# STUDYING THE IMPACT OF AN AI MODEL OF CONCEPTUAL SHIFTS IN A CO-CREATIVE SKETCHING TOOL

by

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ABSTRACT

PEGAH KARIMI. Studying the Impact of an AI Model of Conceptual Shifts in a Co-Creative Sketching Tool. (Under the direction of DR. MARY LOU MAHER)

Sketching is a critical part of the early stages of the design process, facilitating ideation and the exploration of conceptual designs. Digital sketching tools have been introduced as a method for augmenting and supporting the sketching process. In contrast, intelligent systems that collaborate with designers on creative tasks are referred to as computational co-creative systems. These systems contribute to a shared creative artifact with users in a process that can support and inspire user creativity. A common occurrence in sketching creativity is the *conceptual shift*, or when a drawn object is re-interpreted as belonging to a different object category. Identifying and capitalizing on conceptual shifts is an important part of the creative process as they involve re-interpreting input in a new context, category, or domain.

We introduce a co-creative design system called Creative Sketching Partner (CSP), which involves collaboration between a designer and an AI agent on a shared design task. Our AI model for making conceptual shifts can analyze and extract visual and conceptual features from the user's sketched object and then identify a relevant object to display in order to encourage user creativity. We describe our computational model in identifying and generating conceptual shifts, followed by different scenarios to demonstrate the results of our algorithm in a design context.

Our tool is intended to encourage creativity, facilitate creative ideation, and overcome design fixation. In addition, we want our tool to support different forms of creativity, such as combinatorial, exploratory, and transformational, depending on the parameters selected for the operation of the model. We presume that the degree of similarity between the user's and the system's sketches is associated with a range of cognitive models of creativity in a design context. We report on the findings of an empirical study that analyzes different design scenarios in which the user sketches in response to a proposed conceptual shift. The findings show that high visual and conceptual similarity is associated with combinatorial creativity and low visual and conceptual similarity is associated with transformational creativity.

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# CHAPTER 1: INTRODUCTION

## 1.1 Research Motivation

Creative systems are computational systems that either model human creativity in some manner or are designed to support and inspire creativity. Over the last few years, three main approaches to these systems have emerged: fully autonomous creative systems, creativity support tools, and co-creative systems. Fully autonomous creative systems, part of the field of computational creativity, are designed to generate creative artifacts or exhibit creative behaviors [5, 6, 7]. Creativity support tools, on the other hand, are technologies that can support human creativity by accelerating or augmenting some facets of the creative process [8, 9, 10]. Finally, co-creative systems incorporate concepts from both fully autonomous systems and creativity support tools: they enable human users and computer systems to work together on a shared creative task [11, 12].

In this thesis, we introduce a co-creative sketching tool called the Creative Sketching Partner (CSP), which involves collaboration between a designer and an AI agent on a shared design task. The system utilizes a computational model of conceptual shifts [13] to guide users toward different aspects of the design space based on the amount of visual and conceptual similarity to the user's sketch input. The model takes the user's sketch and compares it with a sketch of another category with a measure of conceptual and visual similarity. Conceptual similarity is a measure of the distance between the meaning of the two categories using a word embedded model. Visual similarity is a measure of the distance between the visual features of the two sketches. Leveraging the amount of conceptual and visual similarity can encourage designers to explore new design ideas and lead to more creative outcomes.

How to operationalize creativity has been studied in many computational creative systems; however there is less literature on doing so in co-creative systems. Karimi et al. [14] introduced a typology of ways to evaluate creativity in co-creative systems. It was found that current co-creative systems tend to focus on measuring the usability of the system, which demonstrates an opportunity for adopting metrics from computational creative systems in order to empower co-creative systems with the capacity to measure the creativity of their contributions to the output. For our conceptual shift model, we adopt one of the most commonly measured components of creativity from computational creative systems: novelty [15]. Novelty is associated with measuring how different an artifact is compared to another set of artifacts [15]. The novelty can be based on a comparison with a universal set of artifacts, which we will call a universal measure, or on a set of artifacts that the user has previously experienced, which we will call a personal measure. In this thesis, we use a universal measure based on a large dataset of labelled sketches and deep learning that enables two kinds of representation: one that enables a measure of visual similarity and one that enables a measure of conceptual similarity. From these metrics, we have constructed a universal composite measurement of novelty that is a combination of the distance between feature vectors in the visual space and the conceptual space.

We report on Wizard of Oz and CSP user study to explore how our proposed model affects the design creativity of users. We investigate if our co-creative sketching tool can inspire the user's creativity by helping them re-interpreting their initial design and develop novel and creative ideas in the early stage of their design process. We intend for our tool to support a range of cognitive models of creativity, such as combinatorial, exploratory, and transformational. Combinatorial creativity involves adding two sets or subsets of design ideas together; exploratory creativity is when we explore alternative design ideas in the same design space and transformational creativity involves changing the overall search space in which the design creativity occurs [16]. We presume that, when a system provides stimulus in the form of design concept responses that are highly novel (less similar) to the user's design, it leads to more transformative creative outcomes. In these cases, the designer is able to draw upon distant visual and conceptual features to inspire their creative process, such as adding features from another design domain. In contrast, when the system displays stimulus design concepts that are less novel (highly similar) to the user's design, it corresponds to less creative outcomes. The features of similar designs do not provide highly novel input to the process, leading to design iterations that share many attributes with the designer's original sketch.

## 1.2 Thesis Statement and Research Questions

Thesis statement: *An AI model of conceptual shifts in a co-creative sketching tool can facilitate ideation, overcome design fixation, and guide users towards different types of creative design by varying the amount of conceptual and visual similarity to the user's drawn sketch.*

Based on this thesis statement, we ask the following research questions:

- Ideation

  —How does an AI model of conceptual shifts facilitate ideation in the early stage of a design task?

- Design Fixation

  —How does an AI model of conceptual shifts trigger the seeing-as mode perception of the users?

  —How does an AI model of conceptual shifts affect overcoming design fixation?

  —What aspects of a co-creative design system help to overcome design fixation?

- Design Creativity

—What types of design creativity can be observed in the user's response to AI-based conceptual shifts?

—Does the degree of similarity between the user's input and the system's response correlate with different cognitive models of creativity in the user's response?

## 1.3 Thesis Structure

The structure of this thesis is as follows: chapter 2 provides background in computational co-creative systems, computational support for sketching, and deep learning in sketch domain. Chapter 3 describes the role of conceptual shift in design and its implications for a co-creative system in design sketching. This includes design fixation, visual analogy, characterizing design creativity, conceptual blending, and ideation. Chapter 4 describes the AI model of conceptual shift and the algorithms for visual and conceptual similarity components. Chapter 5 provides an ontology for the three types of design creativity, including combinatorial, exploratory, and transformational. Chapter 6 discusses the results of the Wizard of Oz user study to explore our research questions. Similarly, chapter 7 explores the research questions through the CSP user study and describes the user experience with the system. Future plans and limitations are discussed in chapter 8.

# CHAPTER 2: BACKGROUND

Three fields are germane to this thesis: computational co-creative systems, computational support for sketching, and deep learning in sketch domain.

## 2.1 Computational Co-Creative Systems

Co-creative systems involve collaboration between multiple participants with the requirement that at least one party is an AI agent. Co-creative systems share characteristics from both computational creative systems [5, 6, 7, 17] and creativity support tools [18, 19, 8, 9]. They are distinguished by the interactive nature of the AI agent working alongside the human user on a creative task. The system is not meant to autonomously generate creative products, which is the main objective for computationally creative systems. They are also not meant only to support user creativity like creativity support tools, as the system's contributions may sometimes oppose the user's ideas in order to prompt them to explore the creative space more fully. Co-creative systems participate in a shared creative process where the user and system both make contributions to the same artifact, though these contributions need not necessarily be symmetric. In our research, we define co-creativity as:

*"Interaction between at least one AI agent and at least one human in which they each take action based on the response of their partner and their own conceptualization of creativity during the co-creative task."*

The collaboration dynamics between the user and creative agent can vary in co-creative systems. In some cases, the co-creative agent is meant to inspire the user's creativity and help them generate novel ideas, such as the Drawing Apprentice [20], which analyzes the user's sketch input and generates similar or complementary responses. In this scenario, the agent can be said to take on the role of a follower in the collaboration since the agent is mostly reacting to the user's input. This follower configuration is prevalent in co-creative systems as the user input provides content for the system to act upon. One reason this configuration is popular is because of the open-ended nature of creative collaboration in which the user and agent are situated. The user could take a variety of creative paths, and without some initial input, it is difficult to determine how the system should behave.

Another co-creative interaction configuration is accompaniment wherein the agent and user perform actions simultaneously. Examples of this include the music [21] and dance [22] domain where interaction is typically synchronous. In the music domain, there are two main examples, GenJam [23] and Shimon [21]. GenJam is a jazz improvisation system that detects what type of music is being played and selects an accompaniment based on predetermined rules of jazz improvisation. GenJam's actions are restricted to selecting among pre-programmed improvisation routines, which inherently limits the system's capacity to generate completely novel musical forms and thus limits its creativity. Shimon is a robotic maramba player that listens to the musical composition of the user and generates an accompanying melody in real time. These systems observe and adapt their actions in real time rather than following the user in a turn taking fashion.

One final co-creation interaction paradigm is mixed-initiative co-creation, where the system helps the user achieve a particular goal, such as game level design [12]. Here, the system can be queried to provide feedback and additional ideas about what actions to take in the creation process. For example, in the Sentient Sketchbook [24], the system can analyze the game level design and evaluate its playability as well as suggest additional features to add to the game level. The interaction model can be defined as query-based, where the user determines when and if the system will provide any input to their creative process. In mixed-initiative co-creation, the system can serve as an expert that can provide detailed feedback and commentary about the creative product, as well as generating its own content as an example for the user.

Another consideration when designing co-creative systems is how to know whether the system is effective. To address this question, we provided a framework showing several ways of evaluating a co-creative system [14]. The framework provides answers to questions such as who evaluates the creativity, e.g. the system itself, human judges, etc., what is to be evaluated, such as the process, user, or the creative product, when does evaluation occur (formative or summative) and how the evaluation is performed, e.g. methods and metrics. By situating the existing co-creative systems into this framework, we concluded that most existing co-creative systems tend to focus on evaluating the final product and the usability of the system. Adopting metrics and methods from computational creativity systems can lead to co-creative systems in which the AI agent is self-aware and evaluates its own creativity during the co-creative process.

## 2.2 Computational Supports 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) [25] 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 [26] 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 design in the early stages of design.

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) [27] 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 uses speech recognition to automatically create a visual representation from the user's words. Scribing Speech [28] is an example that transforms the spoken word into a dynamic visual representation in real time. The CSP introduced in this thesis uses visual and conceptual representation of an object category associated to a design task to suggests 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

In visual tasks, it is important to learn the representation of objects efficiently. Unlike traditional hand-designed methods, deep neural networks (DNNs) have shown successful results in large-scale visual domains, primarily using convolutional neural networks [29]. The availability of large training datasets and large computational resources is a key factor for their outstanding performance on previously challenging visual recognition tasks [30]. In the sketch domain, DNNs have led to improvements in various problems, including classifying sketch objects [4], generating sketch drawings [31], and identifying visual trends of international drawings among nations [32]. 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 [31] is the first toward this representation. In order to learn 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 the stroke is drawn or not.

One potential application of DNNs in the sketch domain is the ability to create generative models [33] 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 [31]. 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 [34] shows that the output of each layer can capture specific information such as texture, orientation, and shape. 1D-convolutional layers is 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 point 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 the pen is lifted from the paper or not, 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 a 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 in our dataset. The implementation details and the architecture of the model is described in section 4.2.2.

# CHAPTER 3: THE ROLE OF CONCEPTUAL SHIFT IN DESIGN

In this section, we describe the implications of conceptual shift model for a co-creative design system. This includes overcoming design fixation, making analogy, characterizing different types of design creativity, enabling conceptual blending, and facilitating ideation. We elaborate on each of these benefits to demonstrate the utility of conceptual shift model for a design task.

## 3.1 Conceptual Re-Interpretation

One important factor in the creative process is the ability to re-interpret ideas from different perspectives in order to see the same input in new ways. Boden describes three types of creativity: combinatorial, exploratory, and transformational [35]. Combinatorial creativity involves combining two sets of design concepts or a subset of them. Exploratory creativity refers to developing new ideas by traversing an established conceptual space. Transformational creativity refers to fundamentally changing that conceptual space through the act of developing a new idea, i.e. changing the rules of the game. The types of conceptual shifts introduced by a co-creative sketching tool have the capacity to result in combinatorial, exploratory, or transformational creativity. They help designers expand their conceptual space to include concepts that may not otherwise be considered. This type of re-interpretation could help users establish more fluid boundaries between categories.

The continual process of re-interpretation in a co-creative sketching tool may also train users to explore different ways of seeing their input. Suwa and Tversky [36] describe two distinct modes of perception used in design called seeing-that and seeing-as. Seeing-that describes a functional type of perception that looks at the concrete properties of a sketch and considers the role they play in the overall design. Seeing-as is a more interpretative process where elements in a sketch can be viewed through different perspectives, such as seeing a collection of shapes in an architectural drawing as a face. Once the collection of objects is seen as a face, the designer might decide to add ears or a nose. Suwa and Tversky found that architects continually shift between seeing-as and seeing-that to help generate and refine their sketches. This in turn could help users become accustomed to the seeing-as mode of perception by demonstrating how drawn structures could relate to a variety of highly different objects.

