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Article

Is AI image generation a creative or optimize tool in product design process?—The usage of AI image generation tools for vehicle shape as an example

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Abstract: This study explores the shape thinking processes and decision-making factors of designers when using AI image generation tools for conceptualizing the shapes of two-wheeled vehicles through four design tasks. Eight designers were invited to create hand-drawn sketches based on a specific aesthetic direction (technological geometry), followed by a shape divergence exercise using two AI graphics tools, Stable Diffusion and Vizcom, to generate images from text prompts. After selecting the designs closest to their original concepts and their favorite designs, the designers used an iPad to explore different shape directions (technological biology) for partial shape modifications. Finally, retrospective interviews were conducted to understand whether there were differences in designers' thinking process regarding the use of various AI tools for shape conceptualization, as well as their focal points regarding design modification and shape thinking at different stages of the process. The research findings indicate that current AI tools are more suitable for shape divergence. If designers wish to achieve shape convergence, they need to be more familiar with the various settings of AI image generation tools and understand which prompts significantly influence specific shape characteristics. Designers' perceptions of shape modification primarily revolve around: 1. Outline contours, 2. Parting lines, 3. Variations in surface curvature, and 4. The resulting features (light and shadow effects). Furthermore, it is recommended that future AI image generation tools, if developed as professional assistive tools for product design, should provide two modes—shape divergence and convergence—focusing on both the main shape and details. Additionally, it is suggested that developing AI-3D technologies should address the four key aspects of shape manipulation presented in this study, offering adjustments for overall appearance and detailing the contour lines of parts, including the manipulation of surface curvature and shape positioning.

Keywords: artificial intelligence; image generation; design process; vehicle shape design; motorcycle design

1. Introduction

Generative artificial intelligence (AI), whether through text-to-image or image-to-image processes, can assist ordinary people in creating visual outputs similar to those produced by designers. However, the value of designers or the design work is the various creative exercise before producing the final drawing and the various possibilities iterated through the process of divergent and convergent thinking.

This study argues that while AI currently surpasses human capabilities in terms of image refinement and drawing efficiency, it lacks of styling thinking process. For AI to assist designers in a manner that is closer to human thinking, it must align more closely with the design process and designers' thinking during computation. This research approaches the issue from the perspective of form generation, analyzing the key points and processes that designers focus on during conceptualization. Through experiments involving AI tools in design tasks, this study examines the role of AI tools in the divergent and convergent processes of product shape generation, exploring the strengths and weaknesses of various generative AI tools when applied to existing design workflows. Additionally, it proposes the functionalities and characteristics that AI tools (assistants) should possess from the perspective of design, providing a reference for the development of professional generative AI tools. The main contribution of this study is to use a quasi-experimental method allowing professional designers to use two AI tools, convergence and divergence, to propose their shape thinking in practical vehicle design process, and to summarize the feedback from 8 designers to propose further AI solutions development that meet the needs of professional product design work.

1.1. Research background

In recent years, machine learning has been widely applied in various fields of artificial intelligence, particularly in predicting user needs. Jiang (2022) and Jiang and Luo (2022) conducted extensive surveys on graph-based deep learning and graph neural networks in the areas of traffic forecasting and communication networks, highlighting the opportunities for AI technologies across different domains. The deep learning theory has also been applied to Generative Adversarial Network (GAN) AI technology (Goodfellow et al., 2020), and leads to two methods: text-to-image and image-generated image, and is further developed for various easy-to-operate (communication) tools. The emergence of tools such as Midjourney and DALL-E has enabled the general public to easily produce stunning images through text prompts (Lee and Chiu, 2023). However, for designers, the design process is not merely about producing images; it involves continuous contemplation and iteration of forms during the image generation process, ultimately resulting in shapes imbued with meaning. If designers rely solely on the images provided by AI as the final outcome, they undoubtedly forfeit the most valuable aspect of their role—their critical thinking. The use of diffusion model techniques can further enhance control over image details, seemingly aligning more closely with designers' needs, and even allowing for direct re-rendering of specific areas for visual communication. However, what aspects do designers consider when using AI tools for form design, and what are their expectations of these AI tools? Similar to Jiang's survey on AI applications in traffic forecasting, this research acknowledges the potential of AI in generative design applications. It specifically focuses on the roles played by various AI generation tools in the design process and how these tools can be better aligned with the genuine needs of designers.

Since the widespread adoption of Chat GPT and generative AI applications in 2023, the interaction between humans and computers has evolved from a command-response model to a new paradigm of communication through text and images. Computers can now engage in dialogue with users and generate unexpected images, almost as if they possess a semblance of life. The development of artificial intelligence (AI) has narrowed the gap between amateurs and professionals (Friedman, 2005), leading to concerns among artists and image professionals about potential job displacement. For designers who rely on visual communication, this has meant confronting the reality that certain specialized tasks have been supplanted by AI, such as the replacement of traditional sketching courses with generative AI-based curricula in some institutions. Designers with practical experience using AI tools report that AI can assist in early-stage concept development, quickly produce simple sketches, and even generate final rendering effects (Chiu, 2024). However, experienced designers still believe that the final product shape should be determined by the designer (Lin, 2024), and that AI tools have room for improvement in practical design applications. This study posits that advancements in generative AI technology have enhanced the realism of image presentation. Nonetheless, current AI image generation remains akin to a "black box" of large data calculations, where using AI tools can be like rolling dice—occasionally producing unexpectedly good results but lacking transparency and reproducibility. This issue arises because AI engineering has yet to address the true needs of designers by integrating the design process and decision-making modes of designers into AI-assisted tools.

