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Effects of different human-in-the-loop approaches on human-AI co-design: a comparison between Human-learning HITL approach and Machine-learning HITL approach

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ABSTRACT

The speed at which the quantity of data is increasing stymies the deployment of some AI tools for design as the basis for training the tools is not stable. Also, selecting which data can be used as training data is a challenge. To address these issues, the concept of human-in-the-loop (HITL) approaches have been proposed. HITL includes human knowledge in the model-building processes to mitigate the high volume requirement of training data. Although how to apply AI in a design process and the effect of Generative AI tools (such as ChatGPT and Midjourney) in design processes has been explored, limited attention has been given to how different HITL approaches affect design performance. This study thus aimed to explore how different HITL approaches (Human-learning HITL approach and Machine-learning HITL approach) affect solutions of human-AI co-design. Fifteen participants were recruited to undertake two design tasks under the guidelines of Human-learning HITL and Machine-learning HITL approach respectively. The solutions from participants were assessed using four criteria (novelty, aesthetics, functionality, and feasibility). The results of the study indicated that the solution generated from Human-learning HITL approach is better compared with that of the Machine-learning HITL approach, especially in terms of aesthetics and functionality of the solution. The study supports the importance of expressing human insights through prompts on improving human-AI co-design solutions compared with providing more training data to AI.

Keywords: Collaborative, design; AI/KBS; process; Interactive; Product.

1. INTRODUCTION

Machine learning and deep learning, both artificial intelligence (AI) principles, have been applied in various areas, such as computer visualization and natural language processing [1]. AI can help designers expand their abilities in discovering user requirements, visualize ideas, and test designs by predicting human judgment and preferences [2, 3]. Research in design areas, especially in product design, has started to explore the potential of AI in human-AI co-design processes.

1.1 AI tools in design

Some AI tools have been developed to help the overall design process. For example, Janin et al. (2020) [4] developed ImageCascade which provides functionality in both idea generation and expression processes

[5]. In addition, ImageCascade can provide semantic labels, color palettes and multiple tag clouds to help mood expression.

In idea generation, AI tools can be used to augment creativity [6-8]. Masaki et al. (2023) [9] developed an AI system that handles large-scale text and image data to generate various ideas. Ji et al. (2018) [10] developed a computational tool that can be used for creative idea generation based on analogical reasoning and ontology. Karan et al. (2023) [11] promoted the potential of using Large Language Models (LLMs; such as ChatGPT) for idea generation in innovation [12]. Lee et al. (2023) [13] explored the effects of Midjourney in the early design stage. Sarica et al. (2021) [14] used semantic technology to stimulate the generation of ideas. Li et al. (2023) [7] reported the positive effects of Generative AI in idea generation. However, although there have been various AI tools developed to help design processes, researchers have also reported that many of the tools exist at a research or concept level and need further development to be practically applied.

The potential to assist idea expression processes in design using AI tools has been explored by a number of studies. John (2022) [15] developed TaleBrush, which can facilitate the under-constrained and iterative expression of user intents through sketching-based story generation. Yunlong et al. (2023) [3] presented Reprompt which is based on automatic prompt editing to refine AI-generative art towards precise expressions. However, copyright issues behind the AI tools in assisting idea expression processes are still a challenge [16].

In addition to research developing AI tools to help design processes, some research has also aimed at detecting the effects of generative AI tools (such as ChatGPT and Midjourney) on design processes. For example, Wu et al. (2024) identified the potential of ChatGPT in describing the target design features, and Midjourney in shaping the best colors for a product [17]. Zhao (2023) presented evidence that AI tools increase the creativity of ideas [18].

1.2 Human-in-the-loop in design

Although various AI tools have been developed, the accuracy and success of AI tools in design processes requires a significant quantity of training data [19]. The vast increase in the quantity data has stymied update of tools as the basis for the tools is not stable requiring retraining of the models. Also, selecting which data can be used as training data is a challenge [20]. To solve the problems, the concept of human-in-the-loop (HITL) processes have been proposed [21]. HITL aims to include human knowledge in model building processes. In human-AI co-design processes, HITL is adapted to include human knowledge in design development processes. For example, Pan et al. (2019) [22] used machine learning and Electroencephalograph (EEG) to enable AI to present images from human generated ideas.