Figure 3.1 shows an instance where users might reinterpret their initial input and think about their idea from new perspectives. For example, when the designer sketches a ceiling fan, the system generates a flower. This might lead the designer to make an analogy and explore the idea of organic growth in their design task. This could lead them to consider creative and potentially transformative blade designs. Visual reinterpretation might be combined with further analogical reasoning in this case, such as if the designer considered designing the ceiling fan lights to look similar to the pollen in the center of a flower. Seeing one object as another object has the potential to enable designers to generate novel and inspiring ideas to facilitate creative sketching.

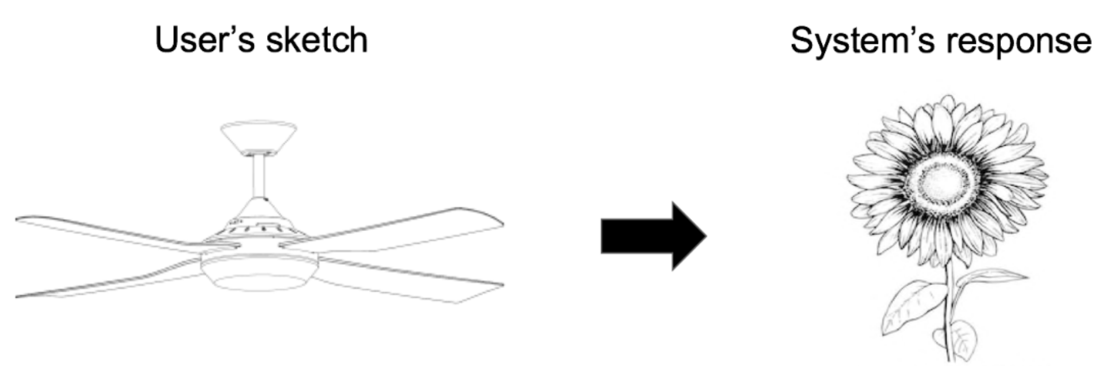


Figure 3.1: Re-interpreting one concept (ceiling-fan on the left) as another concept (flower on the right), based on their visual similarity.

## 3.2 Visual Analogy

Analogical reasoning in design facilitates creativity by revealing functional, behavioral, and structural similarities between two domains [37]. During a design task, analogies are made between the elements of a design space. In the visual domain, designers often make analogy by associating a source sketch to a target sketch. This form of association can lead to transformation of one concept to a new concept that the designer might later discover. Gero et al. [38] introduced a computational model of analogy-making based on situated similarity. Situated similarity occurs when the correlation between two concepts depends both on the past experience of the designer and the situation in which the designer is observing. The input to the model is a triplet of concept, situation and the designer's experience. The analogy-making model transforms the input into a new concept through three interactive processes: formulation, matching, and mapping. Formulation refers to constructing the way the designer is observing his or her situation, matching is the process of discovering which source concepts can be associated to the target concept, and finally mapping is the process of constructing the associations between the two concepts.

One important process of modeling creative analogy-making is association [39]. Grace et al. [40] has introduced a computational model of association based on reinterpretation. The model has three processes: representation, matching, and mapping. Unlike many computational analogy making models, in this work the representation is done in parallel with the mapping process, such that the mapping process changes the representation of the object and enables new search parameters in each iteration. The representation step represents the source and target object as vector images that captures the polygonal shape of the object using the contour of their outlines. The mapping step maps the source object to the target object if there is some overlap between their relationships. The last step, reinterpretation, changes the representation of the source and target object such that it will affect the search space for the mapping process.

Our computational model of conceptual shifts can be compared to analogy making in a design task. In this work, the input to the model is a source sketch drawn by the designer and the output is a target sketch that is visually similar and conceptually different. The model maps the source sketch to the target sketch through two processes: learning and clustering. The learning step extracts the features from labelled sketches and the clustering step groups each category of sketches into different subcategories based on visual similarity. These processes are explained in more detail in Chapter 4.

## 3.3 Conceptual Blending

Like analogical reasoning, blending aligns two partial structures (two inputs). However, blending also projects selectively to form a third structure, which is the blend [41]. The blended structure is not only the composition of the two inputs, but instead has its own organization. This new organization can lead to novel and creative conceptualizations, which play an important role in art and design thinking [42]. The blend has an emergent structure that happens in three ways [43]: composition, completion and elaboration. Composition happens when the projection from the inputs provide new relations that did not exist in each input individually. Completion is when past knowledge and cognitive models allow the composite structure to be seen as part of a larger structure within the inputs. Elaboration happens when this new structure can then be extended according to the emergent logic of the blend.

Although conceptual blending is a challenging task for AI research, there are a few computational models of conceptual blending. One such model is Goal Driven Conceptual Blending [44], where the context and goal of the situation influence the projection of features from the base spaces to the blended space. A 'semiotic base space' is introduced based on work by Brandt et al. [45] that constrains how the blend is 'run' relative to the contextual details of the situation. This computational model is used to produce efficient and creative blends that take context and goals into account in their construction. The Divago system described by Pereira [46] is another conceptual blending approach that explores how numerous blends can be generated by the same input spaces given which features are projected into the blended space. Instead of using goals and context to constrain the projection, like the previous approach, Divago uses genetic algorithms to sample from the generated blends to find the most fitting blend.

There are different methods to determine which objects to select for a blend. Work in the design field by Taura et al. [47] has shown that objects with high dissimilarity tend to lead to more creative outcomes when they are synthesized. The authors argued that high dissimilarity is associated with higher creativity and low dissimilarity is associated with lower creativity. In order to evaluate their hypothesis, they conducted an experiment involving three different design sessions where subjects are asked to combine a pair of nine different objects. The objects are divided into three different groups based on their dissimilarity (high, intermediate, low). In each design session, subjects are asked to combine a primary object with an object from one of the three groups. The results are evaluated by 10 subjects using a five-point scale for "creativity". It is observed that the highest creativity ratings are given to the sketches in which entities are from high dissimilarity groups.

Identifying conceptual shifts has the potential to enable conceptual blending, in which two sketch categories are combined and displayed on the canvas. Combination can be done in different ways, such as superposition (displaying sketches on top of each other) or adjacency (side-by-side combination). Moreover, the selection of candidates for blending can ranges from highly similar to highly dissimilar. Figure 3.2 shows different scenarios for visual conceptual blends. In the first two scenarios, the sketch candidates share high amount of visual information and are examples of adjacency scenario; whereas, in the third and forth scenarios, the sketch candidates share very small amount of visual information and demonstrate the superposition scenario.

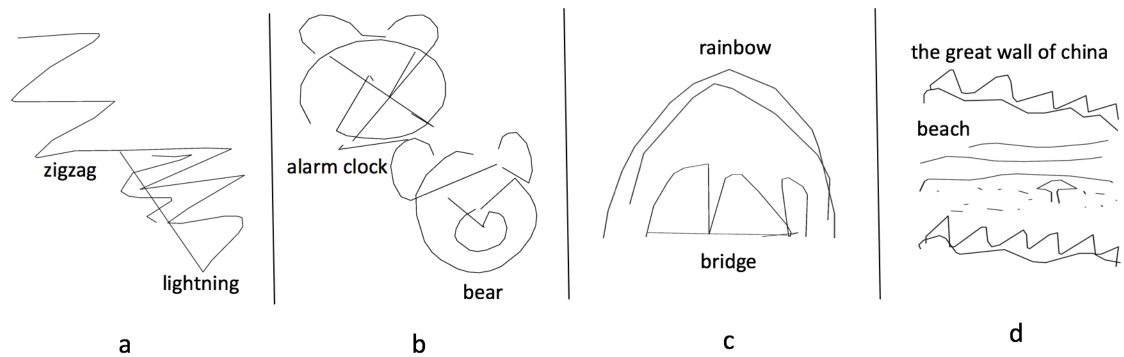


Figure 3.2: Examples of conceptual blends: Highly similar sketch concepts that are displayed side-by-side (adjacency) (a,b), highly dissimilar sketch concepts that are displayed on top of each other (superposition) (c,d) [2].

## 3.4 Design Fixation

Sketching in design is a challenging task that requires iterating and generating on new design ideas for a given design problem. Such design professionals as architects and industrial designers often have difficulty disengaging with the ideas they have developed over time. This effect, which is called fixation [48], prevents designers to employ the structure and/or function of other objects in their design problem. To further understand the problem of fixation, Jansson and Smith [49] 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 design cognition field has identified approaches that can be served 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 [50]. 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 from the existing problem [51, 52]. At the individual level, this can be achieved by performing a non-related task or having 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 stimulus to encourage divergent thinking through multiple sequential ways [53, 54].

An AI model of conceptual shift is considered an extrinsic approach that could help users overcome design fixation. When presenting a conceptual shift successfully triggers seeing-as perception, a designer could be distracted from fixation, and potentially develop novel contributions to their design. This could lead to the discovery of innovative solutions for a design task.

## 3.5 Design Creativity

Creative designs have the potential to change the behaviour of a society through the values they induce and their existence [16]. Designers often improve their initial design by adding more substances or transforming their original design into a new design space. Over the last several years, digital tools have been introduced as a way to support design creativity [55]. These tools offer a variety of functions that allow designers to rapidly explore alternatives, share their digital sketches and even suggest new ideas to facilitate creativity. In contrast, AI researchers have developed computational models to generate novel and creative artifacts [5]. Boden has introduced three ways of producing new ideas through AI techniques: "producing novel combinations of familiar ideas, exploring the potential of conceptual spaces, and making transformations that enable the generation of previously impossible ideas" [56].

Alternatively, Gero [16] has introduced six different forms of creative designing processes that can be the basis for computational aids. These creative processes are combination, exploration, transformation, analogy, emergence, and first principles. Combination happens when two distinct design concepts are added. Exploration is about exploring what variables may be appropriate and entails both goal and decision variables. Transformation involves changing one or more variables of a design concept through external processes. Analogy is characterized by mapping between structural elements of two dissimilar objects and then drawing inferences about the object one started with based on analogous one. Emergence is when extensional properties of a design concept are identified beyond the intentional ones. First principles use computational knowledge to relate function to behaviour and behaviour to structure.

The CSP introduced in this thesis can be considered a computational aid to design that can support the first three of these forms of creativity in a co-creative design context: combination, exploration, and transformation. Figure 3.3-a shows an example of combinatorial creativity, in which the straight lines in fence are combined with the bridge sketch to create a new design. Figure 3.3-b demonstrates an example for exploratory creativity, in which the symmetries observed in the inspiring object (floor lamp) leads to creating the same pattern for the streetlight. Finally, Figure 3.3-c shows an example for transformational creativity, in which the shape contour of the inspiring object (aircraft-carrier) change the structure of the seat of the chair for the new sketch.

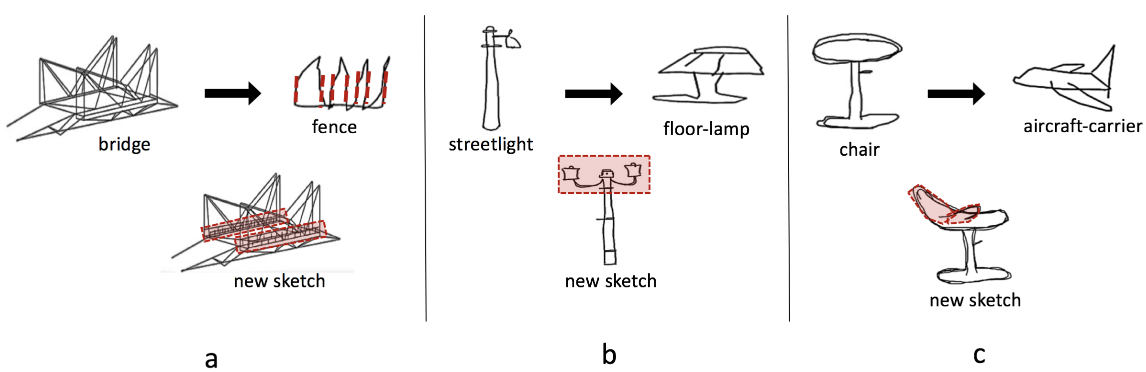


Figure 3.3: Examples for combinatorial (a), exploratory (b), and transformational (c) creativity.

## 3.6 Ideation

The CSP could potentially facilitate creative ideation. Designers could engage with the CSP in a free association drawing game where both designer and system contribute ideas to a shared canvas. Once the designer sketches an initial object the system would generate a response by drawing a potential conceptual shift. The designer would then leverage the system's contribution to generate a new idea, to which the system would again respond, and so on. The system would provide structurally similar results from different categories to help designers see how their input relates to other categories. Revealing these categorical links can help designers find new connections between categories and spark new ideas for them to explore. This process could help designers overcome fixation.

While there are many ways to evaluate creativity and creative thinking, the Torrance Test of Creative Thinking (TTCT) is a well-established approach [36]. In the TTCT users are evaluated with respect to fluency (amount of content generated), flexibility (number of categories covered in responses), originality (uniqueness), and elaboration (detail). Playing the free association game with the CSP could help designers be more fluent due to the reduction of fixation on any one idea. The continual association with other categories could help the designer generate more diverse ideas, potentially also increasing the flexibility of their ideation process.