1.2. Research objectives

Human-computer interface development requires tools to be user-friendly initially to achieve widespread acceptance. As tools transition into specialized fields, they must incorporate various hardware and software configurations to address specific needs. Generative AI has received acclaim in the design field for its efficiency and convenience, yet its inherent unpredictability can result in outcomes similar to rolling dice, although the outcomes are fantastic. This study explores the application of different AI tools in design scenarios, focusing on the integration of divergent and convergent processes within the design workflow. By analyzing designers' perceptual processes in form decision-making and identifying the types of assistance needed at various stages, this research aims to offer recommendations and references for developing advanced AI design tools in the future.

The use of AI tools by designers can either drive AI or be driven by AI, depending on their mastery of form. In the divergent and convergent processes of design, AI can generate new shapes by deconstructing and recombining graphical data based on the text or images provided by designers. The critical issue is whether the process of form finding and AI-assisted image regeneration will preserve the designer's original concept or follow AI's suggestions toward different directions. This study focuses on examining the key factors in designers' decision-making when selecting AI-generated shapes and aims to propose functionalities or options that AI should offer to become an effective professional design assistant.

The objectives of this study are as follows:

(1) To understand the strengths and weaknesses of different AI tools in the application of shape design processes through design tasks.

(2) To use observational methods and retrospective interviews to explore designers' shape recognition, cognition, and decision-making processes.

(3) To summarize the key aspects of form exploration and iteration that designers focus on.

(4) To identify designers' practical needs of AI-assisted tools during form divergence and convergence.

1.3. Research questions

Current AI image generation tools are primarily developed by programmers and information engineers, without considering the specific needs of particular users or tasks. Although AI's computational capabilities can theoretically expand infinitely, the development of human society shows that various professions exist. We do not expect a single omnipotent device to function both as a physician for our physical and mental health and as an architect to build our houses. An ideal AI system should be able to adapt to different professional needs, presenting different capabilities to help users complete tasks more effectively and enjoyably. This study approaches the issue from the perspective of product design, focusing on the exterior design of transportation vehicles. It aims to address practical application needs by observing and analyzing the process of designers using AI tools for shape thinking. Understanding the key factors in designers' decision-making and exploring how future AI tools can assist designers in working more efficiently are central to this research. The goal is to develop AI tools that align more closely with designers' thinking processes, rather than merely generating visually appealing images. This research will provide insights and references for the development of AI tools in various specialized fields.

2. Literature review

Vermillion (2023) pointed out that if designers intend to use AI to perform creative tasks, they should focus more on the actual creative process while adopting a more critical perspective towards AI-generated images. Additionally, they should develop new creative workflows. This study aims to understand how designers perceive stylistic differences and determine decision-making factors during the divergent and convergent phases of design. The literature review covers the fundamentals of AI technology, design processes, stylistic perception, and the application of AI in the field of design.

2.1. AI image generation and design

Russell and Norvig (2016) state that developing AI within an Information System requires adapting to different environments and task-specific characteristics, transforming AI into a human-like thinking agent. For designers, image generation is the most direct way to communicate design concepts. Whether through text-to-image or image-to-image generation, AI seems to accomplish the task; however, whether AI iterates on design concepts as a designer would becomes the key to its effectiveness in assisting design. Stable Diffusion allows for image control through prompts (Zhang and Agrawala, 2023), and its ControlNets demonstrate significant efficacy in controlling image generation. The canny mode can extract lines from the input image and adjust the similarity to the reference image through the control weight value. Vizcom's image generation technology is also highly advanced, capable of converting sketches into rendered images and using influence values to control the reference image's ratio (Chiu, 2024). In this study, AI image generation variables are controlled with reference sketches provided by the designer as the boundaries for image generation. Additionally, prompts and parameters are provided as a means for AI to assist designers in thinking about and evaluating design concepts. This approach facilitates understanding the key elements designers focus on during subsequent interviews.

2.2. Design process

The Design Council (2005) proposed the Double Diamond design model, which includes four phases: Discover, Define, Develop, and Deliver. Howard et al. (2008) divided the product design process into four major stages: task analysis, concept design, structural design, and detailed design, noting that innovative design behaviors primarily manifest in the earlier stages of the design process, while the later stages tend to involve more conservative, convergent actions. Hsiao and Chou (2004) pointed out that the convergent phase of the design process is a stage where the goal is to identify the best sub-solutions or optimal design. Using motorcycle design as an example, they employed quantitative methods to evaluate whether the design met the initial objectives, ultimately converging on the final design proposal.

Ma et al. (2023) integrated Stanford University's five steps of design thinking—empathize, define, ideate, prototype, test—into the Double Diamond model to demonstrate how designers first need to assume the role of users. They emphasize the process of diverging abstract concepts and converging concrete situations, followed by iterative testing and optimization of designs. If AI-generated images are considered as a tool to assist designers in performing stylistic divergence and convergence to seek the optimal design, then it is necessary to follow the stylistic direction defined by the designer, define shape description, generative images, form finding and shape decision, iterating through the process of progressively narrowing the scope of divergence and convergence (shown as **Figure 1**).

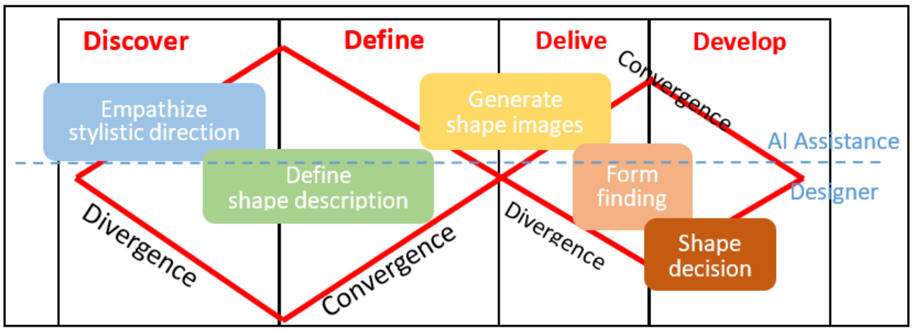


Figure 1. The AI image generative assistant process (Modified by this research).