1.3 Human-in-the-loop approaches

Two potential approaches to achieving HITL in a human-AI co-design process, include Human-learning HITL and Machine-learning HITL approaches.

Human-learning HITL approach. A person can work together with an AI tool through an iterative design process. In this kind of HITL approach, the person keeps providing feedback based on what has been generated by the AI tool through some form of prompt. An example of this is “the solution is now not feasible, can you make it more feasible?” This iteration will stop once the AI tool generates a solution that satisfies the designer’s expectations.

The nature of this kind of HITL approach in co-design processes is that the person keeps learning from what has been provided by AI. The person can express their views directly through prompts and ask the AI tool to make changes. During this process, the person has a high degree of freedom to select what they want to adjust using a prompt and they can directly tell the AI tool what it needs to do. In other words, this HITL approach is controlled by human learning and interaction [23].

Machine-learning HITL approach. A person can provide positive examples (data) which they think are the same or similar to their expectations. Then, they can ask the AI tool to learn from the examples that the person has provided and generate solutions that are more likely to satisfy the person’s expectations. The prompt under this HITL approach is likely to be an expression such as “Can you learn from this image/these

images and improve the solution you have generated?” or “Can you learn from this image/these images and generate a solution for *[design task]*?”

The nature of this kind of HITL approach in co-design processes is also that the person keeps learning from what has been provided by AI. However, distinct from the Human-learning HITL approach, in this Machine-learning HITL approach, a person cannot express their views directly through prompts and ask AI to make changes. Instead, the person will provide training data and ask AI to learn from training data to improve the solutions. During this process, a person will have limited freedom to teach AI apart from providing training data and asking AI to learn from data. In other words, this HITL approach is mainly based on machine learning ability [23].

1.4 Research gaps

Although the concept of HITL has been explored and how human and AI can cooperate in a design process in a number of studies, the research has mainly focused on how AI can provide help in different design stages. There is still a gap on understanding how different HITL approaches (such as Human-learning HITL approach and Machine-learning HITL approach) affect design performance.

Therefore, this study aims to explore how different HITL approaches (Human-learning HITL approach and Machine-learning HITL approach) affect the design performance of human-AI co-design. The research objectives of this study are

- (i) To explore the performance (novelty, aesthetics, functionality, and feasibility) of Human-learning-HITL-approach generated design;
- (ii) To investigate the performance (novelty, aesthetics, functionality, and feasibility) of Machine-learning-HITL-approach generated design;
- (iii) To compare the different performance (novelty, aesthetics, functionality, and feasibility) of designs generated from Human-learning and Machine-learning HITL approach.

The hypothesis of this study is that:

H0: The performance of Human-learning-HITL-approach generated design is better than that of Machine-learning-HITL-approach generated design

H1: The performance of Machine-learning-HITL-approach generated design is better than that of Human-learning-HITL-approach generated design

Within this study, Midjourney was selected to represent the AI tool. Product design processes were selected to represent the design processes.

The results of this study were expected to be used to explore whether Human-learning HITL approach or Machine-learning HITL approach can lead to better design performance. In this way, this study can provide suggestions on how to further develop high-efficiency AI tools to help designers in a human-AI co-design process. In addition, the results of the study were expected to help designers develop higher quality solutions.

2. METHODOLOGY

To achieve the research goals, 15 participants were recruited to finish two design tasks under the guidelines of Human-learning HITL approach and Machine-learning HITL approach respectively with the help of Midjourney. The results of their outputs were then assessed by three experts in design areas. The protocol is presented in Figure 1.

2.1 Study 1 HITL design study

Participants. 15 participants (average age = 26.8; SD=4.58) were recruited to participate in this study. There were 7 male and 8 female participants and were studying product design. All self-reported that they could use prompts to communicate with Midjourney and had experience in using Midjourney to finish design tasks within the previous month.