The multiple input to multiple responses use case shown in Figure 3.4 could lead the designer to generate many versions of a target concept to see what types of conceptual shifts the system might generate. Seeing the different categories, the system generates might inspire the designer to explore a wide variety of concepts to see the system's responses.

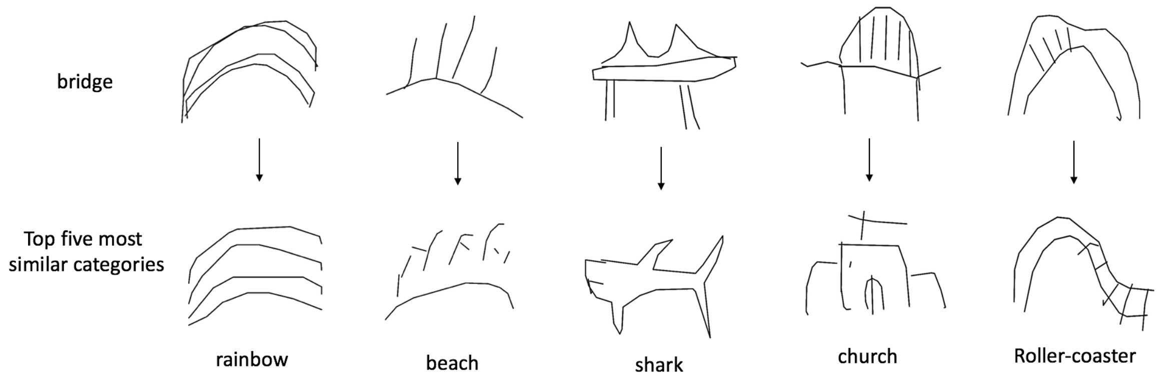


Figure 3.4: Example of a use case scenario that shows the system's conceptual shift responses to multiple bridge sketches in order to facilitate the design ideation.

# CHAPTER 4: AI MODEL OF CONCEPTUAL SHIFT

Our model for identifying conceptual shift categories consists of two components: visual similarity and conceptual similarity. Visual similarity is determined by selecting sketches that share the same underlying structural characteristics. On the other hand, conceptual similarity identifies the degree of similarities between category names. We have implemented this model in the domain of human drawn sketches. In this section, we describe our approach for quantifying conceptual shifts, the dataset that we used for our study, and the methods for computing conceptual and visual similarity between sketches.

## 4.1 Quantifying Conceptual Shifts

Quantifying conceptual shifts is challenging because concepts are not typically represented or evaluated numerically. Our premise is that the larger the shift, the more creative the resulting design. In order to quantify the scale of a conceptual shift between two sketches (in our case the user's sketch and the system's proposed response), we need a representation space in which we can measure similarity or novelty. The more similar the second sketch is to the first, the less novel the second item is and (we presume) the less likely that it will trigger a conceptual shift. When the two items are less similar, the more novel stimulus and (again, we presume) the more likely it will result in a conceptual shift. We focus on novelty in generating conceptual shifts because it has been shown to be a key component in predicting creativity [57]. The assumption in measuring novelty is the existence of a representation that allows objective measurement of difference. In [57], the corpus of designs in the design space were represented as a set of features that formed the basis for correlation and

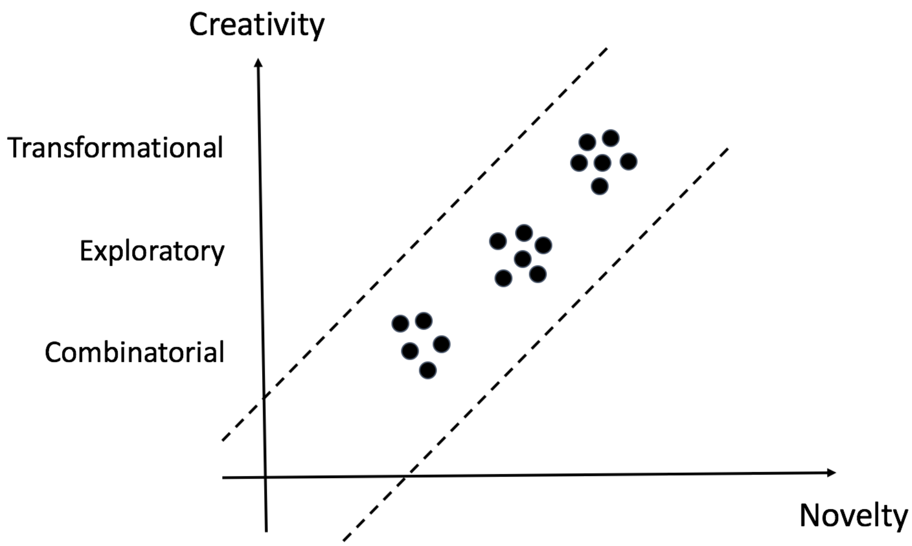


Figure 4.1: Our presumption of the relationship between the novelty of the co-creative system's response and three types of design creativity.

regression analysis. The feature set was extracted from a database in which the information about the designs was manually entered as a set of features with categorical and numerical values. This representation enabled various ways to measure novelty, but not a single novelty score.

In the CSP, we measure novelty by comparing two sketches: an initial sketch presented by the user and a second sketch selected from a large dataset of sketches. We determine novelty as a combination of two aspects of the sketch: the visual similarity based on the visual data and the conceptual similarity based on the label for the sketch. We use deep learning models to extract a vector representation in two design spaces: a visual space using a large dataset of sketches, and a semantic space using a word embedding model. We consider the novelty to be a combination of the classification of visual novelty in the visual space and conceptual novelty in the word embedding space.

We classify novelty into three categories: low, intermediate, and high. Low novelty occurs when two sketches share a large amount of visual and conceptual information, intermediate novelty is when two sketches share some visual and conceptual information, and high novelty occurs when two sketches share little visual and conceptual information. We presume that low novelty lies within the expectation of the user, and that the system's response might be most likely to help the designer add more details to their initial design. Intermediate novelty could instead inspire the designer to explore possible new design ideas associated with their initial design. High novelty has the potential to widen the user's thinking process, making it more likely to help them incorporate new design features from a completely different design space. Therefore, our presumption is that low novelty is associated with combinatorial and less creative outcomes, intermediate novelty is associated with exploratory and some creative outcomes, and high novelty is associated with transformational and more creative outcomes. Figure 4.1 illustrates our presumption using categories of creativity: combinatorial, exploratory, and transformational from Boden [56] and Gero [16].

## 4.2 Conceptual Shift Algorithm

In this section, we describe an AI model of conceptual shifts. The model selects an object from a database of sketches to be displayed on the canvas as a stimulus during a co-creative session. Our model has two components: visual similarity and conceptual similarity. Visual similarity recognizes pairs of sketches from distinct categories that share some underlying visual information. Conceptual similarity identifies the semantic similarity between the labels of the sketches.

Figure 4.2 shows the computational model the AI agent uses to select a sketch of the desired level of novelty in response to the user's input. The visual similarity module computes the distances between the cluster centroids of distinct categories and maps the user's input to the most similar sketches from categories to which it does not belong. The conceptual similarity module takes the pairs of selected category names from the previous step and computes their semantic similarity. This section first introduced the dataset used for our AI model and then describes how CSP generates

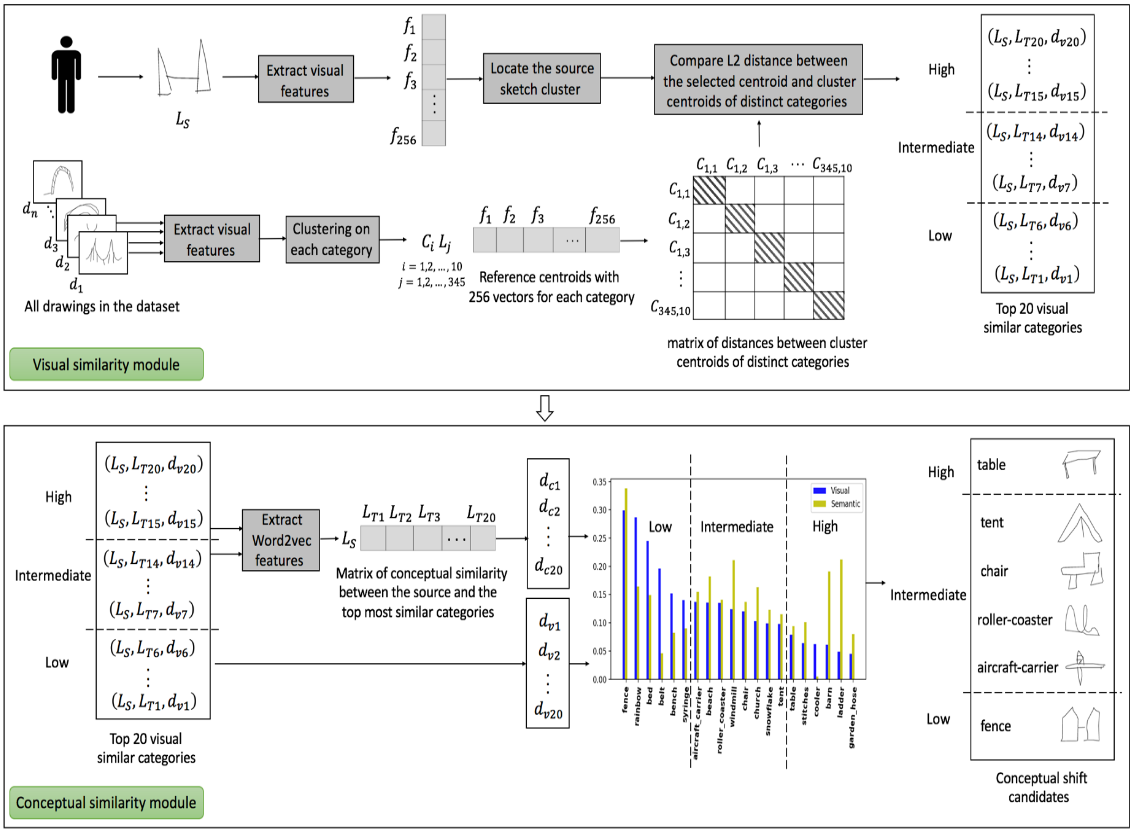


Figure 4.2: Computational steps for identifying conceptual shifts. Top: Identifying visually similar categories to the user's input. Bottom: Balancing visual similarity with conceptual similarity and identifying conceptual shifts with high, intermediate, and low novelty [3].

a numerical value for visual and conceptual similarity and determines the conceptual shift candidates based on high, intermediate, and low novelty.

### 4.2.1 Quick Draw Dataset

The dataset we used for implementing our algorithm is a public benchmark called QuickDraw! (QD) [58], 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 five fields: *key-id*, *word*, *countrycode*, *recognized*, *timestamp*, and *drawing*. Key-id is the unique identifier that is assigned to each sketch. Word is the category name, and countrycode is the place where the player was located. Recognized is a binary number that identifies whether or not the drawn sketch was recognized as belonging to its category. Timestamp refers to the date and the time that the sketch was created, and drawing is an array that represents the coordinates of the pen strokes for a drawn sketch. For the purpose of our study we use only the four fields including, key-id, word, recognized, and drawing. The data is preprocessed by first removing the sketches that are not recognized as belonging to their assigned category, and the height and width of the bounding box coordinates for each sketch is then normalized to have values between 0 and 1. The final step computes the differences between successive points of each stroke in a drawing.

### 4.2.2 Visual Similarity Module

The visual similarity component entails identifying sketches from another categories that share some visual information with the user's sketch input. In preparation for calculating visual similarity, we have 2 steps: a learning step and a clustering step. In the learning step, the sketches are used to build a vector representation. In the clustering step, we use the resulting feature vectors for sketches in each category to create clusters of visually similar sketches. This process provides a feature vector representation for calculating the novelty between the user's initial sketch and sketches in the QD dataset using visual similarity.

#### 4.2.2.1 Deep Learning Model of Sketches for Visual Similarity

As in the case of natural images, sketches can also be processed as a grid of pixels, $(h, w, d)$, in which $h$ is the height, $w$ is the width, and $d$ is the number of channels. However, in this case, $d$ will be 1 because the sketches are monochrome.

To develop a representation for visual similarity we employed a convolutional neural network (CNN) model due to their success in providing high level visual information and discriminating visual appearances, such as shapes and orientations. We started with a pre-trained model, VGG16 [59], with 13 convolutional layers, two fully connected layers, and a softmax output layer (see Figure 4.3). The model is primarily trained on the ImageNet dataset [60] that contains more than 20 million labeled natural images. We then fine-tune this model on the QD dataset with the objective of classifying a sketch into one of the 345 categories. We use 30,000 training samples and 10,000 validation samples per category, and trained for 1.5 million training steps. Observation shows that the accuracy reaches 52.1% after 1 million steps and remains the same afterwards. We extract a neural representation of each sketch by taking the output of the first fully connected layer, for 4096 values per sketch. However, this model has low accuracy and a high computational cost because of the large number of parameters in the VGG16 architecture and processing sketches as a grid of pixels.