2.3. Form finding process

Aesthetics play a significant role in shaping various products, as demonstrated in researches on emotional design and Kansei engineering (Hsiao and Chen, 2006; Hsu et al., 2000; Osborn et al., 2009). Perez et al. (2017), using the example of vase design, transformed the features of product shapes into parameters, linking design rules with aesthetic characteristics. Tang et al. (2013) converted consumers' perceptions of product contours into parameters and used an artificial neural network to generate different mobile phone designs. This study focuses more on how designers perceive differences in form details when using AI to adjust designs. Fang (2023) pointed out that AI image generation tools do not truly understand the thinking process of industrial design but instead search for multiple images with the highest probability of matching the given keywords, extracting and merging parts of them. The image-to-image generation operates on a similar principle, merging the user's input image with images found through prompts according to the user-defined ratio. Fang mentioned that AI currently cannot replace designers in the form convergence process, which relies on core design capabilities, the key area this research aims to explore. Krish (2011) proposed a practical generative design method to assist designers in form finding within a specific solution space. If AI-generated images are seen as a tool to assist designers in performing stylistic divergence and convergence to seek the optimal design, then the process of form finding should involve iterating through the designer-defined solution space by progressively narrowing the scope of divergence and convergence.

2.4. Applications of AI in design

Collins et al. (2021) highlighted in a literature review that AI applications have been implemented across various fields; however, accurately conveying human thought through natural language remains a significant challenge. Kulkarni et al. (2023) noted that AI-generated text-to-image methods can assist designers in expressing design concepts. However, Lee and Lin (2023) pointed out that using text-to-image generation for form convergence is challenging, as AI's differing interpretations of certain product-related keywords can lead to significant variations in the generated images. In a study where Lee and Chiu (2023) used AI-generated images as stimulation for designers' hand-drawing motorcycle sketches, they found that the divergent forms generated by AI prompted designers to explore a broader range of design approaches. Chiu (2024) conducted a study using both AI text-to-image and image-to-image methods combined with prompts to test the impact on six design students and six professional designers when expressing motorcycle design concepts with AI tools. The study results similarly indicated that current AI tools are more suitable for the early stages of design or form ideation. This research adopts a similar experimental framework to Chiu (2024) to explore the functions and operational methods required by current AI tools to assist designers in form convergence. It examines the thinking processes of designers in form convergence by using image-to-image generation as a means for form ideation, focusing on the design of complex two-wheeled vehicles. Motorcycle design encompasses multiple disciplines, including aesthetics, engineering, and ergonomics, requiring designers to consider both the overall appearance and the details of various components, thereby providing insights into designers' behaviors, thinking patterns, and key areas of focus in form design.

Currently, most applications of AI-generated imagery primarily modify the input text descriptions or adjust the seed parameters to alter the similarity of the generated images to the original pictures. This study is based on the convergence and small-scale divergence processes in design practice. We conducted preliminary tests to control the seed parameters of AI-generated images within a defined range for shape divergence according specific shape, thereby preventing the production of excessively varied shape images during the experimental process.

3. Research methodology

This study employs four design tasks, combined with observational and interview methods, to collect information on design behaviors. Subsequently, content analysis is used to explore the cognitive processes and key factors involved in designers' decision-making regarding form generation. Finally, the study synthesizes the necessary functions and support mechanisms that AI design tools should provide. The four tasks involving the exterior design of electric two-wheeled vehicles, testing the AI tools in both divergent and convergent design processes. Eight designers (Pa~Ph) with comprehensive design training (over six years) and practical experience (over two years) were invited as participants. Among them, there were three vehicle form designers, two vehicle digital modelers, and three electronic product designers (seven males and one female, aged 24 to 27). The participants used Stable Diffusion and Vizcom to transform hand-drawn sketches into rendered images, followed by refining the designs through text and image modifications. By observing the participants' use of AI tools and conducting retrospective interviews to understand their form decision-making processes, this study identifies the key factors influencing design changes.

3.1. Experimental design

To explore the iterative process of divergence and convergence under specific shape conditions, and to compare the images generated by two AI tools through text-to-image generation, this study designed four tasks (shown as **Figure 2**). The four design tasks are as follows: 1. Initial shape convergence, defining the solution space for the shape based on the technology-geometric inspired motorcycle image board provided in this study (see **Figure 3a**), to facilitate design sketching towards specific shape directions; 2. Small-scale shape divergence, using AI tools (Stable Diffusion) to generate rendered images from hand-drawn sketches through text and images; 3. Small-scale shape divergence using different AI tools, employing the Vizcom tool to once again execute text and image generation, allowing designers to compare the output of different AI tools; 4. Selecting from the AI-generated images produced in Task 2 or Task 3, the design that is closest to the original hand-drawn image (initial shape idea) and the most preferred image generated by AI to compare, and then using Vizcom for digital hand-drawing in specific design direction through PAD (AI-assisted design) to make alterative designs in technology-organic line inspired (see **Figure 3b**). To avoid the influence of color differences on the selection results, researchers will first convert all AI-generated images to grayscale and appropriately adjust brightness levels. Throughout the process, researchers will observe and record the unique points of participants operating the AI as subjects for retrospective interview inquiries, and the entire session will be video recorded. During the retrospective interviews, audio recordings will be made, which will then be analyzed through verbatim transcriptions.

