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EXPLORING THE IMPACT OF GENERATIVE STIMULI ON THE CREATIVITY OF DESIGNERS IN COMBINATIONAL DESIGN

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ABSTRACT

The ideation process has a significant impact on the initial concept generation and final product creativity of the design. Visual stimuli play an important role in the process of innovative product design. With the increase in computing capability, generative design methods are widely implemented. In this paper, features of design targets and combinational objects in 2 combinational design tasks are fused using adversarial neural generative networks to form the generated stimuli. It is also used with combinational object pictures to investigate the impact on creativity in design ideation. The study invited designers to use and subjectively self-evaluate the two stimuli in a design task. Through analysis of participant data (n=20), the results showed that the generative stimuli had an advantage over the combinational image stimuli in terms of the smoothness of creativity in the design ideation of outcomes. And there is a positive correlation between designers' years of design education and their tendency to prefer generative stimuli. Based on the results obtained, ideas are provided for the study of the influence of visual and generative stimuli on the designer's ideation process.

Keywords: Creativity, Design ideation, Computational design methods, Artificial intelligence, Stimuli

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1 INTRODUCTION

Design ideation, alternatively design idea generation, exists in the early stages of design, where creativity plays a significant role (Sarkar and Chakrabarti, 2011). Although the mechanism underlying ideation processes still need to be studied, they are considered crucial when it comes to creative outcomes in design (Cash and Štorga, 2015; Moreno et al., 2016). Therefore, research into ideation is essential to provide designers with a better approach to design and to increase the creativity of design outcomes. Some researchers have focused more on the definition and generation of new design problems(Obieke et al., 2021). However, there is also a major trend towards research that explores potential solutions and aids generated by computational methods.

External support is often needed at the design ideation stage, regardless of the designer's experience and expertise (Dorst and Cross, 2001). The processing of external information or sources of inspiration, also known as stimuli, is one of the integrated approaches to support design ideation (Du et al., 2015). In design ideation, much of the creativity required comes from the stimuli that the designer seeks out or interacts with (Gonçalves et al., 2011). Using associations and combinations from accumulated experience and knowledge is a common strategy for ideation. Although it may lead to fixation, the use of stimuli can facilitate combination and creative processes (Gentner, 1983; Howard et al., 2009; Bacciotti et al., 2016; Vasconcelos et al., 2018; Goucher-Lambert and Cagan, 2019).

According to cognitive psychology, people tend to produce mappings and output behaviors that are similar to the stimuli from the design resource (Howard et al., 2008). Among the types of stimuli, including verbal/textual (Shi et al. 2017, Sarica et al. 2023), visual/pictorial (Han et al. 2018a, Chen et al. 2019, Wang et al. 2021) and physical objects (Gonçalves et al., 2014). Pictorial stimuli are considered to be a better way of stimulating both professional and novice designers than text and objects, helping them to generate complex thinking, original solutions and sketching (Sarkar and Chakrabarti, 2008; Bettaieb, 2022). Therefore, the study about selection of pictorial stimuli can have a positive impact on the creativity of design ideation.

For traditional methods of creative support, finding design materials (such as pictorial stimuli) is an important task. The materials found by manual methods often do not meet the requirements for creative stimulation (Chen et al., 2018). With the spread of computer-aided design (Jonson, 2005), a change has occurred in the way designers use computers. From the simple visualization of the designer's creative output to involvement in requirements and parameter analysis to the latest artificial intelligence-aided design, the role played by computers in the design process is gradually moving towards the center (Chen et al., 2018). Whether parametric design, generative design (Agkathidis, 2016) or the latest generative models such as DALL E (Ramesh et al., 2022), Imagen (Saharia et al., 2022) or Midjourney (Oppenlaender, 2022) ultimately produce images or 3D models are based on given set of conditions. These generative images are ideal for supporting creative design processes.

This paper uses two different stimuli, pictorial and generative, to facilitate designers' combinational design ideation phase (Han et al. 2018b, 2019). Based on a survey of designers' subjective feedback, the paper explores how the two stimuli perform differently in terms of the three indicators of novelty, usefulness and smoothness in facilitating design ideation. More specifically, the experiment sets two design tasks that require a combination of concepts: horse and bike; arch and headphone. The experiment is delivered to participants as a combination of two stimuli. Then, the feedback of designers with different years of experience on their creative design ideas after receiving the stimuli was quantified. The following two research questions (RQs) guided the paper:

- RQ1: How do image stimuli and generated stimuli influence the novelty, smoothness and usefulness of the designer's creativity in the ideation phase of a design ideation task for conceptual integration, respectively?
- RQ2: How does a designer's experience affect the effectiveness of these two types of stimuli?