In order to solve this problem, we tried another representation of sketches: a sequence of pen strokes, inspired by the work done by Ha and Eck on Recurrent Neural Network drawing [31]. In this case, each stroke is a list of points with 3 elements: ($\Delta$x, $\Delta$y, $p$). $\Delta$x and $\Delta$y are the coordinates with respect to the previous point, and $p$ is a binary number that determines whether the stroke is drawn or not (i.e. just moves the pen). Here we use a deep learning model called Convolutional Neural Network-Long Short Term Memory (CNN-LSTM) [4]. The model has three one-dimensional convolutional layers and three LSTM layers (see Figure 4.4). We train the model from scratch on the QD dataset with the same objective, training, and validation samples as the CNN-only model. Results show that, after 1 million training steps,

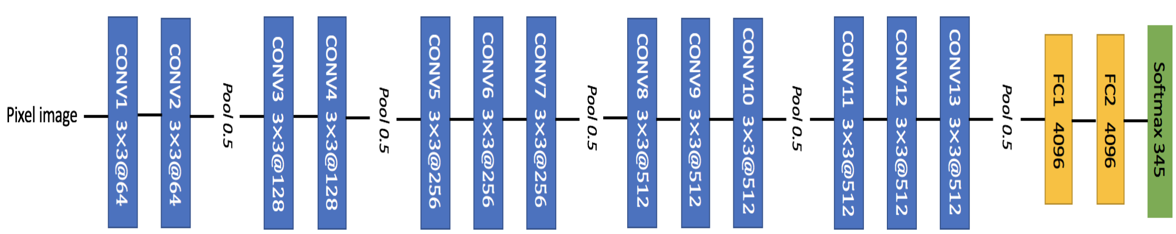


Figure 4.3: The neural representation of sketches, drawn from the activation of the first fully connected layer (fc1) in the VGG-16 Convolutional Neural Network architecture [1].

accuracy reaches 73.4% and remains the same afterwards. Each sketch is represented by the last LSTM layer, for 256 values per sketch. Table 4.1 summarizes the results for accuracy and the average-per category inference time for both models. Accuracy measures a true positive rate, while inference time represents the total amount of time it takes to extract features from all sketches of a category. The CNN-LSTM model is clearly both faster and more accurate, and we use it hereafter.

Table 4.1: Classification accuracy and the average elapsed time using two different deep learning models.

| | VGG-16 | CNN-LSTM |
|---|---|---|
| Accuracy | 52.1% | 73.4% |
| Inference time | 18,000S | 960S |

#### 4.2.2.2 Clustering visually similar sketches in each category

The sketches in a category exhibit a large variability visually. For our visual similarity measure to be meaningful, we group the sketches in each category into clusters and use the feature vector of the cluster centroid as the representative sketch. This process is a form of denoising, where the intra-cluster variability is suppressed. We perform clustering using a K-means algorithm and determine the optimal number of clusters via the elbow method. By analyzing the variance versus the number of clusters, we observed that for most categories the optimal number of clusters is between 7 and 12-we set the number of clusters to 10 across all categories. Figure 4.5 shows the

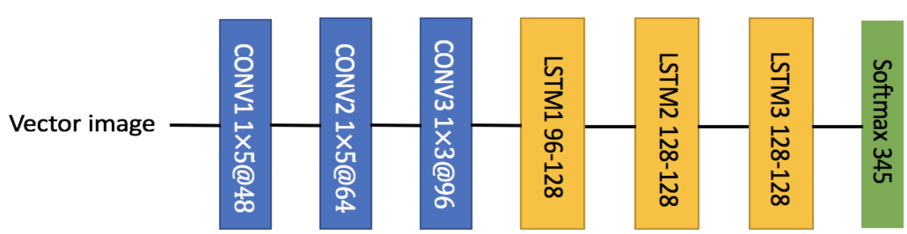


Figure 4.4: The neural representation of sketches, drawn from the activation of the last LSTM layer in the CNN-LSTM architecture [4].

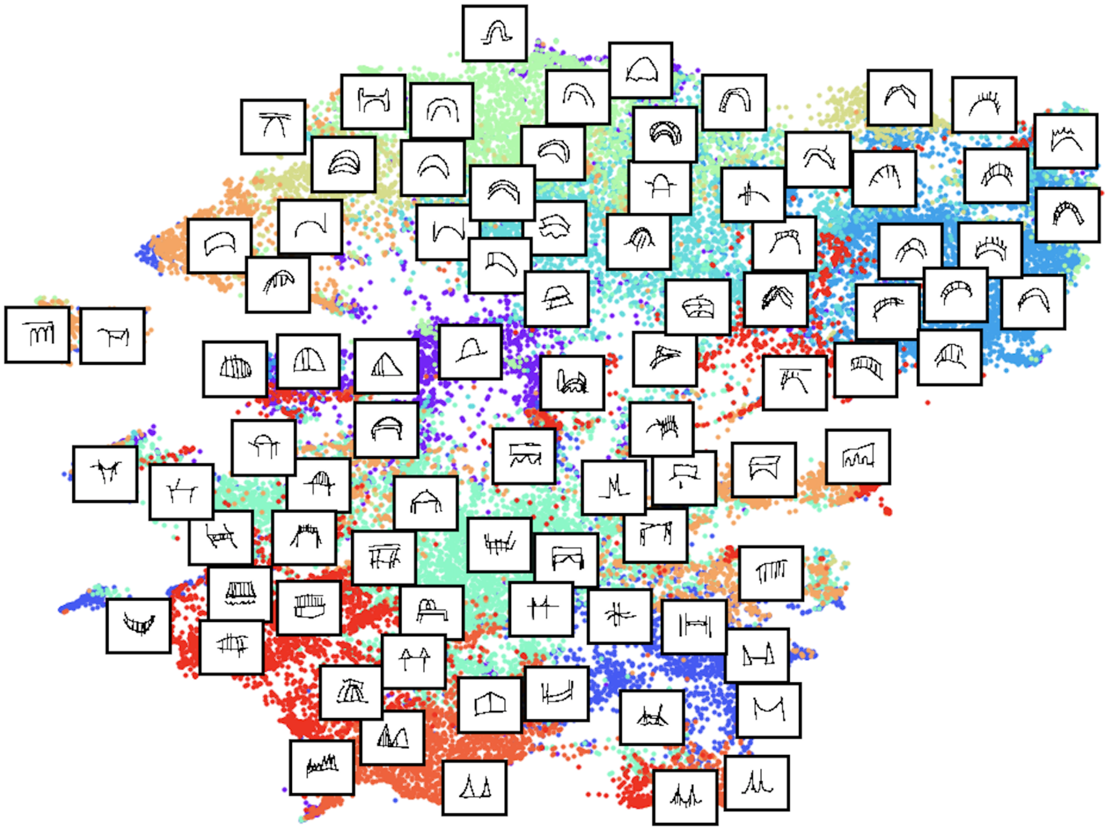

Figure 4.5: Visualization of embedding results in a 2D scatter plot using LargeVis [2]. Each color represents a different cluster.

manifold embedding visualization of 40394 selected sketches for the category "bridge". As the results show, sketches with similar style are grouped in the same cluster.

The distances between the cluster centroids from distinct categories are computed and stored in a matrix of size 3450 $\times$ 3450: 10 clusters of sketches for each of 345 categories. Given the source sketch and label from the user, $L_S$, we first extract visual features using the pre-trained CNN-LSTM model that produces 256 values. We then locate the representative cluster within its category (according to the label of the user's sketch) by selecting the closest centroid based on the L2 (i.e. Euclidean) distance. Using the distance matrix, we then select the top 20 most visually similar target clusters from other categories, $L_T$ , as the ones with minimum distance from the representative cluster. The similarity is computed as $1 - d_v$, where $d_v$ is the

Euclidean distance normalized across the most visually similar candidates. As the similarity values for the selected target sketches change smoothly, we classify those that fall in the top 33rd percentile of the distribution as low novelty (high similarity), between 33rd and 66th percentile as intermediate novelty (intermediate similarity), and above 66th percentile as high novelty (low similarity).

### 4.2.3 Conceptual Similarity Module

The conceptual similarity module uses a word embedding model [61] trained on the Google News corpus with 3 million distinct words. The visual similarity module provides a set of candidate sketches to the conceptual similarity module based on the categories of low, intermediate, and high novelty. We extract the word2vec word embedding features (Mikolov 2016) from these category names. The similarity between the category of the source sketch and the selected target sketch is computed as $1 - d_c$, where $d_c$ is the cosine distance between the feature vectors of category names. The larger number indicates that the two sketch categories are more likely to appear in the same context, whereas a smaller number indicates that the two are less associated with each other. In order to determine the conceptual shift categories, we balance the visual similarity component with the conceptual similarity. This is done by selecting candidates for which the difference between visual and conceptual similarity values are below 0.05 and the similarity component is computed as the average of visual and conceptual values.

Table 4.2: Semantic and visual similarity values between "bridge" category and the top 20 conceptual shift categories.

| Conceptual Shift Categories | Visual Similarity | Conceptual Similarity |
|---|---|---|
| Fence | 0.299 | 0.338 |
| Rainbow | 0.274 | 0.164 |
| Bed | 0.245 | 0.149 |
| Belt | 0.196 | 0.046 |
| Bench | 0.152 | 0.082 |
| Syringe | 0.140 | 0.09 |
| Aircraft-carrier | 0.137 | 0.155 |
| Beach | 0.136 | 0.182 |
| Roller-coaster | 0.135 | 0.141 |
| Windmill | 0.124 | 0.211 |
| Chair | 0.120 | 0.137 |
| Church | 0.103 | 0.163 |
| Snowflake | 0.099 | 0.123 |
| Tent | 0.098 | 0.115 |
| Table | 0.079 | 0.094 |
| Stitches | 0.064 | 0.101 |
| Cooler | 0.062 | 0.005 |
| Barn | 0.061 | 0.191 |
| Ladder | 0.049 | 0.212 |
| Garden-hose | 0.045 | 0.08 |

Table 4.2 shows the conceptual and visual similarity values between the "bridge" category and the corresponding top 20 potential conceptual shifts. As it is shown, in some instances the conceptual and visual similarity values are very close to each

other, indicating that there are some clusters of the two sketch categories that share the same amount of visual and conceptual information. In some other instances, however, the conceptual and visual similarities are very different, indicating that the two sketch categories have some instances that share the same visual information but are less likely to appear in the same context or vice versa. Example of this is a potential cluster of "bridge" and a potential cluster of "ladder." As Table 4.2 shows, the conceptual similarity value for the two categories is high, whereas the visual similarity is low, showing that there are no instances of the two categories that share high level of visual information despite belonging to the same contextual space.

## 4.3 Conceptual Shifts Visualization

To demonstrate the results of our computational model, we show the output of our algorithm for nine different conditions. Table 4.3 shows all nine conditions for a sketch category. $H_V$ and $L_V$ are the high and the low visual similarity conditions, respectively, and $H_C$ and $L_C$ are the high and the low conceptual similarity conditions, respectively. Finally, $M_V$ and $M_C$ are the medium visual and conceptual similarity conditions, respectively.

Table 4.3: Nine different conditions for visual and conceptual similarity components.

| | | |
|---|---|---|
| $H_V$ $L_C$ | $H_V$ $M_C$ | $H_V$ $H_C$ |
| $M_V$ $L_C$ | $M_V$ $M_C$ | $M_V$ $H_C$ |
| $L_V$ $L_C$ | $L_V$ $M_C$ | $L_V$ $H_C$ |

**High Visual and high Conceptual Similarity Condition.** In this condition, the system's response (target sketch) shares high amount of visual and conceptual information with the user's input (source sketch). Figure 4.7 shows an example of such a condition. As shown, the triangle part of the fence mimics the same structure of the outer part of the bridge, and the same applies to the straight lines observed in both the source and the target sketch. Moreover, the semantic relationship between the words “fence” and “bridge” implies that both concepts are used for protection and for pedestrians and/or cars safety.

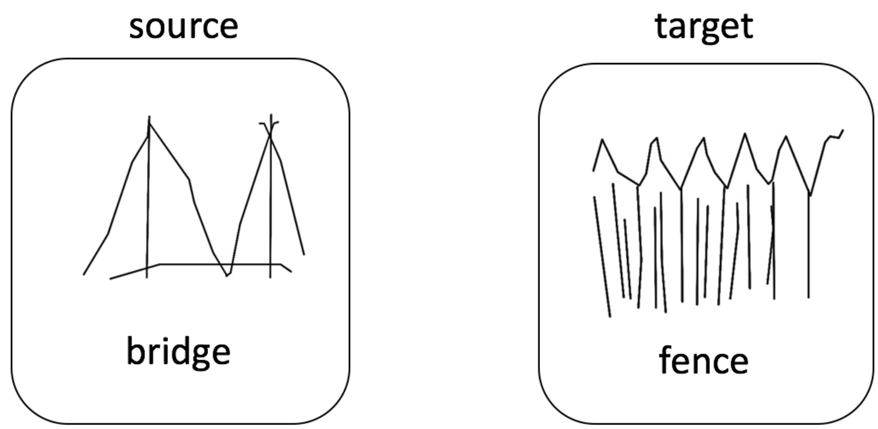


Figure 4.6: An example for $H_V$ and $H_C$ condition.

**High Visual and Medium Conceptual Similarity Condition.** The second condition refers to a scenario in which the target sketch shares high amount of visual similarity with the source sketch and the concept is intermediately similar. As Figure 4.8 shows, the source and the target sketch both have curvy parallel lines. However, the concept of bridge implies a different function (protection) compared to rainbow (aesthetics), although both can be observed in the same scene or location.