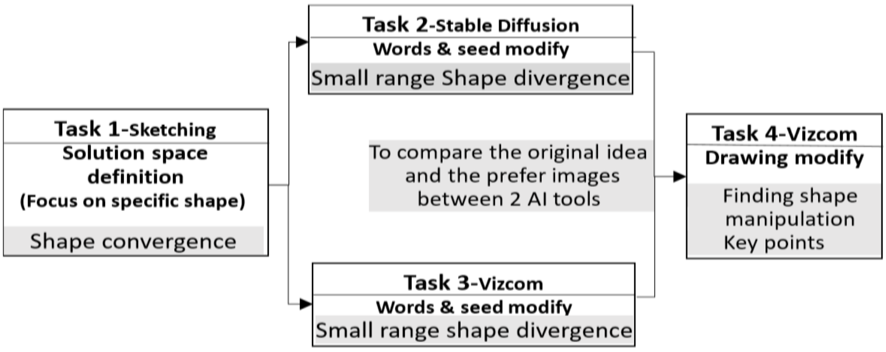
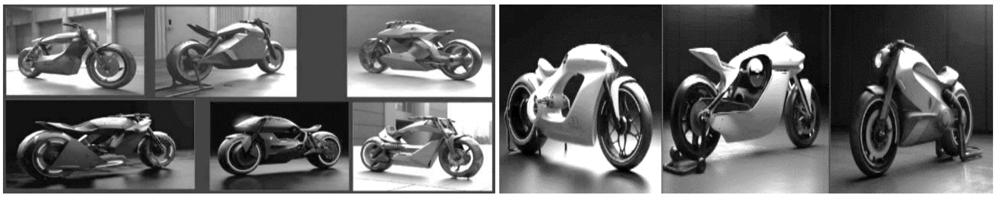


Figure 2. The tasks design for evaluating shape manipulation through AI image generation.



(a) (b)

Figure 3. (a) The reference images of technical-geometric motorsc; **(b)** the technical-organic motors.

Source: Chiu (2024).

Task 1 is primarily designed to focus participants on thinking within a constrained solution space. Tasks 2 and 3, using different AI tools for text and image inputs, serve as approaches for specific range of styling divergence. These tasks aim to validate whether differences in algorithms and operating modes of different generative software affect their position and application in the design process. Researchers will observe and record participants' processes of selection (form finding) or modifying text and images, and subsequently analyze the key factors influencing design decisions. Task 4 involves AI-assisted design modification. In contrast to Tasks 2 and 3, where the control inputs such as text and AI-influenced parameters (e.g., seed) are less, Task 4 allows participants to directly draw on the image to modify specific parts. Participants will then compare the original sketch with the modified image to determine which is more preferred in terms of design.

3.2. Experimental tool and settings

The tools used in this study include Stable Diffusion (with the Control Nets plugin) and Vizcom, both AI technologies were announced before April 2024. The software Procreate on an iPad Pro 1 was employed as hand-drawing tool. The laptop ASUS TUF Gaming model with a 15.6-inch screen, i7 CPU, RTX 3070-8G GPU, and 16GB RAM was chosen as AI platform. Additionally, 10 sheets of A3 paper, pencils, pens, and markers were provided. The experiments took place in a school laboratory or a distraction-free coffee shop. Each participant spent approximately 180 minutes completing the four tasks, including experiment explanations, AI tool introductions, and interviews.

The **Figure 1** in 2.2 demonstrates that shape design requires a series of divergent and convergent shape thinking processes. Currently, AI-generated imagery is more commonly utilized for shape divergence. This research, following the assigned design directions established through experimentation, employed the Delphi method to collect 250 adjectives from online sources and transportation design literature by researchers. Two designers with over ten years of experience discussed and selected 24 adjectives that are suitable for describing technological aesthetics, geometric forms, and biological shapes. These adjectives were categorized into three groups: style, shape, and element, which provided participating designers with a reference to avoid excessive divergence that could generate too many irrelevant images while using AI tools.

Stable Diffusion, utilizing external ControlNet plugin, requires a learning period and continuous adjustment of various parameter settings to achieve the desired image. To balance the differences between tools and considering that the experiment's aim was to understand designers' responses to using AI in design rather than to teach AI tools, researchers pre-tested and adjusted the control net settings to be suitable for two-wheeled vehicles, using control weight to modify text descriptions to influence the generated images. To more accurately observe and analyze participants' thinking processes and decision-making factors when using AI tools, this study limited the operational variables of the two AI tools to prompts and the control weight based on participants' hand-drawing sketches. **Figure 4** (top left) shows the examples of the style, shape, and element glossary by this study for participant as reference. Participants could also add their descriptions based on design needs. **Figure 4** (bottom left) shows the SD operational window and **Figure 4** (right) shows the Vizcom operational window.

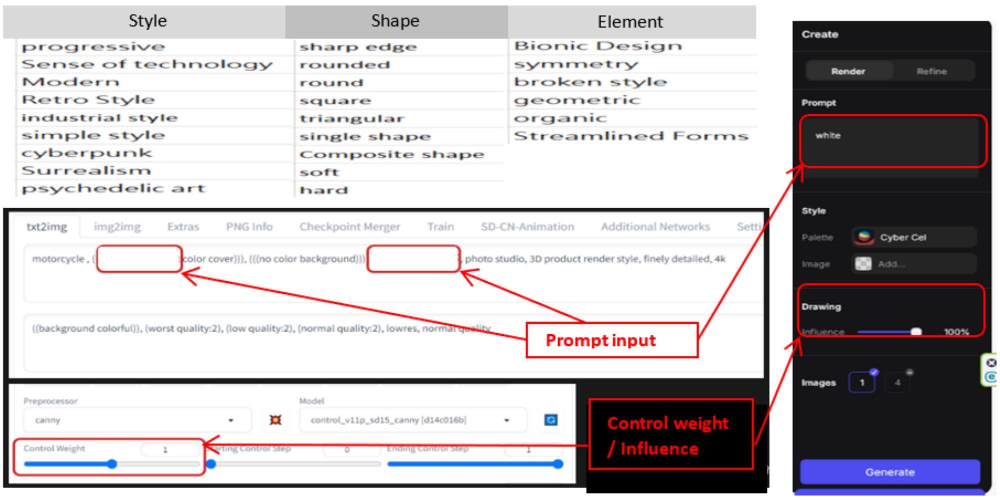


Figure 4. The examples of glossary (left-up) and the control windows of stable diffusion (left-low) and Vizcom (right).