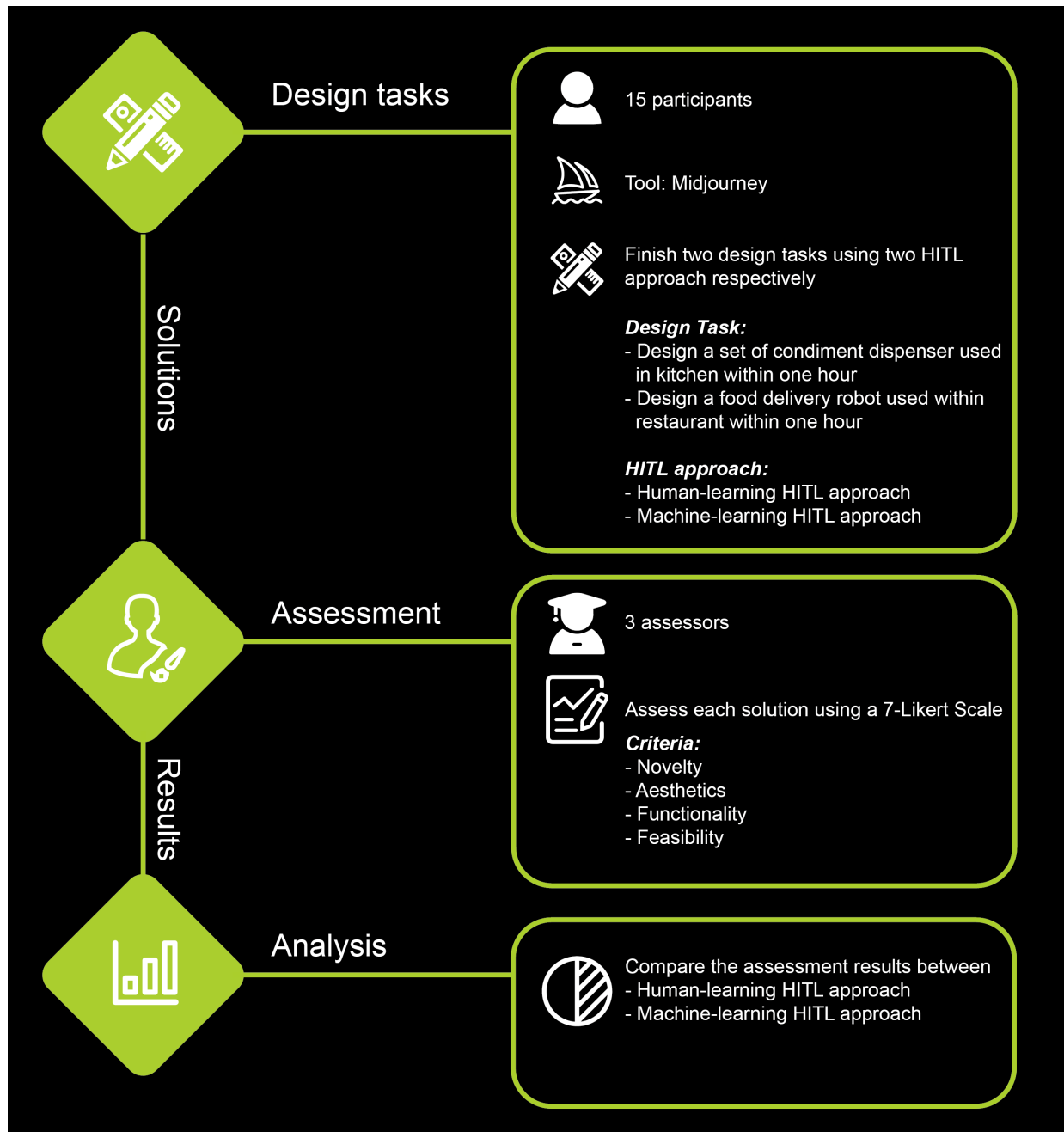


FIGURE 1: STUDY PROTOCOL

Methodology. Two HITL approaches used in this study. The study focused on two kinds of HITL approaches - Human-learning HITL approach and Machine-learning HITL approach. In this study, participants were asked to finish two design tasks under the guidelines of a Human-learning HITL approach and a Machine-learning HITL approach respectively with the help of use of Midjourney.

For the design task undertaken with the Human-learning HITL approach, participants were introduced to the protocols such as they can key in a prompt or expression to provide design guidelines or improvements based on what has been generated from Midjourney. For example, they could use the prompt “Can you make the design more novel?” Once they think the solution satisfies their expectations, they can stop the design task.

