Creative Sketching Partner: An Analysis of Human-AI Co-Creativity

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ABSTRACT

The creative sketching partner (CSP) is a proof of concept intelligent interface to inspire designers while sketching in response to a specified design task. With this interactive system we are studying the effect of an AI model of visual and conceptual similarity for selecting the AI's sketch response as an inspiration to the current state of the user's sketch. Specifically, we are interested in the user's behavior and response to an AI partner when engaged in a design task. By developing deep learning models of the sketches from a large-scale dataset, the user can control the amount of visual and conceptual similarity of the AI response when requesting inspiration from the CSP. We conducted a study with 50 design students to examine the participants' interaction behavior and their self reports. The participants' behavior maps into clusters that are co-related with three types of design creativity: combinatorial, exploratory, and transformational. Our findings demonstrate that the tool can facilitate ideation and overcome design fixation. In addition, analysis suggests that inspiration related to conceptual similarity is more associated with transformational creativity and inspiration related to visual similarity occurs more frequently during the detailed stages of design and is more prevalent with combinatorial creativity.

CCS CONCEPTS

• **Human-centered computing** → **Collaborative interaction.**

KEYWORDS

Design Creativity, Sketching, Collaboration, Co-Creativity

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1 INTRODUCTION

Sketching is a technique used during the conceptual design stage in which the designer is engaged in generating and iterating on design ideas. Creativity has often been associated with the number

of new ideas that the designer can generate for a given design task [29]. Designers often have difficulty moving beyond the ideas they have experienced previously, which is called fixation [28]. This effect prevents designers from thinking beyond the first ideas that come to mind and to include the structure and/or function of other objects in their design solution. To further understand the problem of fixation, Jansson and Smith [17] introduced two types of mental representation: conceptual space and object space. Conceptual space is related to the abstract knowledge of a concept, whereas object space is referred to the elements that can form the object. They argued that fixation occurs because designers use the object space, and the innovative solutions are blocked because they do not move to the conceptual space.

To reduce the effect of fixation, researchers in the design computing and cognition field have identified approaches that can serve as inspiration sources to trigger designer's creative thinking. One such approach is called Design-by-Analogy (DbA), in which inspiration is achieved by associating a design problem to a solution in another domain [27]. The association can be either semantic, using textual representation, or visual, using structural characteristics. Other approaches can be classified as intrinsic and extrinsic methods. Intrinsic approaches are techniques, in which novel ideas are triggered intuitively by disconnecting designers from the existing problem [6, 24]. At the individual level, this can be achieved by performing a non-related task or taking a break. At the group level, different personality types can lead to the emergence of new solutions when working in a team. Extrinsic approaches, on the other hand, are techniques that use heuristic or external stimuli to encourage divergent thinking through multiple sequential ways [3, 32].

Computational tools for sketching are a subset of extrinsic approaches that enable the generation of new design ideas by providing semantic and/or visual stimuli. These tools leverage artificial intelligence (AI) techniques to reduce the fixation effect. The Electronic Cocktail Napkin [11] is an example of an early interface that supports inspiration and ideation in the early stage of a design problem. The tool retrieves and displays digital architectural elements that are visually related to the composition of the user's sketch diagram. Drawing Apprentice is another example of a sketching support tool that responds to the user's sketch with another sketch of the same or a similar category [8]. The stimuli these tools provide comprise several structural characteristics related to the designer's original sketch. This, in turn, leads to incremental iterations where the designer changes individual features of their sketch rather than radically transforming their idea.

To support different forms of design creativity more broadly and to reduce the effect of fixation, we developed a co-creative sketching

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tool called the Creative Sketching Partner (CSP). The tool maps the user's sketch into a sketch of another category that shares some structural and semantic characteristics. The user can control the amount of similarity for both visual and conceptual components to be inspired for its current design. We built an AI model for the mapping process in the visual and conceptual space to help users find connections between the two categories and spark new ideas for the design task to explore.

In this paper, we study the behavior and response of participants in a human-AI co-creative sketching system and report on the findings of a user study that analyses the user's response to the CSP's sketch. We hypothesize that a tool that presents designers with a sketch of another category with which it shares some visual and conceptual similarity can support the design process and allow users to re-interpret their design in a new context or category. Our findings show that the CSP tool encouraged users' creativity to come up with new design ideas while working on their initial design. We also present a qualitative analysis of different types of design creativity associated with the user's response in each iteration based on the degree of visual and conceptual similarity. The results demonstrate that the tool can support a wide range of design creativity including combinatorial, exploratory, and transformational.

2 RELATED WORK

The design and study of the CSP builds on three interdisciplinary research threads: co-creativity, computational support for sketching, and deep learning in sketch domain.