A review of work related to creativity and design ideation is presented in Chapter 2. In Chapters 3 and 4 a comparative quantitative study of the influence of the two stimuli in the combinational design of practical conceptual fusions is presented.

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2 RELATE WORK

2.1 Stimuli as a source of inspiration in ideation

Design ideation can help designers generate visual, abstract or concrete forms of thought effectively and to produce creative outcomes through specific criteria (Jonson, 2005; El-Zanfaly, 2015; Piya et al., 2017). In design ideation, the designer constantly seeks internal and external stimuli and perceives, evaluates, selects, transforms and rearranges the acquired information to produce knowledge (Yang et al., 2005). Internal stimuli are the stimuli of metacognitive knowledge (Flavell, 1979) in memory. External stimuli are stimuli from the environment, including images, verbal presentation and physical objects (Osborn, 1953). In design tasks based on external visual stimuli, pictorial material is important for the quality, novelty and variety of the design output (Duan and Zhang, 2022).

According to the research of Goldschmidt and Smolkov (2006), the presence of different types of visual stimuli could influence performance. Designers are very sensitive to many kinds of external stimuli, especially the visual displays around. Regarding design fixation, Cardoso and Badke-Schaub (2011)'s research shows that diverse and rich visual stimuli can reduce design fixation. At the same time, having more ambiguous stimuli also allows for less fixation and gives the designer a greater number and variety of design outputs. Designers often need to find more diverse ways to address the uncertainty presented by stimuli, leading to increased novelty in ideation (Benami and Jin, 2008; Tseng, 2018).

2.2 Generative image-based ideation approach

With the development of various generative models and tools, the role they play in design has increased. Generative design is widely used in the field of architecture. It allows the design space to be explored by adapting the initial dataset to form possible designs (Agkathidis, 2016; Li and Lachmayer, 2018). Generating models is another direction, of which generative adversarial networks can simulate the learning process of the human brain. The network learns a large sample of images and continuously generates fake images of the same kind by means of a generator. The real pictures are then distinguished from the fake ones by the learning of the discriminator in order to continuously improve the completion of the fake pictures (Goodfellow et al., 2014). Since a well-trained network can continuously produce original content, creative support for design ideation using this technology is considered to have considerable potential. Yu et al. (2019) propose DesignGAN, an unsupervised deep generation method for implementing shape-oriented bionic designs. It maintains the shape features of the input design target image and includes the shape features of images from a specified biological source domain. Li et al（2021) presented the Product Design GAN model (PD-GAN) to generate images of product concepts with emotional preferences. The model studied by Chen et al. (2019) consists of two models, the semantic-intentional network and the visual-concept combination model, which generate images that synthesize different concepts based on the knowledge associations obtained from the semantic network. The method is able to generate a variety of cross-domain conceptual associations and can have advantages in terms of the number and novelty of ideas. Based on the linear controllability of the latent space vector of StyleGAN , the researchers proposed a method for image stimulus generation with feature fusion in conceptual design (Wang *et al.*, 2021).

The process of generative stimuli generation requires that the design semantics are first understood prior to the generation of the visual display. Therefore, this type of approach is suitable for well-defined design problems with specific requirements. Although the use of generative models has become more widespread, there is still much to investigate such as designers are influenced by their use as stimuli in the design ideation phase.

3 METHODOLOGY

3.1 Stimuli preparation

This study focuses on the different performances of designers in combinational design when using images and generative stimuli as a source of inspiration. As there is a concept fusion in design, for the product selection in the experiment, it is necessary to ensure that the change in form brings sufficient impact to the design outcome. As shown in Figure 1, Bike and headphone were chosen as target products for the experiment. The corresponding combinational object were horses and stone arch. This experiment searched Google images and obtained images of horses and arches as stimuli for the image

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group (Stimuli A and Stimuli C in Figure 1.). The generative stimuli come from a computational design generation method with a specific style and feature (Wang et al., 2021). The specific implementation methods are described below.