For the design task undertaken with the Machine-learning HITL approach, participants were asked to provide existing product images (data) through Google image searching. There was no limitation on how many images (data) they could provide. However, these images should be an existing product image (it cannot be a cartoon image or sketch) and these images should be the images that they thought were the same or similar to their expectation for the task. Then, they need to ask Midjourney to learn from the images provided and generate solutions. During this approach, participants can iterate solutions only by providing more images and asking AI to learn from these images to improve the solution. They cannot provide prompts that directly guide Midjourney to improve the solutions. For example, they can only give the prompt “learn from this image and improve the solution”. They cannot give the prompt “learn from this image and improve the *functionality* of the solution”. Once they think the solution satisfies their expectations, they can stop the design.

AI tools used. Midjourney, a type of Generative AI tool, which can generate images from text and image inputs, was selected as the AI tool used in this study. This was out of consideration that existing research has supported the effect of Midjourney in product and creative design [24, 25]. Also, Midjourney is a relatively stable tool that has been commercialized [26].



FIGURE 2: EXAMPLES OF SOLUTIONS GENERATED FROM PARTICIPANTS.

2A) A SOLUTION GENERATED FROM THE TASK - DESIGN A FOOD DELIVERY ROBOT USED WITHIN RESTAURANTS WITHIN ONE HOUR UNDER THE GUIDELINE OF HUMAN-LEARNING HITL APPROACH;

2B) A SOLUTION GENERATED FROM THE TASK - DESIGN A FOOD DELIVERY ROBOT USED WITHIN RESTAURANTS WITHIN ONE UNDER THE GUIDELINE OF MACHINE-LEARNING HITL APPROACH;

2C) A SOLUTION GENERATED FROM THE TASK - DESIGN A SET OF CONDIMENT DISPENSERS USED IN THE KITCHEN WITHIN ONE HOUR UNDER THE GUIDELINE OF HUMAN-LEARNING HITL APPROACH;

2D) A SOLUTION GENERATED FROM THE TASK – DESIGN A SET OF CONDIMENT DISPENSERS USED IN THE KITCHEN WITHIN ONE HOUR UNDER THE GUIDELINE OF MACHINE-LEARNING HITL APPROACH.

Product design tasks. Two design tasks from the China graduate examination for industrial design were selected for this study. Considering that the design performance was to be assessed through novelty, aesthetics, functionality, and feasibility in this study, “design a set of condiment dispensers used in the kitchen within one hour” and “design a food delivery robot used within restaurants within one hour” were finally selected as the design tasks used in this study.

To avoid influence from previous design of the same products, the participants were asked whether they had undertaken the same design tasks before, once the study was finished. All participants reported that they had not undertaken the two tasks before.

Protocol. Participants were asked to complete a demographic information sheet to collect their gender, age, educational background, and whether they have experience in using Midjourney to finish design tasks during the previous month. Then, participants were introduced to what they needed to do under the guidelines of the Human-learning HITL and Machine-learning HITL approaches. Following this participants were asked to first “design a set of condiment dispensers used in the kitchen within one hour (*or design a food delivery robot used within restaurants within one hour*) under the guideline of Human-learning HITL approach (*or Machine-learning HITL approach*)”. Participants were asked to finally select one image generated from Midjourney as the solution for their design task.

Then, participants can have a five-minute break. After that, participants were asked to finish the second task “Design a food delivery robot used within restaurants within one hour (*or design a set of condiment dispensers used in the kitchen within one hour*) under the guideline of Machine-learning HITL approach (*or Human-learning HITL approach*)”. Participants were asked to finally select one image generated from Midjourney as the solution for this design task. Examples of solutions from participants are displayed in Figure 2 (A-D).

2.2 Study 2: design performance assessment study

Three assessors (1 female and 2 males, averaged age = 27) who have experience in product design areas of more than five years were recruited to assess the solutions generated from the 15 participants (30 solutions in total). They were told which design task this solution belongs to, but they were not told whether it was generated based on the guidelines of the Human-learning HITL or Machine-learning HITL approach. Novelty, aesthetics, functionality, and feasibility were selected as the criteria to represent the design performance [27]. Novelty indicated that a solution is new to an individual or history; Aesthetics indicated that a solution can provide a pleasing visual impression; Functionality indicated that a solution can help a person accomplish a task; Feasibility indicated that the solution can be practically achieved [27].