2.1 Co-creative systems

Co-creative systems are a subfield of computational creativity that involve human users collaborating with an AI agent on a shared task in real time. These systems are proposed as a way to inspire and augment the user's creative process, increase user engagement with the system, and stimulate the user to continue creating. Co-creative systems have been developed in different creative domains, including music [1, 14], drawing [8, 21], dance [16], humor [30], and poetry [7]. One important factor that distinguishes different co-creative applications is the type of interaction that can be either open-ended or goal-directed. Co-creative systems with open-ended interaction, such as Lumin-AI [16] and Drawing Apprentice [8], are mainly designed to encourage the user's engagement with the system and are less concerned about the accuracy of the system's response. On the other hand, goal-directed co-creative tools, such as 3Buddy and Sentient Sketchbook [23, 25], are introduced to encourage the user's creative thoughts toward different aspects of the creative space based on the system's response. In these cases, the accuracy of the generated output by the system can affect the user's response in the next iteration. The CSP is a goal-directed co-creative sketching tool that collaborates with designers on a shared design task. The tool guides users toward different types of design creativity based on the amount of visual and conceptual similarity between the user's input and the system's response.

2.2 Computational support for sketching

Computational support for sketching is an interdisciplinary research topic that combines research in human-computer interaction, design science, and artificial intelligence (AI). Computer-aided design (CAD) tools have become a popular method of supporting the design process. These tools offer powerful capabilities to help designers visualize and simulate their designs, but they are often restricted to executing direct commands from the user issued by the interface rather than through sketching. Using sketch as an input method offers more direct feedback to the user and assists in the reflective and iterative process of the early stages of designing. Some design tools have recently emerged that offer this type of sketch-based input and incorporate elements of artificial intelligence to further assist the user. Sketch It, Make It (SIMI) [18] is an example of a sketch-based design application that helps users rapidly create 2D models for use in laser cutting. The system recognizes the user's input sketch and performs different geometric rules based on the designer's intention. The intention is elicited through gestural marks created by the designer. Some examples of the rules that SIMI performs are making a line perpendicular to another line, making two line segments the same length, and latching the endpoints of two nearby segments. SolidSketch [15] is another example of a sketch-based system that enables users to generate 3D parametric models from 2D sketches. In this system, the user can explore different design configuration using 2D sketch input, and this input is transformed into a fully rendered 3D representation of the design object. This approach helps users gain high fidelity feedback about their target sketch in the early stages of design process.

Other types of sketch-based tools incorporate sketch recognition and understanding in the process of digital design. These tools communicate ideas through both visual and conceptual representations. Sketching Knowledge Entry Associate (sKEA) [9] is an example of a sketch-based tool that captures knowledge from visual representations. The system takes a collection of ink strokes and the user's annotated collection of ink to provide a conceptual understanding of the drawn sketch. Other interfaces use speech recognition to automatically create a visual representation from the user's words. Scribing Speech [31] is an example that transforms the spoken word into a dynamic visual representation in real time. The CSP introduced in this paper uses visual and conceptual representation of an object category associated with a design task to suggest a new sketch concept with which it shares some structural and conceptual similarity to support the design process.

2.3 Deep learning in sketch domain

Deep Neural Networks (DNNs) have led to improvements in various problems in the sketch domain. Examples include classifying sketch objects [4], generating sketch drawings [5, 12], and identifying visual trends of international drawings among nations [13]. In each of these applications, DNN models can capture high level visual and sequential information, leading to high classification accuracy and coherent sketch generation. One important factor that distinguishes sketches from natural images is the ability to represent them as a sequence of pen strokes or vector data. Unlike natural images that are modeled as a low resolution, pixel image, sketches can be

modelled similar to the way that humans draw. The work by Ha and Eck on neural drawing [12] is the first to use this representation. In order to teach machines to draw sketch concepts similar to humans, each sketch is encoded as a list of points with three elements: $(\Delta x, \Delta y, p)$. The first two elements represent the x and y coordinates with respect to the previous point, and the third element is the pen state that determines whether or not the stroke is drawn.

One potential application of DNNs in the sketch domain is the ability to create generative models [10] that can learn the way a sketch concept is drawn. A tool with such capability can assist users to complete a drawing, teach them how to draw, and help with the creative process. Sketch-rnn is an example of a generative model that is trained to draw a sketch concept using a sequence of pen strokes [8]. The model is based on a sequence-to-sequence variational autoencoder framework. The input drawing is encoded into a latent vector with floating point numbers and then decoded into a sequence of pen drawings that is close to the input.