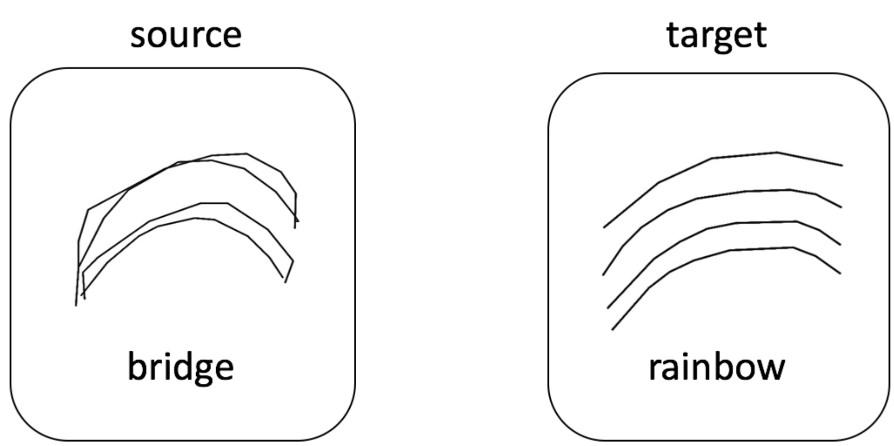


Figure 4.7: An example for $H_V$ and $M_C$ condition.

**High Visual and Low Conceptual Similarity Condition.** In the third condition, the source and the target sketch share high amount of visual information but are less likely to appear in the same context. An example of this is a potential sketch of a bridge and a potential sketch of a belt (Figure 4.9). As shown, both sketches share the rectangular part in the middle and the lines that cross both sides. However, the category names of the source and the target sketch (bridge and belt) are used in completely different contexts; thus, they have low semantic similarity. A bridge connects two disjointed areas and is used to ensure safety for pedestrians and cars, a belt connects to itself as a security device for garments.

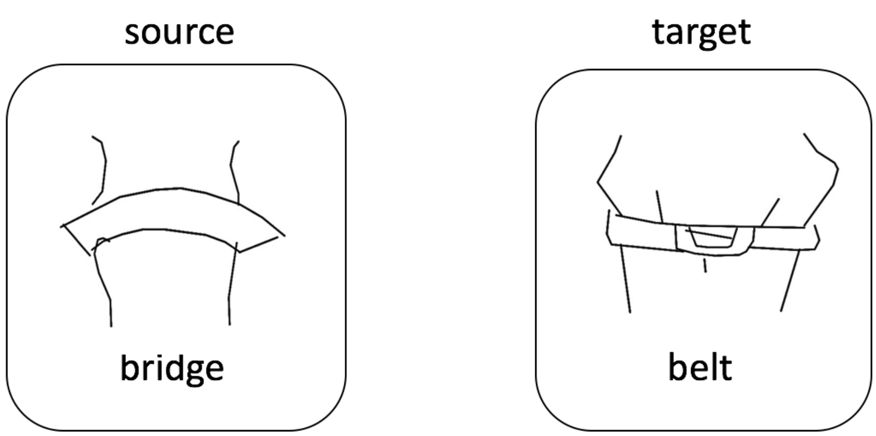


Figure 4.8: An example for $H_V$ and $L_C$ condition.

**Medium Visual and High Conceptual Similarity Condition.** Next, the forth condition occurs when the source and the target sketch share some structural characteristics, and their concept is highly likely to appear in the same context. As shown in Figure 4.10, the source and the target sketch have some underlying visual information, such as the two crossing rectangulars in the windmill that are similar to the two rectangulars on both sides of the bridge. Additionally, according to the Table 4.2 the concept of “bridge” is highly related to the concept of the “windmill.”

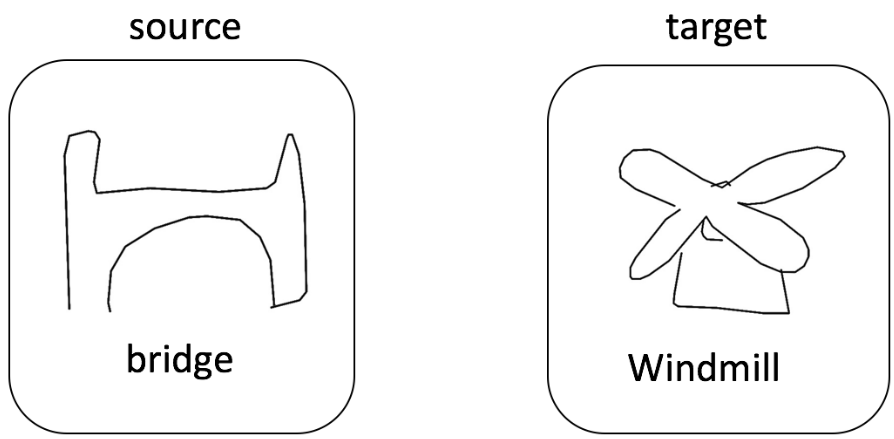


Figure 4.9: An example for $M_V$ and $H_C$ condition.

**Medium Visual and Medium Conceptual Similarity Condition.** In condition five, both the visual and conceptual similarity between the source and the target sketch are intermediate. In other words, the user's input and the system's response share some underlying visual information, and their concept is intermediately relevant. An example of this is a potential sketch of a "bridge" and a potential sketch of a "roller-coaster." As shown in Figure 4.11, the source and the target sketch both have parallel lines surrounded by two curvy lines. Moreover, the concept of "bridge" and "roller-coaster" are intermediately similar because they both connect the two end-points for the pedestrians, but they do not serve the same purpose or function.

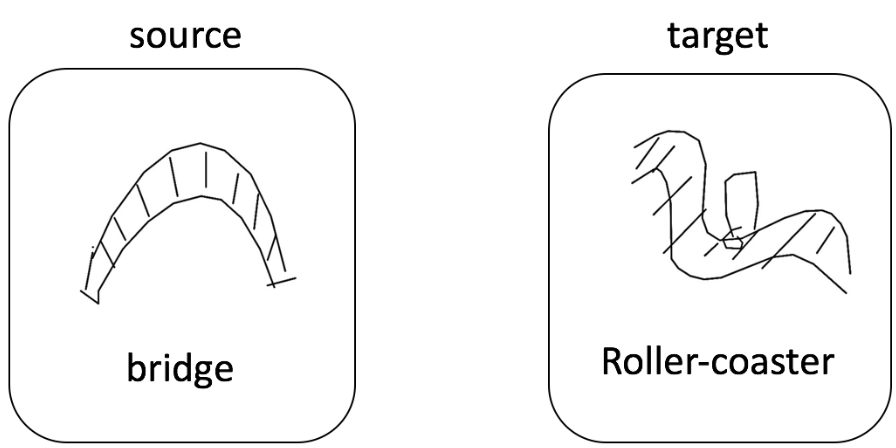


Figure 4.10: An example for $M_V$ and $M_C$ condition.

**Medium Visual and Low Conceptual Similarity Condition.** Condition six refers to a scenario in which the structure of the source and the target sketch is intermediately similar, but their concept is less likely to appear in the same context. As shown in Figure 4.12, the two sketches for "bridge" and "syringe" share some structural characteristics, including the rectangular shape and the parallel lines inside. However, the concept of the two sketches (bridge and syringe) is less associated with each other, which makes them less likely to appear in the same context.

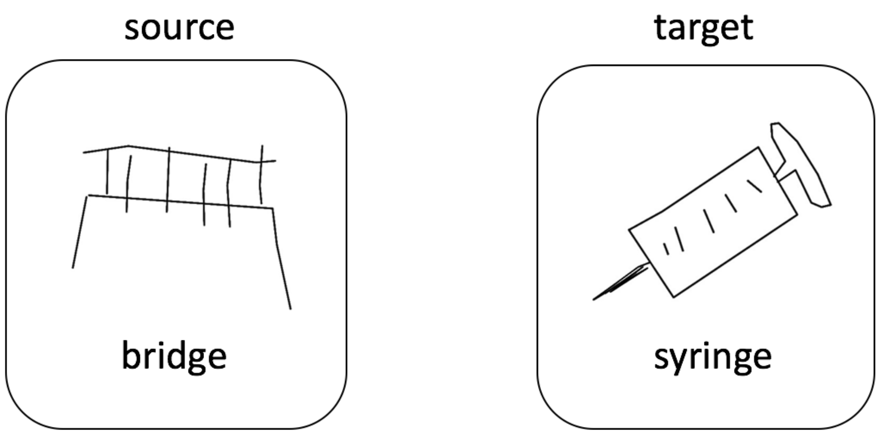


Figure 4.11: An example for $M_V$ and $L_C$ condition.

**Low Visual and High Conceptual Similarity Condition.** The seventh condition concerns the scenario, in which the user's sketch and the system's response do not share high amount of visual information despite belonging to the same contextual space. An example of this is a potential sketch of a "bridge" and a potential sketch of a "ladder," as Figure 4.13 shows. In the figure, the source and the target sketch have little structural similarity, but the concept of bridge is highly related to the concept of ladder as they both serve the same function, in which two endpoints are connected for passage.

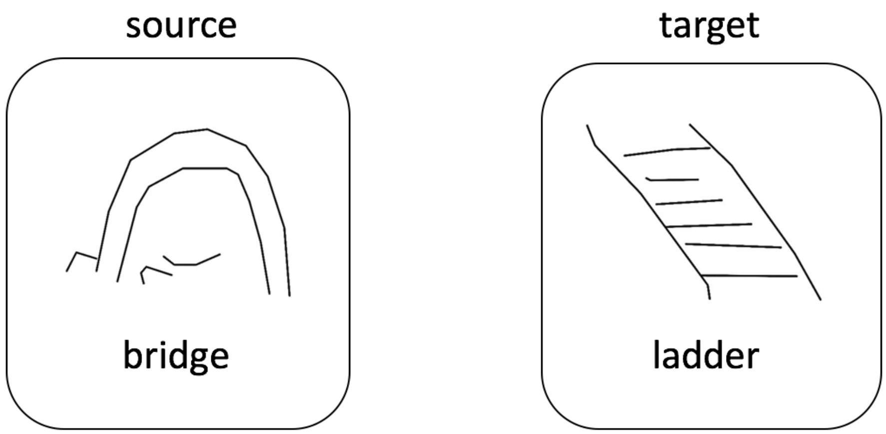


Figure 4.12: An example for $L_V$ and $H_C$ condition.

**Low Visual and Medium Conceptual Similarity Condition.** Condition eight occurs when the source and the target sketch share a small amount of visual information, and their concepts are intermediately related to each other. As shown in Figure 4.14, the concept of "bridge" and "stitches" are intermediately similar because they both are for protection purposes: bridges for pedestrian or car safety and stitches for protecting wounds. However, the contexts in which they are used are different. In terms of visual similarity, they share a small amount of structural characteristics, which is the parallel lines observed in both sketches (Figure 4.14).

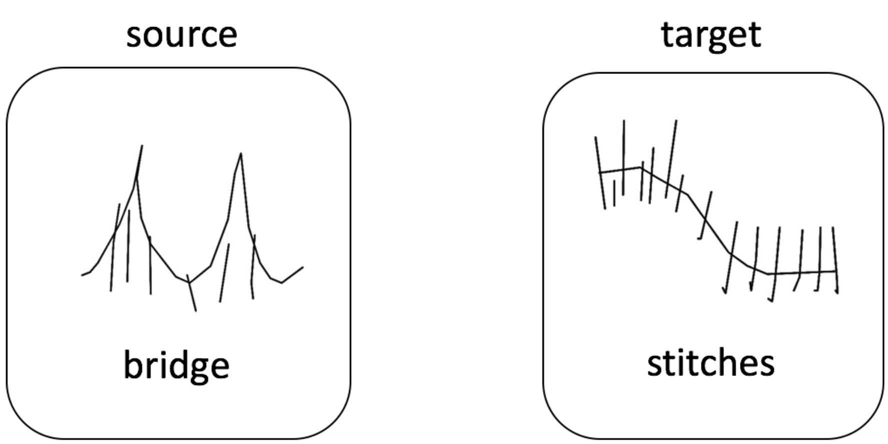


Figure 4.13: An example for $L_V$ and $M_C$ condition.

**Low Visual and Low Conceptual Similarity Condition.** The ninth condition occurs when the source and the target sketch share a small amount of visual and conceptual information. An example of such a condition is shown in Figure 4.15, in which the sketches of the "bridge" and the "table" share a small number of structural characteristics. Moreover, the two category names are less likely to appear in the same context because their function and purpose are completely different. The bridge is used outdoors for passersby, whereas the table is used indoors for holding objects.