Source: this research.

3.3. Retrospective interview

After completing the four tasks, each participant will undergo a semi-structured interview approximately 30 minutes. The interview will focus on issues related to form modification and decision-making, such as the participant's perception of the design characteristics of a technology motorcycle and their definitions of geometric and organic shapes. Additionally, any notable observations by the researchers during the experiment, such as significant changes in vocabulary choice or major adjustments to shape or design elements, will be discussed. Participants will be asked about the reasons for the modification and the thinking processes or shifts in thinking that led to them. The interview will be recorded in both text and audio formats.

4. Experimental results

All eight participants completed the four tasks within the planned 180 minutes. In Task 2, participants generated between 15 to 34 images using Stable Diffusion, while in Task 3, they generated between 13 to 31 images. **Table 1** illustrates the time and amount for 8 participants across 4 tasks. It is important to note that, due to the reliance of AI calculations on network transmission, prolonged calculation times may occasionally occur during the experiment. The average time of task 1 is 26 minutes and 01 seconds, the average time of task 2 is 28 minutes and 02 seconds, the average time of task 3 is 21 minutes and 33 seconds, and the average time of task 4 is 23 minutes and 55 seconds. Although the time spend in AI image calculation is about the same as hand-drawing, participants produced an average of 26 pictures using Stable Diffusion and 23 pictures using Vizcom. In Task 4, participants produce an average of 5 images for design modification through AI tool assistantance in an average of 23 minutes and 55 seconds.

Table 1. The time and amount by 8 participants in 4 tasks.

		Pa	**Pb**	**Pc**	**Pd**	**Pe**	**Pf**	**Pg**	**Ph**	**Average**
T1	Time	25’30	18’10	33’40	28’15	25’23	25’45	19’14	32’15	26’01
	Amount	1	1	1	1	1	1	1	1	1
T2	Time	20’16	12’06	34’07	23’30	37’19	33’22	38’11	26’17	28’02
	Amount	22	34	26	31	30	28	25	15	26
T3	Time	15’30	15’52	22’02	11’24	30’14	28’48	30’15	18’20	21’33
	Amount	31	27	14	23	24	24	26	13	23
T4	Time	22’37	20’17	18’20	26’29	32’14	24’53	22’45	23’38	23’55
	Amount	4	7	4	9	4	3	3	3	5

Figure 5 shows the 34 images generated by participant Pb using Stable Diffusion, the highest number in task 2, while **Figure 6** shows the 14 images generated by participant Pa using Vizcom, the fewest in task 3. This research compiled the images from Task 2 and Task 3 that participants felt were closest to the original hand-drawing of technology-geometric motorcycle sketches, as well as the images where participants used AI tools and hand drawings to modify the design for technology- organic lines (shown in **Table 2**). The analysis focused on the key design changes participants considered while using AI generative tools to conceptualize the design of a technology electric vehicle.

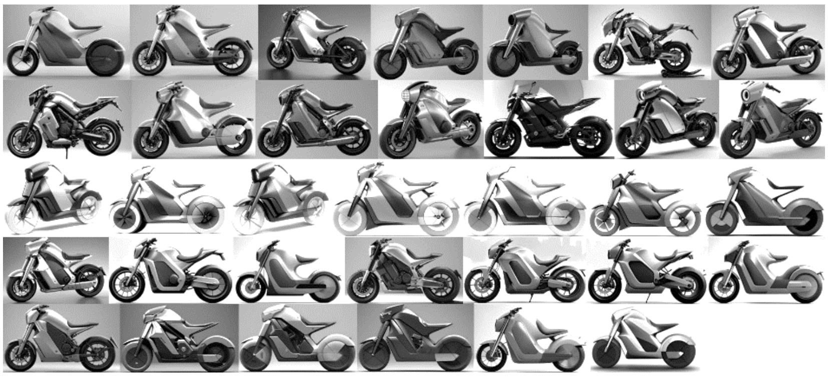


Figure 5. The most images through Stable Diffusion by participant Pb.

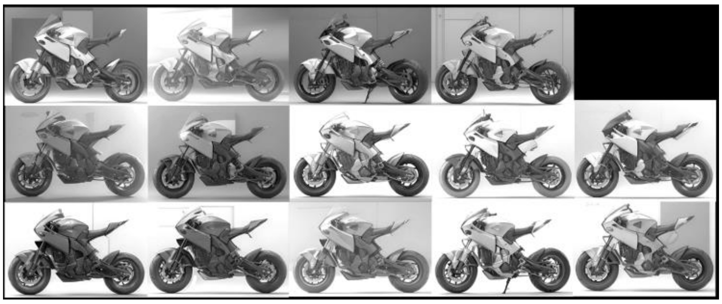


Figure 6. The less images through Vizcome by participant Pa.

Table 2. The results of 4 tasks by 8 participants (This research reorganized).