Classification is another application of DNNs that can provide a qualitative output, in which the user's drawing is interpreted as belonging to a concept or a category. The architecture of a DNN model for the classification task can utilize either convolutional neural networks (CNNs) or sequential models, such as Long Short-Term Memory (LSTM). CNNs are typically used for grid-like structure, similar to natural images. The structure of CNNs consist of convolution, pooling, and fully connected layers. The work done by Zeiler [33] shows that the output of each layer can capture specific information, such as texture, orientation, and shape. 1D-convolutional layers are a type of convolutional layer that can capture the shape of a drawing with one dimension. This is particularly useful for extracting visual features from sketches, as one of the main key points that discriminates different drawings is their shape.

LSTM networks are sequential models that can capture temporal patterns. For the purpose of sketch classification the LSTM network can be used to extract sequential information, such as the direction of the pen, whether or not the pen is lifted from the paper, and when the drawing is ended. By combining 1-D convolutional layers and LSTM layers we can capture both visual and sequential information from the vector representation of sketches. This, in turn, can provide discriminative features for sketches that can be the basis for tasks, such as classification and clustering. In our system, we encode sketches as a sequence of pen strokes and extract their features using a DNN model called CNN-LSTM [4]. The model is able to capture high level visual and sequential information from each sketch.

3 THE CREATIVE SKETCHING PARTNER: CSP

We developed the CSP system to encourage the creativity of users while engaged in a given design task and to study different types of design creativity associated with the users' response. The interface of the tool is shown in Figure 1. There are two main design principles for the CSP system: 1) provide a sketch response to the user and 2) enable users to interactively change the amount of visual and conceptual similarity for the system's response. There are two sliders in the CSP interface that control the amount of visual and conceptual similarity, as shown in section B of Figure 1. The visual

similarity slider controls the amount of structural characteristics shared with the user's sketch. It ranges from 1, meaning low similarity, to 10, which denotes high similarity. Likewise, the conceptual similarity slider ranges from 1 to 10 and controls the degree of semantic relationship between the two category names: the category associated with the user's design task and the category associated with the sketch selected from a large-scale dataset.

The design task is displayed on the top-left side of the interface (section A of Figure 1), and it includes the object to be designed as well as a context to further specify the object's use and environment. When the user begins drawing, they use the left drawing panel (section F of Figure 1) to iteratively create and refine their sketch. At any point in the design process, the user can click on the "inspire me" icon (section C of Figure 1) to be presented with the system's selected sketch, which is displayed on the right drawing panel (section G of Figure 1). An object label is shown for both the user's sketch as well as the system's sketch above their respective drawing panels. The user is then free to make changes to their current sketch based on the inspiration from the system's response or click the "start again" button (section D of Figure 1) to create a new sketch. Some examples of changes include combining some features of the two sketches, modifying some variable values for the current sketch (e.g. size), and changing the overall structure of the current sketch. The user can utilize both the structure and the concept of the system's response as inspiration for their current sketch.

Turn-taking between the user and the system is designed to facilitate a communication channel between the user and the AI agent. Once the user is satisfied with their current drawing, they can adjust the sliders to their desired level of similarity and click the "Inspire me" icon to see the system's response. The system's turn will be a sketch of another object with the corresponding label shown above the right-side panel. In addition, the user can erase some part of their drawing by choosing the Erase mode (section E of Figure 1). Once the erasing is completed the user can switch to Draw mode to continue drawing.

Our AI model for selecting a sketch to be displayed on the canvas is based on visual similarity and conceptual similarity. Visual similarity selects a sketch from a distinct category that shares some structural characteristics, whereas conceptual mapping use the results from visual similarity to identify the degree of similarity between the category name of the object that the user is designing and the category name of the selected sketch from the visual mapping component.

The dataset we used for implementing our algorithm is a public benchmark called QuickDraw! (QD) [19], which is created during an online game where players were asked to draw a particular object within 20 seconds. The dataset contains 345 categories with more than 50 million labelled sketches. Each sketch has six fields: *key-id*, *word*, *countrycode*, *recognized*, *timestamp*, and *drawing*. For the purpose of our study we first removed all sketches that are not recognized as belonging to their category. For the remaining sketches we use only the three fields: *key-id*, *word*, and *drawing*. *Key-id* is the unique identifier that is assigned to each sketch. *Word* is the category name of the object that is represented in the sketch. *Drawing* is an array that represents the coordinates of the pen strokes for a drawn sketch.

Figure 1: The Creative Sketching Partner user interface.