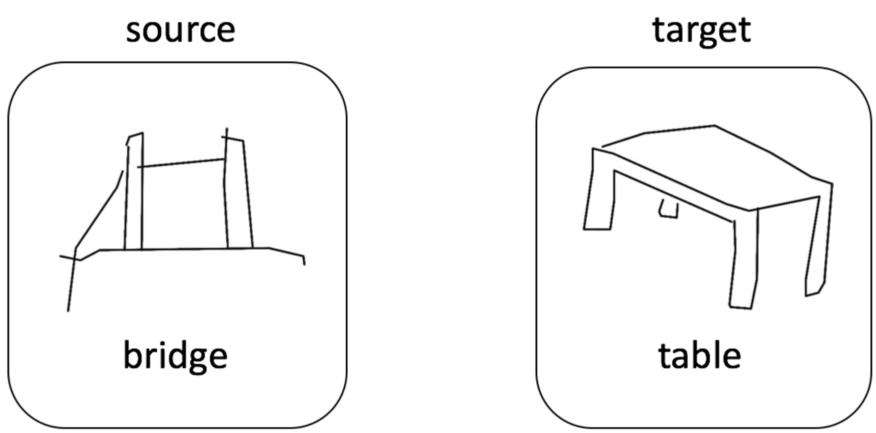


Figure 4.14: An example for $L_V$ and $L_C$ condition.

# CHAPTER 5: COGNITIVE MODELS OF DESIGN CREATIVITY

In this chapter we present an ontology based on the three types of creativity from the Boden creativity taxonomy [56] and the definitions and examples of creative design from Gero [16]. While Boden provides a broad definition of different types of creativity, Gero provides more detail in his definitions and examples. We have operationalized the definitions here for the design task in our conceptual shift study.

## 5.1 CET Ontology

We present the CET ontology as a coding scheme to study the effects of conceptual shifts on cognitive models of creativity. The aim is to code different types of creativity during a co-creative design session. The CET ontology comprises three types of creativity: combinatorial (C), exploratory (E), and transformational (T). These three types of creativity do not simply map to less or more of some scalar value of creativity, but it has been suggested that transformational creativity is the most original and potentially impactful [16, 56, 62].

### 5.1.1 Combinatorial

Combinatorial creativity concerns "the addition of two sets of design concepts or a subset of them" [16]. Boden describes combinatorial creativity as "combining familiar ideas to make unfamiliar combinations, in which the new combinations can be produced either deliberately or unconsciously" [63]. Gero provides two approaches for combination. One approach is based on including ideas from similar designs (e.g. two chairs), whereas the other approach is based on incorporating ideas from dissimilar designs (e.g. chair and cradle) [16]. One key facet of this type of combinatorial creativity is that "the two newly associated ideas share some inherent conceptual

Table 5.1: A framework for three classes of design creativity: Combinatorial, Exploratory, and Transformatinal [1].

| Combinatorial | Exploratory | Transformational |
|---|---|---|
| **Preserving the original form of the source sketch while adding elements from the target sketch** | **Changing the values for some features related to the source sketch based on values in the target sketch** | **Changing the overall design of the source sketch by adding new features from the target sketch** |
| Combine all the features of the source sketch with all the features of the target sketch | Explore creating specific patterns in the source sketch based on the target sketch (e.g. symmetries, repetition) | Transform the shape contour of the source sketch based on features from the target sketch |
| Combine some features of the source sketch with all the features of the target sketch | Explore changing the orientation in the source sketch based on the target sketch (e.g. angle, direction) | Transform the function of the source sketch by adding functions from the target sketch |
| Combine all features of the source sketch with some features of the target sketch | Explore changing the size in the source sketch based on the target sketch (e.g. distance) | |
| Combine some features of the source sketch with some features of the target sketch | Explore adding context to the source sketch based on the target sketch (e.g. river, mountains) | |

structure" [63]. The conceptual structure of one design concept guides the user's design process by being able to add certain features or elements from it.

Based on the definitions described in the literature, we define combinatorial creativity in a co-creative design system as: *Preserving the original form of the source sketch while adding elements from the target sketch.* We divide combinatorial into four categories. The first category involves combining all the features of two design concepts together. In this scenario, the designer combines all the features of their initial design (source sketch) with all the features of the system's response (target sketch). The second category concerns combining some features of the two design concepts together. This category refers to a scenario in which the designer combines some elements of the source sketch with some elements of the target sketch. The third and fourth category involve combining some features of one design concept with all the features of another concept. This corresponds to two possible scenarios: one is when the designer combines some features of the source sketch with all the features of the target sketch, and the second is when the designer combines all the features of the source sketch with some features of the target sketch (Table 5.1).

### 5.1.2 Exploratory

Exploratory creativity involves changing the applicable ranges of values for variables of a design concept [16]. Gero defines exploratory creativity as a design process in which variable values outside the normal ranges have the potential to introduce unexpected behaviors (e.g. increase the size of wings and the plane becomes too heavy) [16]. Another possible definition of exploratory creativity involves traversing an established conceptual space to create novel and unexpected design ideas [63]. Unlike combinatorial creativity, exploratory corresponds to successive design ideas that are not only novel but also unexpected [63].

Accordingly, we define exploratory creativity in a co-creative design system as: *Changing the values of some features related to the source sketch based on values in the target sketch.* In this context, features refer to the elements of a design concept (e.g. armrest, backrest, and legs for a chair); whereas values refer to parameters, such as size and angle. We classify exploratory into three categories. The first category explores the creation of specific patterns in the source sketch based on the target sketch. This indicates that specific geometric properties (e.g. symmetrical structures or repetitive patterns) in the target sketch can inspire the designer to create the same structure for the source sketch. The second category explores changing the orientation in the source sketch based on the target sketch. In this scenario, the user changes the angle or the direction of some elements in the source sketch based on inspiration from the target sketch. The last category explores changing the size in the source sketch based on the features in the target sketch. In this case the user changes the size of some elements in the source sketch based on some variable values in the target sketch. Examples are increasing the size of a light post, changing the distance between legs on a chair, and changing the scale of a bridge (Table 5.1).

### 5.1.3 Transformational

Transformational creativity involves changing one or more elements of a design concept through the act of developing new ideas [63]. Gero defines transformational creativity as a process in which one or more structure variables of the current design object are altered to produce new variables [16]. Another definition of transformational creativity involves creating new structures through transforming one or more dimension of the current design space [63]. Similar to exploratory creativity, transformational creativity also leads to producing novel and unexpected design ideas [63].

Based on the definitions described above, we define transformational creativity in a co-creative design system as: *changing the overall design of the source sketch by adding new features from the target sketch.* We consider two possible methods for changing the design of the source sketch. One is when the designer adds new features from another design space. An example of this is when the concept of fluid movement in a speedboat inspires the designer to add wheels to a chair. Another method is when the designer changes the outline shape of a design concept inspired by the structure of another concept, such as changing the shape of a basket from rectangular to circular inspired by the curvy shape of a hat. Accordingly we classify transformational into two different categories. One category involves transforming the shape counter of the source sketch based on the features from the target sketch. The second category concerns transforming the function of the source sketch by adding functions from the target sketch (Table 5.1).

# CHAPTER 6: WIZARD OF OZ USER STUDY

We posit that presenting conceptual shifts during the co-creative sketching process supports different types of design creativity. This user study was designed to help understand these variations of design creativity associated with the user's response to conceptual shifts. We investigate how combinatorial, exploratory, and transformational creativity correlate to different degrees of similarity between the user's sketch and the system's response. The degree of similarity is determined in two ways: conceptually, by the degree of similarity between words, and visually, by the degree of structural similarity between the two sketches. We presume that high similarity conceptual shift designs are within the expectation of the user, in which the system's response can help the designer to add more details to their initial design. Intermediate similarity conceptual shifts can inspire the designer to explore possible new design ideas associated to their initial design. Lastly, low similarity conceptual shifts have the potential to widen the user's thinking process and help them to add new features from completely a different design space.

## 6.1 Method and Participants

The user study included 24 participants recruited from the College of Architecture at a large comprehensive public university in North America, including 7 undergraduate and 17 graduate students. Gender distribution was 15 males and 9 females. The criterion for participating was whether students use sketching often in their design practice. The study utilized a within-subject design where each participant performed a design task in 3 different conditions. The first condition was associated with the design task of sketching a bridge, and the system produced a result that has a high

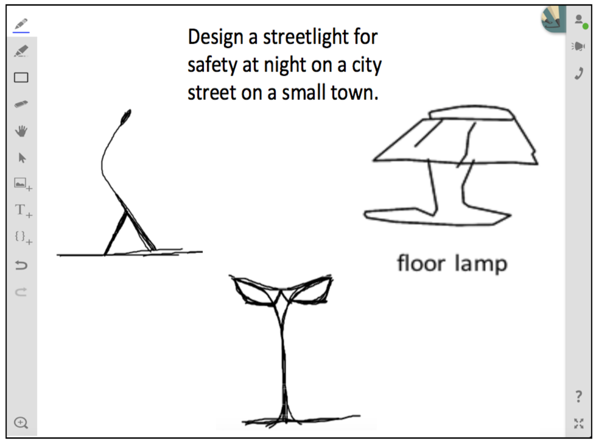


Figure 6.1: Image of co-creative sketching study interface. Top middle: design task, top left: user's initial design (source sketch), top right: wizard's response (target sketch), and center bottom: user's response (new sketch).

similarity to the participant's sketch. The second condition was associated with the design task of sketching a streetlight, and the system produced a result that has an intermediate similarity to the participant's sketch. The third condition was associated with the design task of sketching a chair, and the system produced a result that has a low similarity to the participant's sketch. Each design task lasted approximately 7 minutes. The order of the three conditions were counterbalanced in order to account for any ordering effects.

In this study, we used an online sketching tool, called SketchTogether [64], that enables multiple users to contribute to a shared canvas. This platform enabled us to conduct a Wizard of Oz study where the wizard added elements to the shared canvas in response to the participant's sketch. The instructions for the design task for each session are displayed in the middle of the canvas, and the designer is required to respond to the design task by starting to sketch at the top left of the canvas. Then, the system's response (generated by the wizard) is shown at the top right of the canvas. Based on the inspiration from the system's response, the designer is asked to respond by sketching an iteration of their initial sketch at the bottom-center of the canvas. Figure 6.1 shows the experimental setup of the co-creative sketching tool.

Participants are first introduced to the interface of the sketch tool that they have to interact with during each session. The tasks of the entire session, along with the time frame corresponding to each, are described to the participants. Then, they are asked to perform a training task to ensure their ability to create a sketch and to respond to the wizard's generated sketch with another iteration of their initial design as well as to vocalize the rationale for their design decisions. Moreover, they are told that the goal of the study is to understand how the system's response affects their design process and that they do not need to produce a final design. The entire training session took between 5 to 10 minutes.

After training, participants are required to start the first design task followed by a two-minute break before the second design task begins. The wizard was located in a separate room to respond to the user's sketch in a turn-taking manner. Each design task instruction has two components, including the object label and a context for designing that object, such as "Design a bridge for cars that goes over a large river in the mountains." We provided design tasks for three different categories: bridge, chair, and streetlight. After the last session, we performed a retrospective protocol analysis using a screen recording video that was recorded during the session. We showed the video of the entire session to the users and asked them questions related to their response to the system, which allowed participants to explain their thought process throughout the design session. The semi-structured interview questions we asked are:

- What inspired you to draw this sketch?
- Why did you draw in this way?
- Did you see any relationship between your sketch and the system's response?

The answers to retrospective protocol analysis will be used for qualitative analysis. The entire session for each participant takes approximately 30 minutes.

## 6.2 Qualitative Analysis

To aid in understanding the correlation between the degree of similarity and cognitive models of design creativity we analyze the retrospective protocol transcripts. In addition, we also analyze the participants responses to the interview questions conducted after their interaction session was complete.

### 6.2.1 Protocol Analysis

We employed two independent coders to analyze the retrospective protocol analysis transcripts and the final design sketches for each participant based on the CET framework presented in Chapter 5. The two coders engaged in a blind coding approach where they did not know the condition for each design session. They classified each design session into one of the categories of the CET ontology. This analysis demonstrates the type of design thinking that happened throughout the study.

**Combinatorial Creativity.** When the concept and the structure of the sketch that is presented to the user (target sketch) is highly similar to the user's initial design (source sketch), the user combines their source sketch with the target sketch in some way (Figures 6.2, 6.3, 6.4 and 6.5). We assume that this corresponds to combinatorial creativity, as the main features of the source and the target sketch are preserved. There are four possible ways participants could exhibit combinatorial creativity within our study (Table 5.1). Overall, we observed that all participants engaged in combinatorial creativity while they were in the high similarity condition. We describe those instances below and denote which type of combinatorial creativity they manifested.