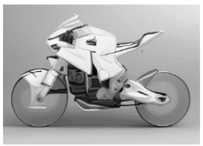
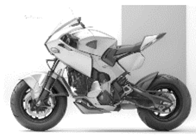
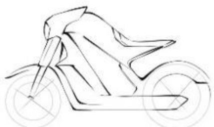
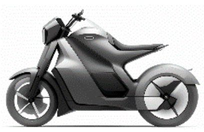
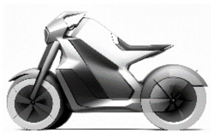
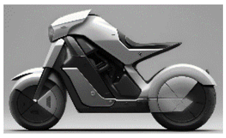
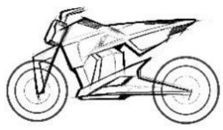
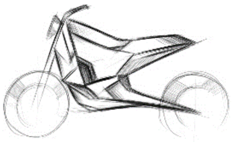
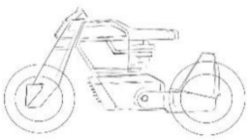
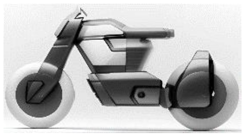
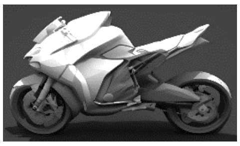
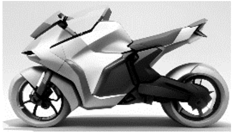
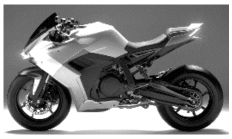
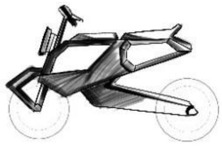
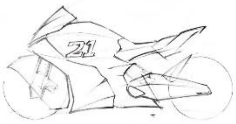
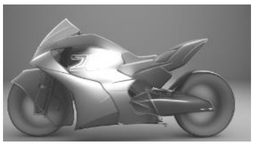
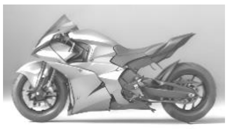
	Task 1 (Drawing)	**Task 2 (Stable Diffusion)**	**Task 3 (Vizcom)**	**Task 4 (Design modify)**
Pa				
Pb				
Pc				
Pd				
Pe				

Table 2. (*Continued*).

	Task 1 (Drawing)	**Task 2 (Stable Diffusion)**	**Task 3 (Vizcom)**	**Task 4 (Design modify)**
Pf				
Pg				
Ph				

4.1. Technology-geometric motorcycle sketch (task 1)

Following the researchers' instructions and the image board reference, all eight participants used the Procreate drawing software on an iPad to create design proposals within 25 minutes. Six participants proposed designs similar to off-road motorcycles with a higher seating position, while participants Pf and Ph presented designs more akin to sports motorcycles. The focus at this stage was on producing sketches with clear design contours, indicating that participants had a concrete idea of the design in mind, rather than simply drawing lines. Notably, participants Pc and Pf used shading to depict variations in surface curvature, demonstrating that they were not only considering the overall design contours but also beginning to think about the details of each part. In subsequent interviews, participants mentioned that sometimes they start with specific details, such as the curvature of a surface or a particular line, rather than the main design outline, and then develop the overall appearance. Participants also noted that the precision of the sketch impacts the final computational results by AI. Participant Pc remarked, "If you already have a clear vision product shape when sketching the lines, using these parameters can significantly enhance the design presentation quickly."

4.2. Stable diffusion: design divergence and selection (task 2)

All participants used the provided vocabulary (Prompts) and adjusted the control weight number as variables to manipulate their hand-drawing reference images through AI tool within 15 min. Each participant's sketch was the primary factor influencing the design, while the prompt was employed to generate different results. For instance, the terms "modern" and "cyberpunk" produced different outcomes when applied to their simple shape designs by participants Pd and Pg. Participants could adjust the weight to alter the extent to which the reference sketch influenced the result. This research observed that participants were highly concerned with whether the input text aligned with their imagination of shape and how it was applied to the sketch. Additionally, participants judged the AI-generated images' similarity to the original sketches based on the contour lines of the overall appearance and the partition lines of the vehicle components. For example, participant Pa focused on the line between the fuel tank and the body; participant Pb extended the contour line of the front fairing to the fuel tank in their sketch; participant Pc concentrated on the line connecting the rear and lower part of the vehicle to the body; participant Pd focused on the variations in the lines between different components (fuel tank-seat-motor-drive); participant Pe examined changes in the seat's extended design among AI images. Each participant had a similar method of selection. Furthermore, participants also paid attention to the surface characteristics presented by shading, such as the level of concavity and convexity of the surface and the surface feature. For instance, participant Pa focused on the lines formed by the side and top of the fuel tank; participant Pe looked at the changes in the folding surface between the fuel tank and the gear components; participant Pf considered the surface selection on the fuel tank and drive components; participant Pg focused on the choices in body cutouts and folding surface variations; participant Ph examined the surface changes at the junction between the fuel tank and the body.

All observations were validated during the retrospective interviews. When participants were asked why they believed the image was closer to the original sketch, Participant Pa remarked: "The overall contour and the connection between the fuel tank and the seat, which are my primary concerns, are more accurately represented compared to my initial sketch." Participant Pb stated: "The folding lines on the side of the vehicle align with my expectations." Participant Pc noted: "The parting elements of main body, particularly the X-like lines, are depicted." Participant Ph observed: "The lines on the fairing have been preserved." Participant Pb added: "The overall contour lines, including the segmented parts' details, are almost fully represented." Additionally, when participants selected the design image deemed most optimal by AI, they evaluated it in relation to the original based on contour lines, segmented parting lines, and surface variations. For instance, Participant Pg commented: "The concave polygon beneath the seat might look quite if it were convex." Participant Ph noted: "The smoother curvature of the fuel tank is also aesthetically pleasing." "The segmentation is very sharp."