Our approach for computing visual similarity between two sketches is based on selecting potential clusters of sketches from distinct categories with which the current sketch shares some underlying structural characteristics. In preparation for calculating visual similarity, we have two phases: online and offline. The offline phase uses a CNN-LSTM architecture to train a model using 30,000 training samples and 10,000 validation samples per category for 1.5 million training steps, then places the feature vector for each sketch into clusters and computes visual similarities between all cluster centroids of distinct categories. The online phase extracts a feature vector for the user's input sketch using the pre-trained CNN-LSTM model and maps the vector into a sketch of another category with a measure of visual similarity. The technical details for online and offline phases of our visual similarity process are described in [22].

As with the visual similarity mapping, we have two phases for conceptual mapping, including online and offline phases. The offline phase computes the conceptual similarity between all category names in the QD dataset using a word embedding model trained on the Google News dataset [26]. The online phase takes the selected 10 sketches based on the visual similarity module and re-ranks the selected pairs according to their conceptual similarity values. After the user adjusts the conceptual similarity slider to a specific value, the system will choose a sketch based on the ordered pairs position. The technical details for online and offline phases of our conceptual similarity process are described in [22].

3.1 CSP User Study

We conducted a user study to explore the response to an AI partner in a design sketching environment. Specifically, we are interested in relationships between the users' creativity, interaction, and sources of inspiration. For this study, we asked participants to engage in a design task using the CSP and collected data about their interaction

behavior, their design sketches, and their responses to interview questions following their design experience.

The study included 50 participants from the School of Architecture: 25 females and 25 males. Participants provided consent according to our IRB approval and were provided with a \$5 gift card as compensation for their involvement. Before the study began, there was a brief training session to familiarize participants with the CSP interface. Training included an introduction to all the features of the interface and how they work to enable the AI partner to provide inspiration during their design task. The facilitator then explained the basic principles of utilizing an inspirational sketch to iteratively develop a sketch of their design, such as adding more details, changing structures, and combining elements based on an inspirational sketch presented by the CSP.

During the study, the participant was given a single design task: design a bridge to cross a river near a national park. Participants are asked to continue iterating on the sketch of their bridge design until they have responded to 3 inspiring sketches from the CSP. They are free to change the visual and conceptual similarity sliders and click the "inspire me" button as many times as they would like to find a suitable sketch from the system to aid in their design. We did not limit the amount of time for the design task since different designers work at different paces, but on average, the participants were engaged in the design task approximately 15-20 minutes. We recorded the screen as a video for the entire session for each participant. After the design task, we conducted a structured interview with the participants about their experience during the design task and asked them to describe what they were thinking while watching a video of their interaction (retrospective think aloud protocol). The questions for the interview are:

- Did you see any relationship between the choices you had for visual and conceptual similarity slide bars and your creativity?

Figure 2: Examples of participants' new sketch based on inspiring sketch for three types of design creativity: combinatorial (first column), exploratory (second column), and transformational (third column).

- Was it more inspiring when the system's output was less/more similar to your input?
- In which iteration you were inspired most? Can you explain why?
- Do you have any comments on the interaction with a computational partner to generate sketches to inspire you?

4 ANALYSIS OF CSP STUDY

We conducted three different analyses to study various types of design creativity in participants' responses, capture human-AI interaction patterns, and their responses about how the AI's sketch inspired their design. We coded the participants' retrospective think aloud data and their new design sketches as combinatorial, exploratory, and transformational creativity [20]. To study the relationship between interaction behavior patterns and the type of creativity, we coded the video data to produce an interaction vector for each participant. In addition, we performed a thematic analysis of the interview data to learn how and in what circumstances the CSP tool inspired the participants.

4.1 Analysis of Types of Creativity of Participants' Sketches

In this section, we describe how we coded the sketches for each participant as a type of creativity adapted from Boden's categories of creativity [2]: combinatorial, exploratory, and transformational. Combinatorial creativity happens when users combine all or some features of their current drawing with all or some features of the system's response. Exploratory occurs when users change parameters of some features associated with their current drawing (e.g. changing the size, scale, angle) based on features of the system's response. Other instances of exploratory creativity is when users explore adding context to their current drawing (e.g. water beneath the bridge). Transformational concerns changing the shape contour

of all or some parts of the current drawing based on the features from the system's response. Other instances of transformational is when users add a new function (e.g. rail on the bridge) based on the features from the system's response. Figure 2 shows examples of participants' sketches for the three types of design creativity. The first column demonstrates examples of combinatorial creativity, such that in the first example, the inspiring sketch (fence) is added to the bridge design; in the second and third example, the inspiring sketch (wall) is added above and beneath the bridge sketch, respectively. The second column shows examples of exploratory creativity. In the first example, the amount of bending for the bridge is changed, whereas in the second example, another layer for car passage is added to the bridge design. In the third example, the base size of the bridge is increased. The last column demonstrates examples of transformational creativity. In the first example, lamp posts are added as a new function to the bridge design. In the second example, the shape contour of the base is changed from curvy to rigid. In the last example, contours are added as a new function to the middle of the bridge.