Each assessor was asked to assess each solution based on its novelty, aesthetics, functionality, and feasibility using a 7-Likert Scale (Score 1 means the solution is completely not novel, aesthetic, functional, or feasible; Score 7 means the solution is excellent in novel, aesthetic, functional, or feasible perspectives). Assessors were given five days to finish the assessment and they were allowed to change the previous marking decisions. The assessment was recorded through the spreadsheet. All three assessors finished the assessment in the given time.

The reasons why the four criteria were used to measure the solutions are that this study aimed to detect whether Human-learning HITL approach and Machine-learning HITL approach will affect the performance of the solutions. The four criteria (novelty, aesthetics, functionality, and feasibility) selected in this study were related to the performance of the solutions and have been verified by prior studies. Novelty as a criterion to reflect the creativity of a design has also received much attention [28, 29, 30]. Aesthetics has been reported as a core element for the success of design [31, 32, 33]. Functionality has been reported as an important index of design performance by Shiu (2017) [33] and Han et al. (2021) [32] and the importance of feasibility has been addressed in [34, 35].

3. RESULTS

This study aims to explore how different HITL approaches (Human-learning HITL approach and Machine-learning HITL approach) affect the design performance in a human-AI co-design. To achieve the research aim, this study compared the design performance (novelty, aesthetics, functionality, and feasibility) between Human-learning HITL approach and Machine-learning HITL approach. The average design performance results generated from Human-learning HITL approach (or Machine-learning HITL approach) were calculated from the average results of three assessors and all solutions generated from this specific approach. The average Kappa results among three assessors were 0.732 which indicated a substantial level of agreement.

TABLE 1: COMPARISON OF THE RESULTS FROM THE HUMAN-LEARNING VERSUS THE MACHINE LEARNING HITL APPROACHES

Criterion	Human-learning HITL approach		Machine-learning HITL approach		P-value
	Average score	SD	Average score	SD	
Novelty	4.94	0.797	4.88	0.741	0.266
Aesthetics	5.00	1.022	4.50	0.654	0.023
Functionality	4.72	0.917	4.38	0.806	0.037
Feasibility	4.67	0.761	4.58	0.881	0.772
Overall	19.33		18.33		

The results of this study are shown in Table 1. The one-way ANOVA was used to analyse the reliability of the results. Based on the results, it can be found that the novelty, aesthetics, functionality, and feasibility of the solutions generated from Human-learning HITL approach were higher than those of Machine-learning HITL approach. The higher results were statistically significant for aesthetics ($p=0.023<0.05$) and functionality ($p=0.037<0.05$) while the higher results were not statistically significant for novelty ($p=0.266>0.05$) and feasibility ($p=0.882>0.05$).

4. DISCUSSION

4.1 Results discussion

The overall design score of solutions generated from Human-learning HITL approach was higher than that of Machine-learning HITL approach. The result supported H0. This result indicated that directly providing human improvement feedback through prompts (such as “The solution now is not feasible enough, can you make it more feasible?”) can lead to a better design performance compared with human only provided images of existing solutions and asked AI to learn from it (such as “can you learn from this image and improve the solution you have generated?”). This may be explained by the level of human intelligence involvement. For the Human-learning HITL approach, a person can directly express their views through prompts where they have more freedom to control where they want AI to improve on the solutions [36]. In this way, the feedback that AI can obtain is more accurate. However, if a person can only be involved in the design processes by providing more training data (as in the Machine-learning HITL approach), the person cannot control what the AI has learned from the new data [37] and how AI may make the improvement. This study, thus, further supports the involvement of designers in a human-AI co-design process.

Through comparing novelty, aesthetics, functionality, and feasibility results between the solutions generated from the Human-learning HITL approach and the Machine-learning HITL approach, it can be found that for all of indexes (novelty, aesthetics, functionality, and feasibility) performance for the Human-learning HITL approach was better than that for the Machine-learning HITL approach. However, based on the one-way ANOVA results, it can be found that the higher results were statistically significant for aesthetics ($p=0.023<0.05$) and functionality ($p=0.037<0.05$). This provided further explanation about the

effect of human-learning processes on design performance. If a person was involved in a HITL human-AI co-design process through Human-learning HITL approach, the aesthetics and functionality were more likely to increase.