4.3. Vizcom shape develop and form finding (task 3)

Task 3 was designed as a contrast to Task 2, aiming to test whether there were differences in design decisions made by participants when using different AI tools, as well as to assess the demand for design support tools. The time participants spent on Task 3 did not significantly differ from that spent on Task 2. However, it was observed that participants focused on different aspects due to the differing characteristics of the two AI tools. The primary difference between Vizcom and SD lies in their image generation styles and the extent and stability of shape variations they produce. Vizcom's lighting and color are relatively subdued, and the degree of shape variation is less pronounced than SD's. Vizcom more accurately represents the material and color of components, leading participants to focus more on the details of the components. For example, during the retrospective interviews, Participant Pd pointed to an image generated by Vizcom and remarked: "This line connects here and aligns with my original expectation, and this surface is close to my imagination, specifically the triangular bend."

After completing Task 2, participants generally became more aware of the prompts they needed, leading them to spend more time adjusting the control weight. However, due to Vizcom's associative calculations is default and the parameter value of seed can not be adjusted such as the control weight in SD which had been pre-tested by researchers to achieve a specific modification range. Consequently, when participants adjusted the value below 70%, they often encountered significant changes with even minor adjustments, while values around 90% resulted in only slight modification. Participant Pe noted: "Since it's controlled by percentages, you can't predict the exact outcome." Participant Pd also commented: "When the influence parameter is set below 70%, the modification becomes too much. However, at 85% or 90%, the results are quite similar, suggesting that beyond a certain threshold, changes become too drastic."

Nevertheless, Participant Pg pointed out: "It can simulate the sketch very closely. For instance, before creating a 3D model, I use it to help judge the three-dimensional space of the design." Participant Pg further indicated: "I can use line drawings to clarify ideas, then quickly generate a complete shape from a sketch with Vizcom, and modify it based on my background image." This demonstrates that Vizcom serves as a more effective tool for shape convergence (expression) than SD.

4.4. Shape modification (task 4)

In Task 4, the design topic was altered from a technology-geometric motorcycle to a technology-organic design. Initially, participants employed input prompts to modify the design, which revealed participants' varied interpretations of prompts and cognition of shape presentation. For instance, Participant Pa noted in the interview that he envisioned the motorcycle as having smooth surfaces and thus did not utilize geometric block structures or segmental parting lines in his drawing. Participant Pa's original sketch depicted small components of the motorcycle using geometric outlines. During Task 4, when the prompt "rounded curve" was input, Participant Pa found that adjusting the influence parameter could not alter specific locations. Consequently, he added layers and manually drew the desired component shapes, then adjusted the influence value from 100% decreasingly. When Vizcom produced a rectangular shape beneath the seat, Participant Pa perceived this form as integrating the seat with the body, diverging from the originally protruding geometric form and aligning with his concept of organic contours.

Conversely, participant Ph employed intersected segmental lines on the vehicle body or the lines formed by the concave and convex surfaces to present geometric shapes. Participant Ph spent considerable time making short range adjustment in parameter and indicated during the retrospective interview that "if the value is too low, the shape becomes entirely uncontrolled, deviating significantly from the original design." When desling with organic design in task 4, Participant Ph utilized input prompts for material and color to achieve the desired effect. She posited that geometric and organic forms are not necessarily mutually exclusive; for example, intricate lines can evoke a geometric structure impression, while larger radii or round corner on curves or contours can convey a organic appearance.

Participant Pf's results and interviews reflected similar perspectives. Some designers leaned towards having a clear design concept and used AI tools to refine aspects such as shape (material or color). Observations of design modifications by all participants revealed a focus on selecting shape features based on primary contour lines, component segmental parting lines, and variations of shadow or high light on surface undulations.

5. Discussion

This study observes and analyzes designers' focal points during design activities and their needs when utilizing AI image generation tools for shape conceptualization through four tasks. Overall, current AI tools are more suitable for shape divergence. If designers wish to engage in shape convergence, they need to become more familiar with various AI parameter settings and understand which prompts significantly influence specific shape features. Designers' perceptions of shape variation primarily involve main body and component 'contour lines, detail segmental parting lines, surface undulations such as lighting and shading and the resulting shape characteristics. The discussion will cover the role of AI and it's advantages and disadvantages in the shape design process, the process of designers using AI tools to make styling decisions, and the focal points of shape interpretation and iteration during the design process. Finally, it will propose requirements for AI-assisted tools that are suitable for the product design process.

5.1. The role of AI in the styling design process—Styling creativity

The process of product shape design involves continuously diverging and converging to find the optimal solution. For instance, in task 1, an image board was used to define design directions and identify design inspirations, completing the initial phase of divergence and convergence. In the later stages of design, divergence and convergence continue, but with the designer's redefinition of the solution space, the range of divergence becomes progressively narrower. Regarding the generation of design drawings from hand-drawn sketches, all eight participants agreed that Stable Diffusion is more suitable for limited-range shape divergence when the broad contours are fixed. It provides designers with various shape references.

Vizcom is particularly well-suited for accurately representing design ideas, whether for refining rough sketches in the early proposal stages or for making adjustments to materials and details in later stages. As Participant Pd noted: "I choose the software based on my needs. For instance, I will use Vizcom to help assess the three-dimensional space of the design before creating a 3D model." Participant Pe also stated: "For earlier-stage development where I want to explore different possibilities, I might use Stable Diffusion because it can break the framework more effectively. However, if I need a quick transformation from a sketch to a model, and then make modifications based on my original image, I think Vizcom would be more appropriate."

For AI-assisted design tools development, it is essential to gather more descriptions from users regarding their shape ideas and to accommodate the processes of shape divergence and convergence. This assist tool should allow designers to determine the extent of divergence and convergence. Because most shape innovations are discovered during the divergence process, while design optimization often occurs during convergence.