We divide each participant session into three different phases. The session starts with the participant drawing an initial sketch in response to the design prompt. Each phase is delineated when the participant clicks the "inspire me" button and starts making changes to their current design based on the system's sketch. For each phase, we record the system's sketch, the settings of the visual and conceptual similarity sliders, and the participant's sketch at the end of the phase. The values for the two sliders are categorized into high, medium, and low. Numbers between 1 to 3 are considered as low similarity. Those between 4 to 6 are medium, and numbers of 7 to 10 are considered high. This corresponds to nine conditions: the combinations of high, medium, and low visual and conceptual similarity (Figure 3). We then coded the 3 sketches produced by each participant as combinatorial, C, exploratory, E, and transformational, T, by reviewing the transcripts of the retrospective

Figure 3: Distribution of the three types of creativity and the total number of instances for the nine conditions.

protocol and the produced sketches. The coding was performed by 2 researchers, and then discussed until the codes for both coders agreed. The coders engaged in a blind coding approach where they did not know the values of visual and conceptual similarity for each design sketch being coded.

We collected the three sketches produced after each iteration from all the 50 participants, which corresponds to a total of 150 generated sketches. Figure 3 shows the CET distribution of the three types of creativity for the nine conditions. The number of instances that the sliders were set to a specific condition is noted in the corner for each condition. H_v , M_v , and L_v denote high, medium, and low visual similarity, respectively. H_c , M_c , and L_c correspond to high, medium, and low conceptual similarity, respectively.

As the results show when the slider for both visual and conceptual similarity were set to high, in most instances (23/43) the user's response fell into combinatorial creativity. In these cases, participants combined either the whole or a subset of the system's response with their current drawing as a new component or structure. Within this condition, exploratory and transformational creativity happened equally (10/43). Our results show that exploratory creativity has two main characteristics. The first is when participants used the system's response as a context for the bridge design. In these cases, they explored adding landscape to their current drawing. Another characteristic is when participants explored changing the values of some parameters of their sketch (e.g. scale, orientation, or repetition). We observed that when the visual and conceptual slider are both high, transformational creativity mainly occurred at the very early stage of the design. In these instances, participants started with a few components, such as a base or arches and

then added a new function to their current design inspired by the concept or the structure of the system's response.

When the slider was in high visual similarity condition (first row in Figure 3), there is a progressively higher percentage of transformational creativity as the conceptual similarity decreases. This suggests that when the concept is less related, users utilize it to re-interpret their design in a new category. In these instances the participants added a new function to their existing design, or they changed the outline shape of their current drawing. On the other hand, there is a decline in exploratory creativity and no combinatorial creativity, which demonstrates that when the system's concept is less associated with the concept of "bridge" it is harder for the participants to combine the two elements together or stay in the same design space.

When the visual similarity is medium (second row in Figure 3), the number of times that transformational or exploratory creativity is observed in the user's response is approximately equal. However, we have an increase in transformational creativity when the conceptual component is high or medium compared to when it is in low similarity condition. In these cases, participants were able to draw a connection between the two concepts more easily and add a new function to their existing drawing. Combinatorial creativity occurred only once when the system was in medium visual and conceptual similarity condition.

When the system was in the low visual and low conceptual similarity condition, all the responses fall in transformational creativity. In these instances, all participants changed the features of their design by using either the structure or the concept of the proposed sketch that shared a small amount of visual information and belonged to a different contextual space. However, when the concept

Figure 4: Clusters of participants based on their interaction behavior.

was intermediately similar, all participants modified their drawing in the same design space, i.e. exploratory creativity.

4.2 Interaction Behavior Analysis

To understand the interaction behavior, we coded the screen-recordings of each participant to capture the whole drawing session from the user study. Each code reports the interactional behavior of the participants with the AI: 'Drawing', 'Erasing', 'Inspiration' and 'No action'. 'Drawing' refers to the event when participants drew in the drawing space. 'Erasing' is when the participants erased any part of the drawing. When participants hit the "Inspire Me" button of the system to seek suggestion from the AI, we coded that as a 'Inspiration' event. When the mouse pointer stays idle, we coded the event as 'No action'. The video for each participant is segmented into 5 seconds and the occurrence of an event is indicated by starting and ending segment. Two individuals from our research group coded 25 videos each after discussing and agreeing to the codebook.

We clustered all 50 participants using the interactional behavior coding. A feature vector for each participant Drawing, Erasing, Inspiration, No action encapsulates the percentage of time spent on each behavior. After data normalization, K-means clustering algorithm was applied to the vectorized data to find clusters of participants based on their interaction behavior. Feature selection was performed to find the best clusters with the most contributing features, which are 'Drawing' and 'Inspiration'.