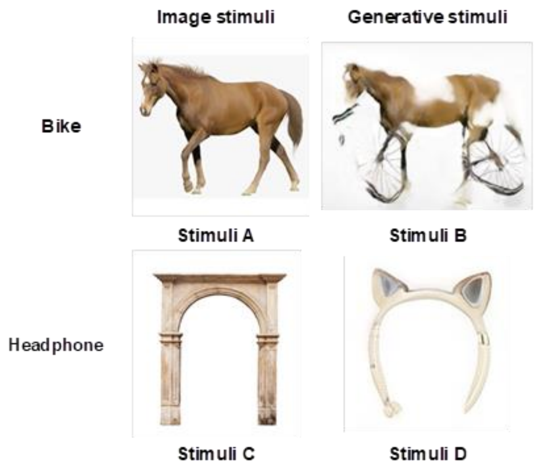

Figure 1. Stimuli used in the experiment

As shown in the Figure 2, for the generative stimuli group, two adversarial generative networks were trained using a large number of images of bikes and headphones, respectively. In this case, there are 2500 bike images and 2300 headphone images in the training dataset. After the training process, the generator in the networks were able to generate fake bike and the headphone images that look like the real one based on given arbitrary vectors.

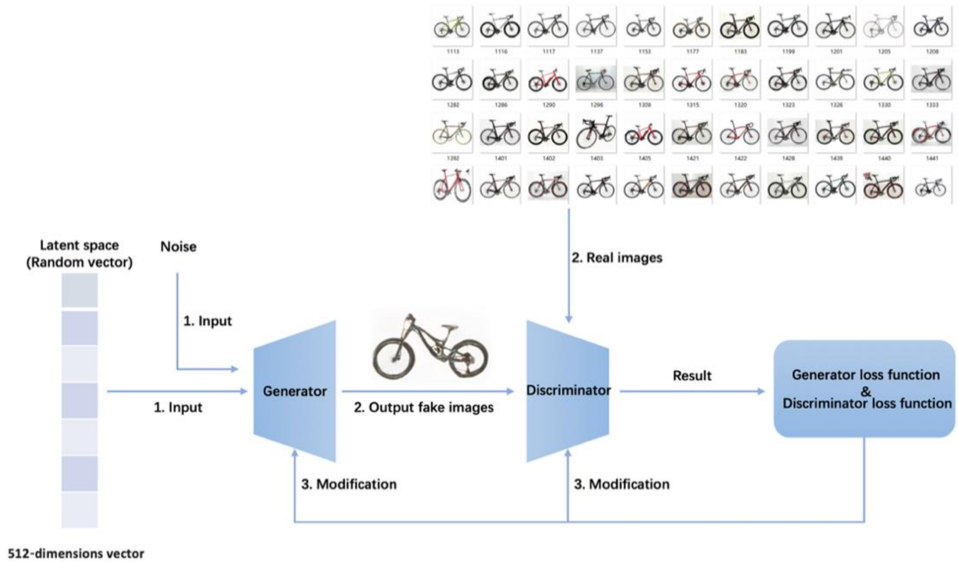

Figure 2. The training process of generative adversarial network (Example of Bike)

After training process, each vector in the latent space of both networks can correspond to generate a product (bike or headphone) picture. In the projection process, the images of Stimuli A and Stimuli C can be reversed through the generator and transformed into two vectors in the latent space of two networks. These two vectors can be re-generated by the generator to produce images that corresponds to fake images with the features of horse and arch.

Then, in Figure 3, the horse vector (reversed by Stimuli A) can be modified to approach one of bike vectors in the latent space (the same in the headphone latent space). A thousand steps in two vectors in this experiment means that a thousand vectors and their corresponding pictures can be generated. In some of these pictures, certain features of the horse picture and the bike are both well preserved. The generative stimuli (Stimuli B and Stimuli D in Figure 1.) are selected from these images.

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In the two generative stimuli images, the features of the target products and the combinational objects are well preserved. In the process of acquiring generative stimuli, the properties of generative networks are exploited so that the step of concept fusion is performed by the network. Whereas in the process of using image stimuli this step is carried out by the human brain.