5.2. The role of AI in designers' style recognition and decision-making—Design optimization

The hand-drawing sketches from the eight participants reveal varying interpretations of the same design topic, technology-geometric motorcycles. Although six participants proposed designs resembling off-road vehicles, their interpretations of the usage context and application of geometric design approach differed. Participant Pe envisioned the motorcycle as operating in urban streets; Participant Pg approached the design from a cargo-carrying perspective; while Participants Pc and Pd offered different interpretations of component segmentation.

Participants were able to select AI-generated images whose contours and component details closely matched their hand-drawing designs, demonstrating that AI can converge within a certain range. However, participants expressed a desire for more precise adjustments. For example, Participant Pa, during the interview, pointed to the SD-generated image and remarked: "I want to see how it looks if the turn signal is elongated or moved down a bit," and added, "Vizcom should allow for erasing the turn signal and redrawing it. Since it is AI, there should be smarter ways to operate."

From the perspective of AI image generation, providing a clear prompt describing each participant's design allows for the generation of corresponding images. This seems to align with the iterative process of providing designers with divergent image references during the shape focus process. However, the 4 task experiments in this study also reveal that even trained designers have different design concepts and approaches to translating those concepts into shapes. If AI image generation plays a role in merely providing various shape variations without the capability to modify specific areas or details, it cannot effectively assist in focusing on (converging on) a particular shape.

Based on participants' feedback on Vizcom, manually modifying the original sketch and then reprocessing it through AI is a viable solution, but it still requires verification of the object's actual three-dimensional form. AI-driven 3D modeling may offer a potential solution, but its accuracy in product design applications still needs improvement. Furthermore, there is a need for more intuitive control methods for shape details in three-dimensional objects.

5.3. Designers' focus on styling changes

According to the observations of participants' interactions with AI tools during the experiment and their selection of AI-generated images that most closely matched their original hand-drawings, this study identifies four key aspects that designers focus on when assessing shape features or manipulating shapes:

(1) The shape of the overall contour lines.

(2) The shape of detailed segmentation or component parting lines.

(3) The degree of surface undulations and the shape of the surface as represented by variations in high light and shadow.
(4) Adjustments, location and modification, of components or design details.

In most cases, participants prioritized these aspects in the stated order. However, some participants, such as Participant Ph, started by focusing on specific shape details, such as desiring a smooth transition between the fuel tank and the seat, and then considered segmentation with different materials by folding lines.

If in the future, AI professional auxiliary modeling design tools can provide designers with calculation models for modeling divergence and convergence based on these key points, or even have the appropriate operating interface when developing AI-3D, they will be able to assist designers more effectively and bring AI image generation closer to aligning with the designer's conceptual thinking.

5.4. Demand for professional AI design aids

The sophistication and completeness of AI-generated images can be so high that even professional illustrators or product designers may struggle to determine if they are the work of a human. This research posits that high-quality rendering images serve as a means of communicating design ideas rather than as an endpoint in the design process. Rather than debating whether AI-generated images are produced by AI or if AI can replace designers, it is more productive to focus on how AI computation can better align with human thinking processes or assist designers by understanding their ideas and perspectives.

This research presents, through a quasi-experimental approach with 4 tasks, the differing needs of designers in shape divergence and convergence processes regarding creative and optimization aspects of shape design, and the key factors they consider when assessing shape similarity. It is suggested that for AI-generated images to evolve into professional tools for product design, it should offer two modes: one for shape divergence and one for shape convergence, focusing on both the overall shape and details. Additionally, in the development of AI-3D tools, adjustments should be provided for the four key aspects of shape control identified in this research, including main body contours line adjustment, component detail's manipulation, surface undulations modification, and positional control. This will allow designers to focus more on concept formation and transformation. After all, AI will not replace designers; rather, it is the designers who cease to engage in their work that risk being replaced by AI.

6. Conclusion and further research suggestion

This study employed a quasi-experimental approach to validate the feasibility of using AI text-to-image and image-to-image tools for divergent and convergent shape design in two-wheeled vehicle design. The text-to-image method allows for the generation of specific motorcycle designs by providing suitable shape descriptions to keep the AI within a certain range. VIZCOM enables designers to modify shape details through hand-drawn methods, serving as partial shape divergence, although it still requires repeated operational adjustments. Overall, tools like VIZCOM that combine text and imagery can enhance the efficiency of shape design for designers in the future.

However, designers must possess a certain competency in shape design to identify potential refinable shape elements within the myriad of images provided by AI.

From the process of designers operating AI tools, it was also observed that even though AI tools offer various creative outputs, designers with shape concepts tend to select from these outputs, integrating them with original ideas or incorporating their unique shape thinking into the AI-generated creativity, rather than abandoning their initial concepts in favor of the AI's suggestions.

The search and computational abilities of AI far surpass those of humans. Therefore, expressing tasks clearly for AI to understand what the user wishes it to execute is a crucial key for the next stage of AI development. For instance, in the experiment, nearly all participants repeatedly entered shape description, indicating that the generated results did not align with their expectations. Among the eight participants, only two selected the same image when choosing the closest to their original shape idea and their favorite design, demonstrating that AI-generated outputs can exceed expectations. The factors contributing to this phenomenon include the user's familiarity with AI tools, but most importantly, it hinges on how effectively one communicates with AI.

The current text and image inputs can correspond to divergence and convergence. Finding efficient ways to combine these two methods will allow designers to manipulate aspects like shape contours, detail components, surface light and shadow, and the positioning and size of parts more easily and accurately for shape iteration. Exploring other avenues of communication with AI presents an opportunity for the next phase of AI development. For example, non-vehicle designers can communicate with AI through a certain process, or with the assistance of AI, they can perform styling design in a way that is close to the thinking of transportation designers.

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