Overall, we found three clusters of participants (See Figure 4). Individuals in the first cluster spent an average time in drawing and maximum time in seeking inspiration from the AI compared to the other two clusters. Individuals in the second cluster spent an average time in drawing and least time in seeking inspiration among all the clusters. Third cluster comprises the individuals who spent the maximum time in drawing and second average to minimal time in seeking inspiration compared to the other two clusters.

4.2.1 Correlation between clusters and creativity. For identifying whether interaction behavior of participants has any influence on their creativity level, we analyzed the correlation between interaction behavior clusters and the creativity level of the final sketch. We found significant correlation between the interaction behavior clusters and creativity level of the final sketches (last iteration) for each participant using CET codes [20]. The null hypothesis was that there is no relation of creativity level of the final drawing with the interval behavior clusters. The value of Pearson Chi-square was 10.798 and P value was 0.029 ($P < 0.05$), showing significant correlation. Therefore, with a 95% confidence level we rejected the null hypothesis and we can conclude that those two variables are not independent.

Chi-square results and distribution of different clusters across different types of creativity (see Figure 5) indicates that individuals in cluster 1, are more likely to complete their drawing with exploratory creativity as almost two thirds (64.3%) of the participants in this cluster completed their last drawing iteration with exploratory creativity. Very few participants from this cluster completed their drawing with combinatorial creativity (7.1%). This suggests that seeking more inspiration from the AI helps designers to change their drawing in a novel way by exploring the conceptual space of system response which is the use of exploratory creativity. This result also suggests that designers who get more inspirations from the AI, are very unlikely to complete their drawing just by combining features from the system response which is considered as combinatorial creativity.

Individuals in cluster 2 have 44.5% probability to finalize their drawing with transformational creativity. There is a 33.3% chance of the individuals in this group to complete their drawing with exploratory creativity and chance of using combinatorial creativity to finalize the drawing is 22.2%. The distribution of the participants in cluster 2 among each category of creativity is fairly close compared to each other. As a result, we can conclude that when designers spend average time in drawing and minimum time in seeking inspiration, the probability of finishing their drawing by different levels of creativity are almost evenly distributed.

Half of the individuals in cluster 3 completed their drawing using transformational creativity although results indicate that compared to the other two clusters, more individuals completed their drawing with combinatorial creativity in this cluster (38.9%). This cluster

	C	E	T	Total
Cluster 1	7.1%	64.3%	28.6%	100%
Cluster 2	22.2%	33.3%	44.5%	100%
Cluster 3	38.9%	11.1%	50.0%	100%

Figure 5: Distribution of different clusters across different types of creativity.

indicates designers who spend the maximum time in drawing and moderate to minimal time in seeking inspiring responses from the AI, are either expected to transform the conceptual space of drawing unexpectedly, which is the use of transformational creativity or to use combinatorial creativity.

4.3 Thematic analysis

To understand how the system's response can help designers come up with creative ideas for their initial task we analyzed the participants responses to the interview questions conducted after the design task was complete. We aimed to explore the relationship between stimulus similarity and design thinking. We performed a thematic analysis of the responses the participants gave to the interview questions. Overall, three main themes were found from the interview answers.

- CSP helps in design ideation
- CSP helps to overcome fixation
- CSP inspires with varying similarity

In the following section, we elaborate on each of these themes.

4.3.1 CSP helps in design ideation. The results show that the CSP tool has the potential to help with the early stage of the design process. As designers start working on their design problem they often have difficulty iterating on their initial design and coming up with new design ideas. Presenting designers with a sketch of another object can aid with exploration and help them to incorporate ideas from the structure or the concept of another sketch that they might not have considered. P45 demonstrates that the tool helps when working on their project stating: *"It did inspire me. Especially if I was working on a project I think that would really help. Mostly likely the initial parts of the design."*

P42 also describes how the tool can help with the early stage of design, reporting *"I think it's helpful for the beginning of the design process. Like when I don't have any idea it gives me new ideas."* This demonstrates how the tool could help users overcome creative blocks that can sometimes be associated with a blank page. P39 elaborated on the previous sentiments by mentioning how quickly the tool can give them new ideas: *"I definitely think that this is a good way to just get idea[s] very fast. If you ask me to design a bridge the first time I don't know where to start with, but with this I kind of felt it is a good way to kind of quickly create something."* Helping designers rapidly iterate on their early designs helps to explore the conceptual space of the design and populate their process with many ideas. Similarly P31 emphasizes this rapid ideation and employing the system's ideas into their design task, saying *"it did generate something faster that helped me thinking of a way that I can apply it to my design, instead of sitting and counter playing for hours."*