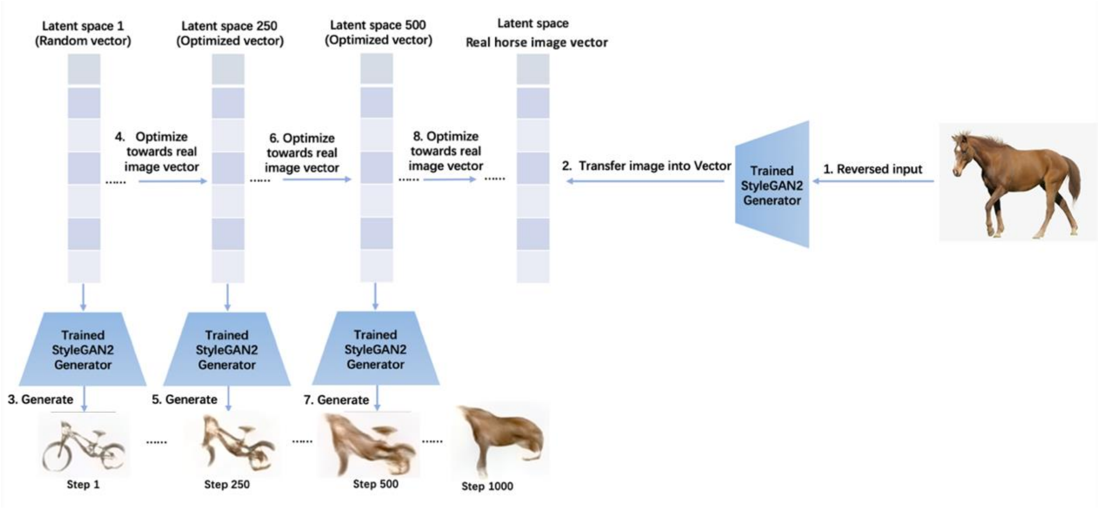

Figure 3. The projection process of generative adversarial network (Example of Bike)

3.2 Participants

As shown in Table 1, 20 participants with backgrounds in design education and/or design working experience were invited to conduct the experiment. The participants were between the ages of 21-30 and included 5 male and 15 female designers. 9 of them are undergraduate students and 11 are postgraduates. 11 of them had work experience, while 8 of them had less than 2 years of work experience and the other 3 had more than 4 years of work experience. All participants were asked to experiment in their daily work environment using remote chat software to minimize the impact of the physical environment on creativity (McCoy and Evans, 2002). The participants participated in the workshop voluntarily with high interests in the topic.

Table 1. Participant demographic information

Number of participants											
Gender		**Years of Education**			**Years of work**			**Background**			
Male	Female	1-2	3-4	5-6	0-2	3-4	5-6	Product/ industrial	UI/UX	Graphic	Jewellery
5	15	2	7	11	17	2	1	11	6	2	1

3.3 Creativity assessment

In many of design studies, the creative performance is determined by an assessment of the design output. However, in this study, the evaluation of creativity comes from the designers themselves. Based on summaries in the literature, The novelty and usefulness are considered as the core elements of creativity (Massetti, 1996; Chulvi et al., 2012; Han et al. 2021). In the experiment, designers need to give the results of measuring both methods in a non-verbal, non-quantified sense of self. As these two indicators of creativity are difficult to measure in the real world, the experiment guides designers to place the design results within a functional (F)-behavioural (B)-structural (S) framework (Gero and Kannengiesser, 2004) to help participants give feedback.

In design work, the common stimuli evaluation calculate the quantity of design ideas generated as one of the creative indicators (Nijstad et al., 2002; Perttula and Sipilä, 2007). Designers who can produce a greater number of ideas for a task are considered to be more creative. However, in this study, the designers produced a very similar number of ideas per sketch in the task. Also, there was an equal limited amount of time (10 min) to design for each participant in the experiment. In terms of objective data, this means that the speed of the design is the same for each participant. However, in fact,

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designers' ideation process after receiving the stimuli took place in their minds and could be different to each other. Therefore, this study sets up another indicator of responsiveness to creativity in the experiment: smoothness. After completing the stimulus design task, participants will determine which stimuli performs better on smoothness based on the length of time they experience to ideate, the number of pauses in thinking and the number of times they feel confused after being inspired by two stimuli. Overall, the results of the designer's choice of preference for the two stimuli on the three indicators are shown in Table 2.