*Combine all features of the source sketch with all the features of the target sketch* Our data showed that 4/24 participants described their experiences with the system in high similarity mode by combining all features of the source sketch with all the features of the target sketch to create a new design. In the case of P1, P11, P16, the

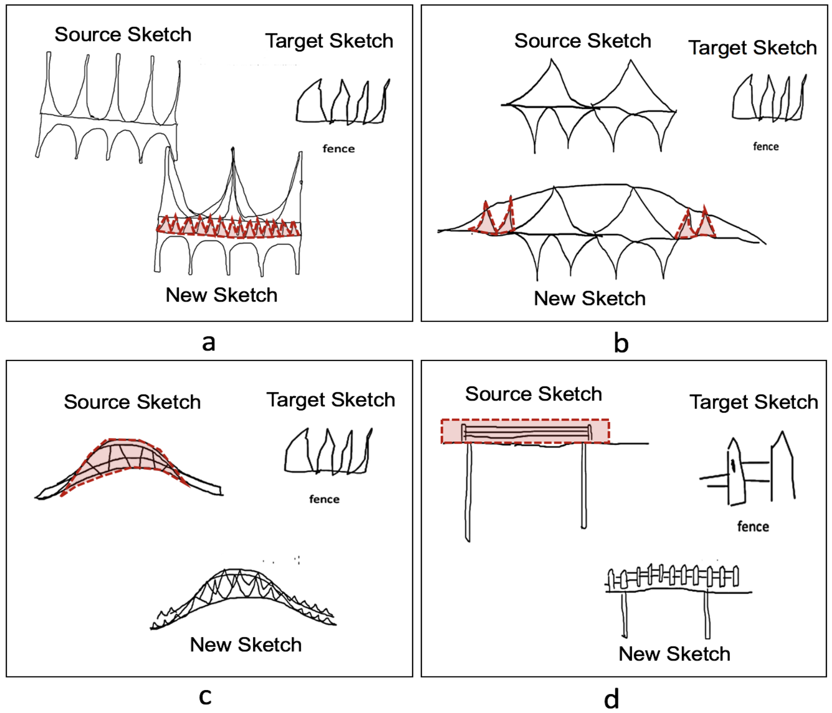


Figure 6.2: The target sketch is applied repeatedly (marked as red) to the source sketch (a). The target sketch is added disjointly (marked as red) to the source sketch (b). Part of the source sketch (marked as red) is replaced with the target sketch (c,d).

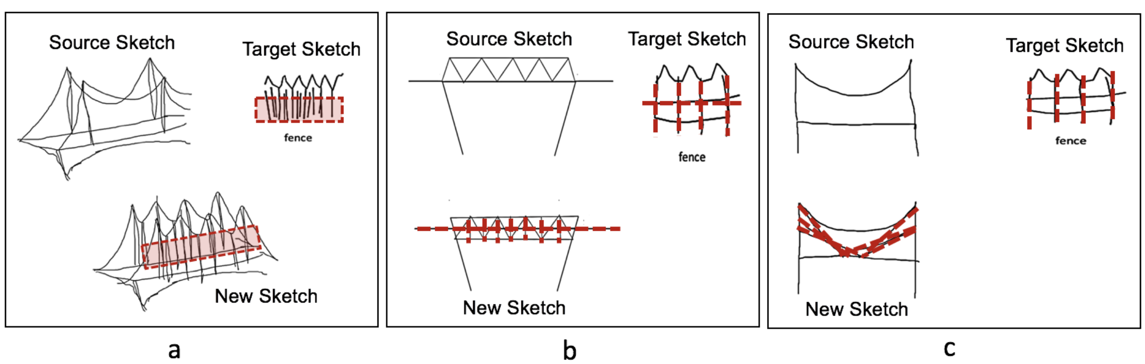


Figure 6.3: Part of the target sketch (marked as red) is applied to the source to add more suspension (a-c).

structure of the initial sketch and the target sketch were maintained. In these cases, the target sketch is applied repeatedly to form a part of the source sketch (Figure 6.2-a). In the case of P13, an extended bridge was designed by dividing the design feature of the target sketch into two equal parts on the same scale and attaching it to both sides of the initial sketch (Figure 6.2-b). This shows that the way in which the participants applied the target sketch of the fence to their drawings was different. When the design feature of the target sketch was very similar to the initial design (high similarity), the structure of the new design was not significantly different, even though all elements of both sketches were combined in a complex manner.

*Combine some features of the source sketch with all the features of the target sketch* This case appeared only twice (2/24) in our dataset. In the case of P10, only the outline of the bridge was maintained, and the red part of Figure 6.2-c,d was replaced with the target sketch. The structure of the initial design was not changed considerably, although some of the existing design was deleted and replaced with new design elements. Based on the newly combined elements, we can conclude that the new sketch is not a simple morphological transformation, but is instead the emergence of design ideas from the fence, such as protection and safety.

*Combine all features of the source sketch with some features of the target sketch* Our data showed that 7/24 participants described their experience with the system in high similarity mode by combining all features of the source sketch with some features of the target sketch to create a new design. This case has two major characteristics. First is to add new design features to the initial sketch as components (4/24). For instance, it is possible to apply a part of the target sketch as it is (Figure 6.3-a, b) or apply a part of the target sketch after changing the angle or direction (Figure 6.3-c).

The second major characteristic of this type of combinatorial creativity is to add new structures to existing sketches (3/24). In the case of P17 (Figure 6.4-a), the initial design shows an unstable bridge. However, a more stable bridge was designed

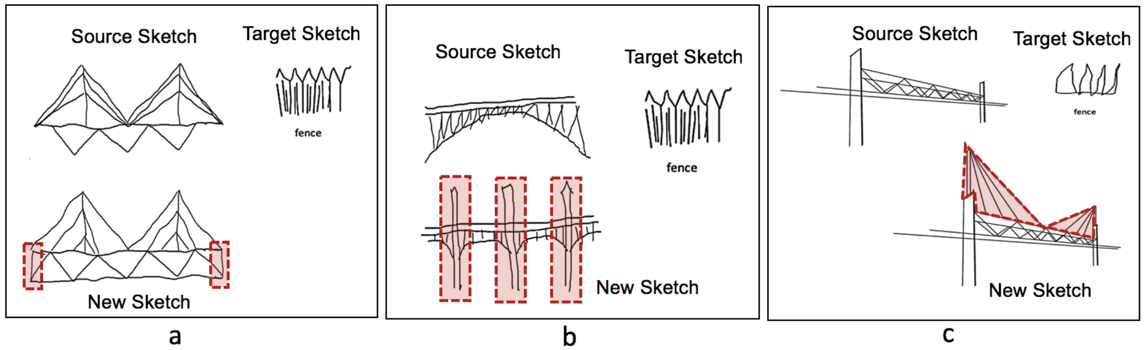


Figure 6.4: Some elements of the target sketch (marked as red) are applied to the source in order to finalize the structure (a), to uphold the bridge (b), and to add tall posts on top of the bridge (c).

by adding a straight line taken from the target sketch to both ends of the initial sketch. In this case, the structure of the initial design is changed by the inspiration from a part of the target sketch. In the case of P20, pillars were established on the existing design, inspired by the straight line of the fence. Moreover, the large mass was divided into small parts based on the repetitive fence shape (Figure 6.4-b). In the case of P25, a new shape was also added to the initial design, owing to the inspiration from the sharpness of the fence (Figure 6.4-c).

*Combine some features of the source sketch with some features of the target sketch* Finally, within this category, 11/24 participants described their experience with the system in high similarity mode by combining some features of the source sketch with some features of the target sketch to create a new design. In this case, we found that the structure of the initial design is slightly modified, unlike the previous cases. A suspended bridge shape was designed by moving the baseline upward and arranging triangles, similar to the top part of a fence (Figure 6.5-a). Alternatively, additional columns were added to the bridge, which mimicked the straight lines of a fence. P4 also actively reflected the design source of the target sketch by abandoning the existing style (Figure 6.5-b). It parallels the structure of the target sketch instead of the initial design.

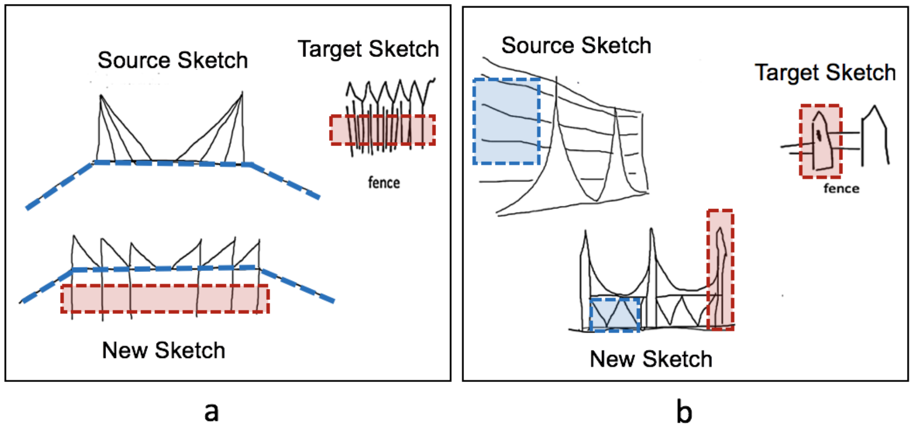


Figure 6.5: Some elements of the source sketch are preserved (marked as blue), while some elements from the target sketch are added to the source (marked as red) (a,b).

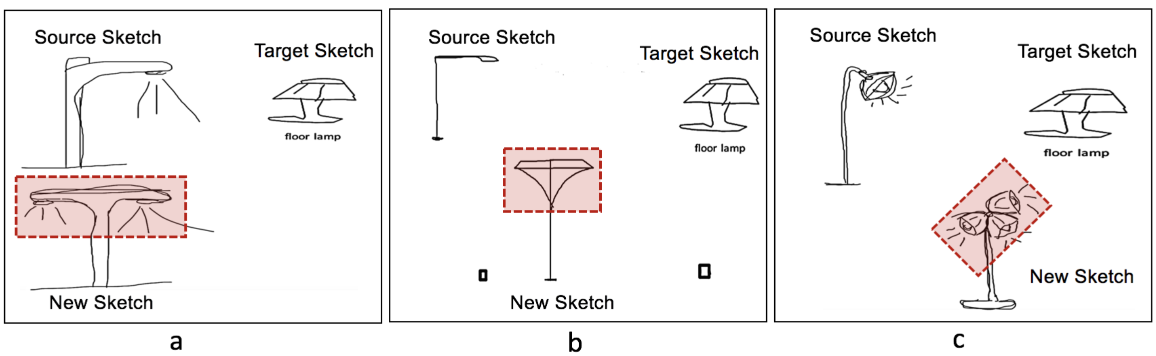


Figure 6.6: A symmetrical structure (marked as red) is applied to the source sketch (a-c).

**Exploratory Creativity.** When the sketch that is presented to the user (target sketch) shares some structural characteristics with the user's initial design (source sketch) and the concept is intermediately similar, the user modifies the source sketch by giving new values to some features of their original design (Figures 6.6, 6.7, and 6.8). We assume this corresponds to exploratory creativity because the user is making some changes to the initial design in the same design space. Based on the CET framework, there are three ways participants could demonstrate exploratory creativity within our study (Table 5.1). Our observation shows that 18/24 participants engaged in exploratory creativity while they were in the intermediate similarity condition.

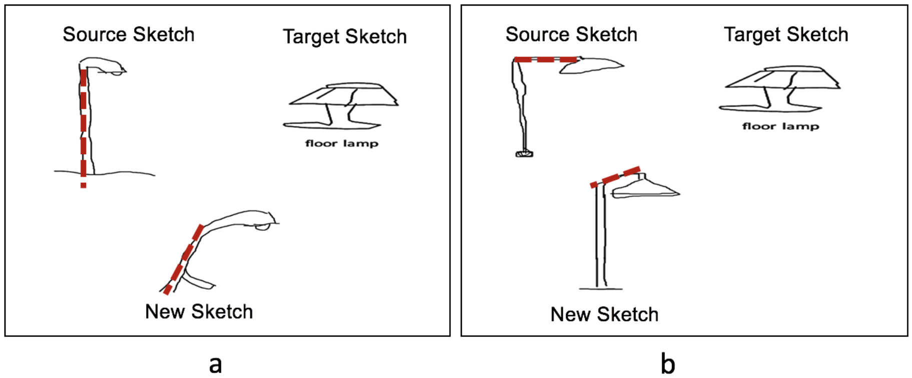


Figure 6.7: The orientation of some elements (marked as red) in the source sketch is changed (a,b).

*Explore creating specific patterns in the source sketch based on the target sketch* Overall, 8/24 participants described their experience with the system in intermediate similarity mode through creating specific patterns in the source sketch based on the target sketch to create a new design. 7/8 participants who belong to this case were inspired from the symmetric structure of the floor lamp. In these instances, the source sketch was made to be more symmetric by adding another light source to the other side of the light post. Among them, 3/7 participants symmetrically copied the lamp part of the initial sketch as it is without modification (Figure 6.6-a), whereas 4/7 participants explored new design ideas by changing some design elements that were present in their source sketch. For instance, the size of the lamp part increases, and the top and bottom are reversed (Figure 6.6-b), or a new type of lamp is designed, as exemplified by P3's design. In the case of P8 (1/8), the participant does not simply arrange the new lamp symmetrically but develops a new design type by enumerating the design object repetitively (Figure 6.6-c). In this case, the lamp part of the street light acts as a major element that guides the design, and the pole component is a subsidiary element that informs the length, the angle, and the slope of the light to create balance in the design. It indicates a scenario that explores other design elements to express a major design concept, which is symmetry.

*Explore changing the orientation in the source sketch based on the target sketch* This case appeared only twice (2/24) in our dataset, in which new design ideas are explored by adjusting the orientation of some features in the source sketch. The two participants changed the orientation of these altered design elements in the source sketch without significantly changing the type or the shape of the initial sketch (Figure 6.7-a,b). Both participants responded that they changed the angle of a pole to adjust the angle of the light from the street light, in response to the floor lamp that has a downward focused light. These two cases have the least number of changes in terms of the shape in exploratory creativity.

