

1. AI Output Instability: Uncontrollable results require frequent revisions. 2. Trial Fatigue: Constant prompt modifications and image searches lead to exhaustion. 3. Low Commercial Value: Clients hesitate to pay for high-probability trial-and-error. 4. Compatibility Issues: Lack of large models tailored for industrial design causes distorted outputs.

Opportunity Intervention Points.

1. Continuity of Design Process: Reference images serve as a medium for human-machine communication. 2. Explosive AI Output: Generates numerous new images from references to inspire creativity. 3. Designers' Feedback Role: Designers are participants in AI, not just users. 4. ComfyUI and Stable Diffusion: Enables self-developed AI engines for better accuracy and reproducibility. 5. AI's Long-Distance Connection Ability: Long-distance references stimulate creativity and aid connections.

4.2 Development Directions for Human-AI Collaboration Mechanisms in Industrial Design

Through case analysis, we identified dilemmas and opportunities for enhancing AI and industrial design coordination, guiding future mechanisms for human-AI collaboration.

1. Bidirectional Feedback Interaction.Iterative interaction forms the core of AI-designer collaboration. AI generates design inspiration through reference images, while designers optimize results through filtering and feedback, creating a bidirectional feedback mechanism.

2. Tool Enhancement and Creative Inspiration.The primary function of AI is to enhance creative inspiration and accelerate the output of ideas. By using long-distance reference images, AI expands designers' creative thinking, reduces trial costs, and improves design efficiency.

3. Dataset Specialization and Platform Optimization.A key challenge for AI platforms is the alignment between datasets and design needs. Designer-led AI platforms will increasingly serve as effective pathways for integrating into industrial design, addressing discrepancies between output and actual requirements.

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