3.4 Experiment design

As shown in the Table 1, Information was first collected on each participant, including gender, design discipline, years of education and years of work (if applicable). Each participant will work independently on two design tasks. Next, a combination of stimuli (Stimuli A+D or Stimuli B+C) was chosen as the experimental material, and it was ensured that a similar number of participants received each combination. Then, participants conduct 2 designs sketches based on the given stimuli combinations. Each design needs to produce a hand sketch as a result. The time limit for each design was limited to 10 minutes. At the end of the design task, each participant was asked to choose the stimuli that worked better in each of the three indicators, based on the experience of the design. The Table 2 records the results.

Table 2. Participants' preferences for the two stimuli on three indicators

Indicator	Preference	Number	Percentage
Novelty	Generative Stimuli	11	55%
	Image Stimuli	9	45%
Smoothness	Generative Stimuli	16	80%
	Image Stimuli	4	20%
Usefulness	Generative Stimuli	12	60%
	Image Stimuli	8	40%

4 RESULTS AND FINDINGS

The study conducted an analysis of the data based on participants' subjective preferences for the two sorts of stimuli in three indicators. As shown in Table 2, it demonstrates the participants' choice of the two methods in terms of novelty, smoothness and usefulness. It can be observed that without classifying the participants, a similar number of choices were made for both methods in the novelty and usefulness indicators. In contrast, in terms of smoothness, the percentage of participants who found generative design more helpful was 80%, more than those who choose for image stimuli. What can be seen visually is that generative stimuli can increase the smoothness of design ideation to a certain extent compared to image stimuli.

On the other hand, although there was no significant difference in frequency, in a deeper analysis of the data it was found that the designer's education experience can be related to the preference for choosing stimuli in novelty and usefulness. In Figure 4, it can be clearly observed that the designers with 2-3 years of education consider the image stimuli is more helpful in terms of novelty and usefulness. As the number of years of education increases, the proportion of designers choosing generative stimuli in the feedback shows a sharp increase. Among designers with four years of education, the proportions show equal ratings of generative stimuli and pictorial stimuli in terms of promotion of novelty and usefulness. The preference for generative stimuli in terms of novelty and usefulness among designers with five years of design education is 66.7% and 83%. When the number of years of education reaches 6, the proportion is 80% in both cases. This data shows that after 5-6 years of education (normally postgraduate) more designers consider that generative stimuli can bring more novelty and usefulness to their ideation output.

According to the graphs, years of design education can have a significant impact on a designer's choice on the indicators of novelty and usefulness. Designers with more years of education are more likely to believe that generative stimuli bring more novelty and usefulness to their design outputs.

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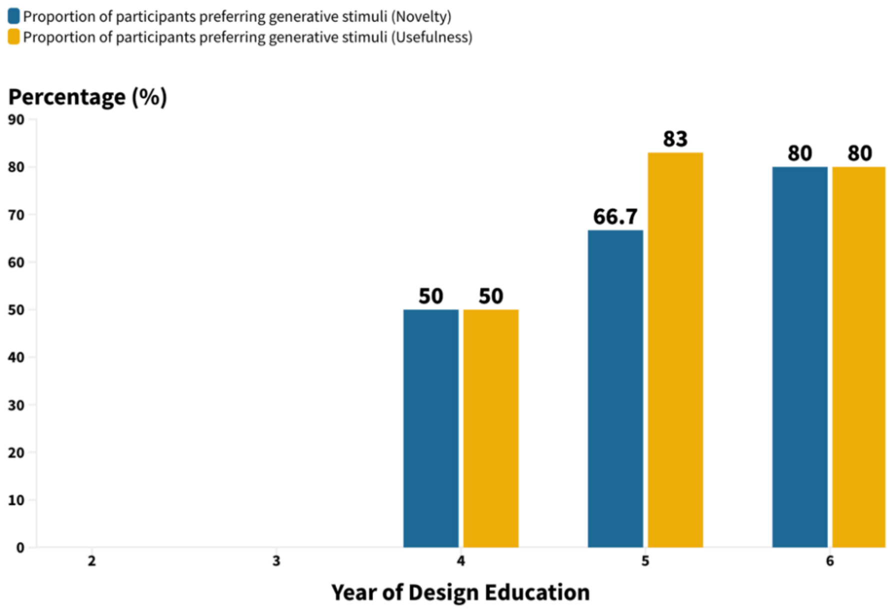

Figure 4. The number of people choosing generative stimuli to bring more novelty and usefulness varies with the number of years of education

5 DISSCUSSION

Based on the results reflected in the data, generative stimuli provide designers with a smoother creative process than image stimuli. In terms of the image stimuli, the designer is given a picture of the combinational object and will search product information from internal sources (memory) based on the perception of the product for the design. Then, they associate product information searched from memory (shape, colour, function, etc.) with combinational object images for inspiration. As for generative stimuli, the approach has made an initial fusion of the two concepts and produced a visual picture. This allows the designer to refine the design very quickly. In addition, vague shapes and detailed representations facilitate the formation of ideas (Howard et al., 2010).