P15 elaborates on the utility of the tool for students working on their projects, stating:

"I would love to use it when my teachers would ask me to produce iterations and I get to a point where I am just lost. This tool is very helpful to see some sort of drawing that makes you think of something else. Because our professors would say sit down and do 25 different versions of your first idea and after about ten it just feels like the same thing over and over. So, having something to just constantly like new ideas pop in your head is really helpful"

In this instance, the designer found the tool useful for a design task with a specific requirement of multiple iterations. In the same vein, p30 says: *"Yeah, I think would be actually very helpful for a lot of students coming up with new design ideas and inspire them more to think out of the box."* Based on these findings, it may be beneficial to employ this tool in an educational design setting.

4.3.2 CSP helps to overcome fixation. Our results demonstrate that the conceptual component of the CSP tool has the potential to successfully trigger the seeing-as mode of perception of the user. In other words, the concept of the sketch presented to the user encouraged them to connect the two concepts by reinterpreting their bridge design in a new domain or category. P39 describes how the conceptual component of the system's response aided their design, stating *"I think the conceptual one was more inspiring to me personally. Especially, when the concept was more similar and the visual was less similar. With the conceptual one I could re-interpreted it in any way I wanted to. With the visual one it is a little bit more strict."*

P41 describes how connecting the function or the purpose of the system's response could be used as a component for their drawing: *"I think when it was more inspiring [when] I could connect it mostly conceptually like for the lighting part, it wasn't similar to the bridge but I thought of the concept and using those lights as a lamp post for my bridge."* Here, the system's response helped the user integrate new ideas and elements into their drawing based on the image of the system. Similarly, P7 express that connecting the functions of two concepts can aid with the design process, stating *"for me I was able to draw connection between something you know used for one purpose can be used for another purpose."* P7 achieved a conceptual shift to help reconceptualize the design by understanding how an object can be repurposed.

P21 was able to connect the concept of ceiling-fan to their drawing and explore new possibilities for their design task, reporting: *"the ceiling fan.. just I was thinking above water. It reminded me that of the space below, so it just provided a whole new area of design that I had not considered."* In this case, interacting with the system revealed a new part of the design space that was previously inaccessible possibly through fixation on their current design. P35 also described how the presented concept of rain inspired them to modify their design by adding a shelter to the existing design: *"it inspired me to look at how a bridge would function, in terms of what could rain do to a bridge in terms of being able to improve further the design."* This user generated the idea of the 'sheltered bridge' based on the sketches presented by the system, which shows the user was able to expand the design problem and consider it from a new angle.

P27 reinforces this idea that the system can help users think differently and more creatively given the concept of sketches it presents, stating:

"I think the conceptual part of the slider was more important, because it forced me to think differently. So, when I saw the suggestions that are completely irrelevant I started to think in a very different way and I tried to use my imagination to see how this can make a good bridge. And I think creativity is directly related to the conceptual slide."

This shows how participants often reinterpret their current sketch in terms of the conceptual component of the system sketch by utilizing its behavior and function to redefine their design.

4.3.3 CSP inspires with varying similarity. Based on our findings, varying the amount of visual and conceptual similarity can aid the design process in different ways. High similarity shares many underlying structural characteristics with the user's input and can inspire the user to add more details to their initial drawing; whereas low similarity forces the user to utilize the concept and to re-interpret their drawing in a new category or context. Overall, 10 participants found both high and low similarity conditions inspiring. P3 describes how both levels of similarity could be inspiring in different ways, stating

"I feel like both of them are equally inspiring because even with a project with architecture sometimes you might have something that you like to see like a precedent that is really similar to the project you are doing, so that could help you with your design or you may see something totally different from what you originally had. That can be equally more inspiring because it could take you to a whole another direction and take your design to the next level"

In this instance, the designer found different degrees of similarity equally inspiring based on the type of change they want to apply to their design. Likewise P43 found both levels of similarity influencing their design, reporting *"It really depends. The more visual similarity it inspired me to add more suspension, but when it was less visually similar like the table design or snowflake it really inspired different ideas."* This user added more structure when the system was in high similarity condition and incorporated different ideas from another category when the system's output was less similar to the current drawing.