In addition, this result further indicated that human learning ability in learning aesthetics and functionality is stronger than AI. This may be because aesthetics is relatively subjective [38], which brings challenges for an AI tool to learn [39]. Thus, this study supported existing views that for art, AI may be a useful tool [40]. The difference in functionality performance, may be because Midjourney is trained through images. This data training method may affect the ability of Midjourney in learning functionality, which may be hard to express through images in an obvious way [13].

The one-way ANOVA results also revealed that although novelty and feasibility of solutions generated from the Human-learning HITL approach were better than that of the Machine-learning HITL approach, these higher results were not statistically significant (novelty, $p=0.266>0.05$; feasibility, $p=0.882>0.05$). This may be because AI has been supported to be useful in increasing the novelty of solutions compared with without using AI. Since both the Human-learning HITL approach and the Machine-learning HITL approach used AI to generate images, the novelty levels of solutions have increased significantly [41]. Under this condition, including more human-learning ability may increase the novelty of the solutions [42, 43] but this effect is weaker than that of using AI. However, this assumption has not been supported by existing research and needs to be verified in the future.

4.2 Limitation and future research

This study compared the design performance between Human-learning HITL approach and Machine-learning HITL approach, however, the sample numbers of this study were still limited, and may be the reason for not significant results. In the future, more participants with different ages, experiences, and cultures will be recruited. In addition, the study collected 15 solutions generated from Human-learning HITL approach and 15 solutions generated from Machine-learning HITL approach. This limited number of solutions for analysis may reduce the reliability of the results. In the future, more product design tasks will be involved in and then the scores for all measurement will be averaged to see if the same conclusions can be achieved.

Furthermore, this study selected the novelty, aesthetics, functionality, and feasibility to represent the design performance. However, there may be more criteria that can be used to assess the performance of solutions such as value and supervise [44]. In the future, more studies are suggested to detect more design performance (such as valuable and supervise) of the solution generated from Human-learning HITL approach and Machine-learning HITL approach.

Also, this study only compared the novelty, aesthetics, functionality, and feasibility performances of the design. However, there are more criteria worth to be identified such as sustainability, which can be included in future research. Finally, this study used Midjourney to represent AI. However, there are various Generative AIs that can be used in design such as Diffusion AI and ChatGPT. Whether the results from this study can be applied to other AI tools need to be verified in the future.

4.3 Contribution

The results of this study provides supporting evidence that a Human-learning HITL approach can lead to better design performance in a HITL human-AI co-design process, especially in terms of aesthetics and functionality. This study thus can provide suggestions on how to further develop high-efficiency AI tools to help designers. For example, the AI tools for design should either have more advanced algorithms for understanding aesthetics and functionality, or provide a space for human to add their values to aesthetics and functionality of the solution. In addition, the results of the study can help designers develop higher-quality solutions when they cooperate with AI. For example, based on the results of the study, designers can ask AI to help them, but also realize the importance of adding their own insights through prompts to AI. Finally, this study pointed out the importance of human in human-AI co-design processes. Human can provide more information on aesthetics and functionality, which is hard to be achieved by AI through learning from training data.

5. CONCLUSIONS

This study aimed to explore how different HITL approaches (Human-learning HITL approach and Machine-learning HITL approach) affect the design performance of human-AI co-design. 15 participants were asked to finish two design tasks under the guideline of Human-learning HITL approach and Machine-learning HITL approach with the help of Midjourney. The solutions from participants were assessed using four criteria (novelty, aesthetics, functionality, and feasibility).

The study supported the hypothesis (H0) that the performance of Human-learning-HITL-approach generated design is better than that of Machine-learning-HITL-approach generated design, especially from aesthetics and functionality perspectives. This further supports the importance of involving human learning in how to improve the solutions in human-AI co-design. The findings from this study emphasize the importance of continued collaboration between humans and AI in shaping the future of design practice. Also, the results of this study can be used as a cue to develop AI tools which can be used in human-AI co-design processes. In addition, this study gives designers insights into what they need to pay more attention to in human-AI co-design processes.

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