Further analysis found that designers with more years of education were more able to obtain the novelty needed to design from generative stimuli species. For design students with fewer years of education, they are less competent and experienced in design and are more likely to encounter difficulties in translating unfamiliar generative concept images. Designers with more design experience and those who have completed higher education in design are better able to use the generative stimuli they see in a good way to incorporate them into their own designs. Experienced designers often have their own design methods and habits. However, experience and stimuli can also lead them into fixation (Jansson and Smith, 1991). At the stage of ideation under the image stimuli, the experienced designer will have his own inherent perception of the object (horse and stone arch in this case) to be combined. In contrast, generative stimulation replaces the designer with the initial integration of the two concepts. This also can contribute to the increased novelty of the design.

Table 3. Cross-tabulation of preference on novelty and usefulness with years of design education

Name	**Years of Education**	**Novelty**		**Usefulness**	
		Generative	Image	Generative	Image
Education	2	0(0.000%)	2(100.000%)	0(0.000%)	2(100.000%)
	3	0(0.000%)	1(100.000%)	0(0.000%)	1(100.000%)
	4	3(50.000%)	3(50.000%)	3(50.000%)	3(50.000%)
	5	4(66.700%)	2(33.300%)	5(83.300%)	1(16.700%)
	6	4(80.000%)	1(20.000%)	4(80.000%)	1(20.000%)
Total		11	9	12	8

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However, there are still some limitations in the study. The most important of these is the small data sample size. In Figure 4, this experiment found statistical relationships between variables during the statistical phase of the data. However, according to the experiment, there is room for improvement in what can be analysed, both in terms of the amount of data and the type of entry. As shown in Table 3, the majority of those in the data are concentrated in the 4-5 years of educational experience. Although there is a clear trend towards an increase in the number of designers for generative stimuli in terms of total numbers, the numbers are similar in the 4-5-year interval for both. Therefore, more data and smaller data dimensions are needed to validate the model in these two years.

Besides, a wider range of design objectives should be considered when selecting them. Participants in experiments tend to have better design performance when they encounter products that they are familiar with or have done before. Therefore, as many target products and combinational images as possible should be included to solve this problem.

On the other hand, some participants expressed confusion about the generative stimuli. In this case, vaguely shaped stimuli could even make design more difficult. For design creativity, this is a borderline issue of dilemma. Ambiguous stimuli have had better gaining effects in terms of number and creativity of design ideas in previous studies. In fact, pictorial stimuli are a good contrast, providing designers with a clearer functional, behavioural and structural stimulus. In the following research, attention will also be paid to this issue. In combination with some new deep learning models, a search will be conducted for image change boundaries that enable generative stimuli to help designers generate ideas.

6 CONCLUSION

This article describes a study that aims to explore the impact of two different forms of stimuli, pictorial and generative, on the creative ideation process of designers. Although there were some limitations to the study, such as the small sample size (n=20) and the potential specificity of the choice of experimental material, the study led to some useful findings.

Firstly, multiple image fusion approaches, exemplified by adversarial neural networks, can produce fused stimuli with multiple image features. Such stimuli can be useful in design ideation and are considered to be more advantageous in helping designers to obtain faster and more fluent ideation process than by providing directly combinational images. Secondly, the study revealed a significant effect of years of design education on the novelty of using generative stimuli to obtain better product design in the data provided by the participants. In further analysis, achieving a certain level of design learning experience is a prerequisite for being able to make better use of generative stimuli for inspiration.

This research presents new ideas for the study of design tools and. It has profound implications for exploring the effect of visual types of stimuli in the early stages of design conception. It also explores the possibilities for human designers to have the ability to collaborate with the spontaneous innovations of computational creativity in the future.

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