Our results show that 32 participants commented that it is more inspiring when the system's response is less similar to their input. P26 describes how less similar stimuli was inspiring, saying *"I think low similarity is more inspiring. Because part of it is art and art is not about making things exactly like each other but it's about having things or shape in unexpected places. I think the lower similarity was pushing me to be more creative."* This participant found low similarity designs sparking creative thoughts more compared to high similarity designs. Alternatively, P23 reports how less similar outputs can bring a more broad range of ideas to the design: *"it was more inspiring when it was less similar, just because I felt like it could bring ideas into the concept or a little bit more diverse not so straight."* Similarly, P9 was able to re-interpret their current drawing and bring more diverse concepts into the design when the system's output was less similar, stating: *"I think the less similar was helpful because it was more open to interpretation. You know there was a wider spectrum as what can be done with an object unrelated as opposed to something related."* Based on these findings, we can conclude that when two concepts serve various functions, the purpose of one concept can guide adding a new function to another sketch concept.

Finally, 8 participants found high similar designs more inspiring. In these instances, users were able to add more details and structures to their existing sketch. P10 describes how more similar objects were inspiring, reporting: *"It gave me more inspiration when the subject was more similar to mine because I had to guess less and*

inspiration was stronger for me so it kind of helped me to make changes to my initial design. It more helped to finalize the design and add more details to the design." This participant preferred to finalize the original drawing by adding more details and structures rather than changing the existing features.

P17 describes how high similar outputs guide their design, saying: *"I would say it was more inspiring for me when it was little more to the similar, just because those ideas are already close in terms of structure and function. So, it was easier for me to visualize them together."* In this instance, the participant was able to combine two sketch concepts together by incorporating the features of one design concept into another design concept. Similarly, P29 found high similar outputs sparking creative thoughts more: *"More similar in structure. Because like harp it helps to add more structure to your design. When it is more similar it helps to complete your design because they are both structural like things."* As a result, we can conclude that when the two sketch concepts share a high amount of structural characteristics, it helps to finalize the design by adding more details to the existing sketch.

5 DISCUSSION

This paper introduces a co-creative sketching tool that collaborates with designers on a shared design task in real time. The tool supports the design process by helping users to iterate on their design sketches and to incorporate new design ideas from another conceptual space. Our AI model selects a labelled sketch from a large-scale dataset based on the degree of visual and conceptual similarity. Similarity is measured in 2 latent space models: one is created by training a deep learning model on a visual representation of the sketches from the QuickDraw! dataset for measuring visual similarity and the second uses a word embedding model that enables a measure of conceptual similarity. Visual similarity entails identifying a sketch from another conceptual category that shares some underlying structural characteristics, whereas conceptual similarity determines the degree of similarity between the design goal of user's sketch and the selected category name. Our results are a positive indication that measurement in a latent space representation produced by deep learning provides a meaningful measure of similarity in both visual (sketches) and conceptual (words) spaces.

We performed a user study with the system in order to understand how the tool can help design students iterate on their initial design as well as users' interaction behavior with the system's response. Results indicate that the tool can support different types of design creativity as well as spark new ideas particularly in the early stages of the design process. Other findings suggest that low similarity helps designers to use the conceptual component of the system's response and interpret their design in a new context, which is associated with transformational creativity. On the other hand, high similarity designs help combining structural characteristics of system's response with the current drawing, which denotes combinatorial creativity. Other analysis from users' behavior demonstrates that the interaction style of the users is correlated with their level of creativity in the final iteration of the design. Our findings show that users who seek inspiration from CSP are more likely to conclude their drawing with the use of exploratory creativity. On the other hand, users who spent the most time in

drawing and minimal time in seeking inspiration from the system, are more likely to finish their drawing through transformational creativity.

Different types of creativity are associated with specific stages and goals in the design process. Combinatorial creativity helps designers in the last phase of a design sketching session to touch up and refine the sketch by adding elements. Exploratory and transformational creativity is more helpful in the beginning of a design process when designers are more open to explore or transform the conceptual space from the system response. Further investigation is needed to understand the influence of interaction behavior of users and their creativity type to design effective co-creative systems, which can enhance the creativity of designers in different design settings. One limitation of the current CSP user study is having a different number of instances for each phase and the qualitative nature of the study. Future studies will use statistical measures such as chi-squared with more participants to establish the statistical significance of the results.

6 CONCLUSION

This paper presents a co-creative sketching tool called the Creative Sketching Partner. The tool is meant to collaborate with designers on a specific design task in real-time. We described our AI model for selecting a sketch from a distinct category based on a comparison of visual and conceptual similarity to the current state of the user's design sketch. The findings demonstrate that the tool supports creativity in the design process, facilitates ideation, and assists in overcoming design fixation. The visual analogy helps the user add more structure to the initial design (i.e. combinatorial creativity), whereas the conceptual analogy inspires adding new features from a completely different design space (i.e. transformational creativity). We have also found that interaction patterns of designers with the CSP are correlated with different levels of creativity in the final iteration of the sketch.

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