*Explore changing the size in the source sketch based on the target sketch* Lastly, 8/24 participants described their experience with the system in intermediate similarity mode by changing the size of some elements in the source sketch based on the target sketch to create a new design. 3/8 participants enlarged the size of a lamp as the simplest variation. In case of p9, in addition to increasing the size of the lamp, a gradual size increase was applied to the base of the source sketch inspired by the gradual change in the base of the floor lamp (Figure 6.8-a). 2/8 participants changed their initial sketch by reducing the total height of the street light. In the case of P12, the initial sketch was changed to reflect the scale of the target sketch by reducing total height and increasing the size of the lamp component (Figure 6.8-b). In the cases of P1 and P16, they showed a gradual change while several design elements act in combination. In the case of P1, the round shape of the source sketch is made more angular by including elements from the target sketch (Figure 6.8-c). The support of the lamp shows a shape that mixes the source sketch and the target sketch to extend both ends of the base.

**Exploratory and Combinatorial Creativity.** In some instances, when the system is in intermediate similarity mode, the user adds some of the elements from the target sketch, while at the same time changes some features of their initial design

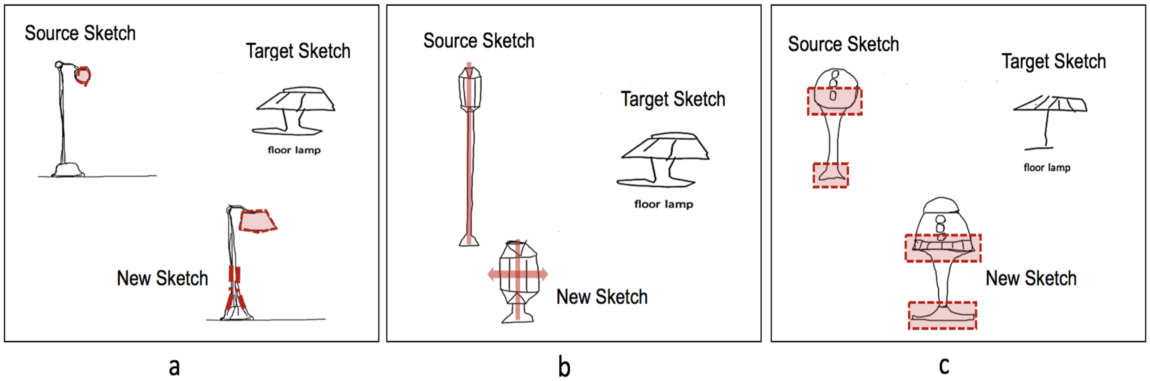


Figure 6.8: The size of some elements (marked as red) in the source sketch is altered (a-c).

(Figure 8-a,b). We assume this corresponds to both exploratory and combinatorial creativity, as the user is utilizing both types of design creativity. Overall, we found that 4/24 participants described their experience with the system in intermediate similarity mode through changing some features of their initial design and combining them with the system's response. Three of the participants created a symmetric light shade design that took inspiration from the symmetry present in the target sketch (Figure 6.9-a). Another participant increased and expanded the lamp size to resemble an LED light, while at the same time incorporated the lamp shade in the new design (Figure 6.9-b).

**Transformational Creativity.** When the concept and the structure of the sketch that is presented to the user (target sketch) is less similar to the user's initial design (source sketch), the user modifies the source sketch based on features and elements from the target sketch (Figures 6.10 and 6.11). In other words, the user moves from the current design space into another design space by searching alternative structures of the source sketch in the new design space. We assume this corresponds to transformational creativity, as the user is changing the design space completely. Based on the CET framework, there are two ways participants could exhibit transformational creativity within our study (Table 5.1). Our dataset showed that all participants en-

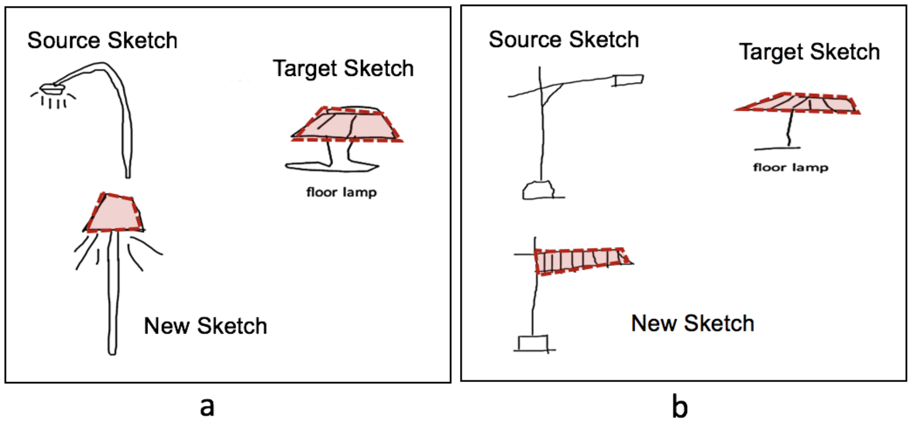


Figure 6.9: A symmetric position in the center is applied while adding the lamp shade (marked as red) to the source sketch (a). The size of the lamp is increased and concurrently the lamp shade is added (marked as red) (b).

gaged in transformational creativity when they were in the low similarity condition.

*Transform the shape contour of the source sketch based on features from the target sketch*

Our results showed that 13/24 participants described their experience with the system in low similarity mode by transforming the shape contour of the source sketch based on features from the target sketch to create a new design. We found 12/13 participants were inspired by the entire shape rather than a part of the target sketch, and they applied it to the source sketch. All participants applied the curvy shape of the speedboat and aircraft-carrier sketches provided by the system to their designs. Among the participants, 6/12 demonstrated that the curvy shape of the target sketch was used to transform the entire outline of the source sketch into a streamlined shape. Additionally, there was a participant that maintained the overall shape of their initial drawing while changing some contours to be curvy like the target sketch (Figure 6.10-a), and creating a totally new shape significantly departing from the existing shape (Figure 6.10-b). On the other hand, 6/12 participants showed the case of applying a streamlined element of the target sketch to only a part of the source sketch (Figure 6.10-c). In the case of p19, the straight-lined elements of the aircraft inspired and

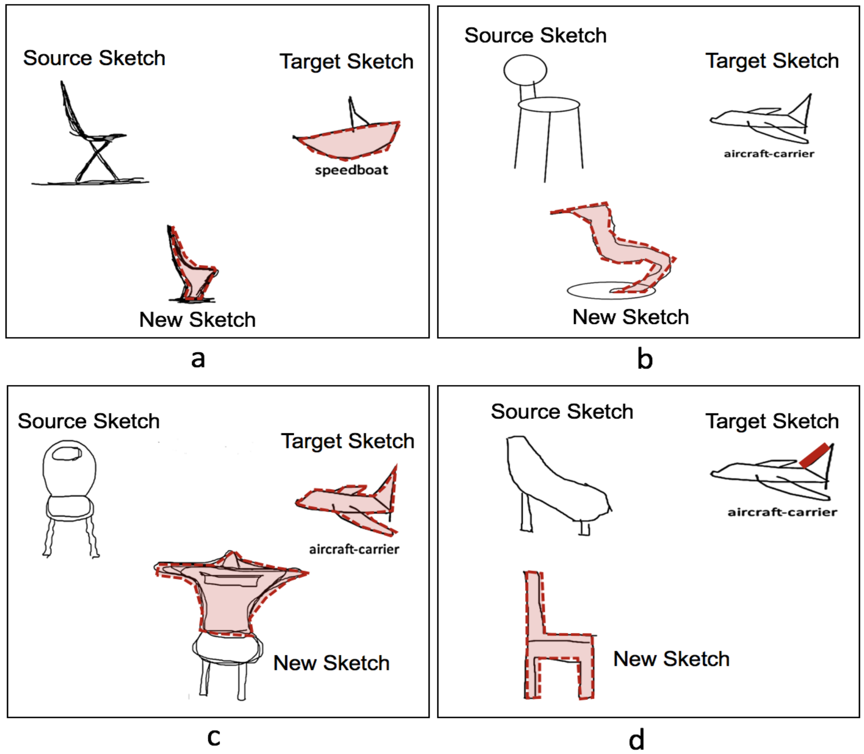


Figure 6.10: Some or all features of the source sketch structure is transformed (marked as red) to resemble the outline shape of some or all elements in the target sketch (a-d).

transformed the user's design. There was initially a curvy chair that was transformed into a rectangular form by adding a straight-lined element (Figure 6.10-d).

*Transform the function of the source sketch by adding functions form the target sketch*

Finally, 11/24 participants described their experience with the system in low similarity mode through transforming the function of the source sketch by adding functions from the target sketch to create a new design. In this case, the design idea is obtained from the function or purpose of the target sketch rather than the shape. For example, one participant utilized the form and function of an aircraft seat to transform their chair design to a reclining chair that is more comfortable (Figure 6.11-a). In another instance, the participant was inspired by the movement of the aircraft in the air, and added wheels to the chair to make it movable (Figure 6.11-b). By recalling the

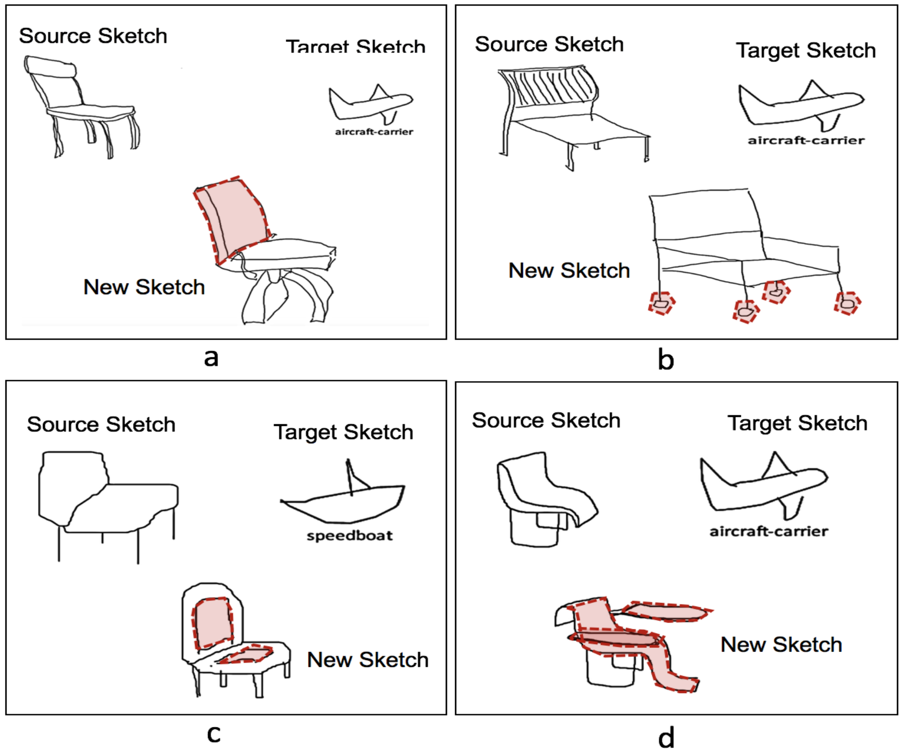


Figure 6.11: The function of some elements in the source sketch is transformed (marked as red) or new functions (marked as red) are added (a-d).

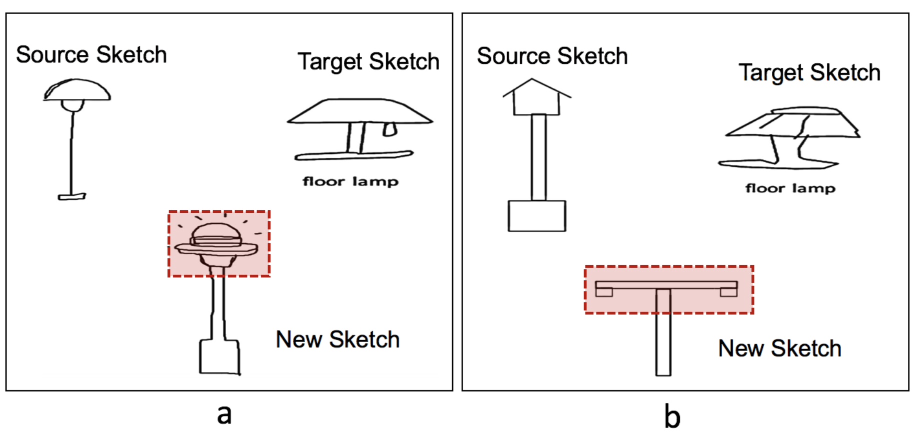


Figure 6.12: A part of the source sketch is transformed (marked as red) (a,b).

cushion feature of a chair installed inside the speedboat (target sketch), a participant transformed their design to include this function (Figure 6.11-c). In 7 instances, the entire outline of the initial sketch is transformed to add armrests inspired by the wings of the aircraft (target sketch) (Figure 6.11-d).

Transformational creativity also emerged twice (2/24) when participants were experiencing the intermediate similarity condition. When the system is in intermediate similarity mode, the user typically modifies the source sketch by giving new values to some features of their original design. However, in this case, the participants added a new design element to the source sketch by getting a new idea from the functions of the target sketch. These instances are not combinatorial nor exploratory creativity because they did not utilize elements of the target sketch or modify the parameters of existing values from the target sketch, instead the participants developed a new design with a transformed shape (Figure 6.12-c,d).

### 6.2.2 Thematic Analysis

To understand how the novelty of 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 tasks were complete. We aimed to explore the relationship between stimulus novelty 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.

- The tool helps with the design process
- High novelty helps changing the design
- Low novelty helps completing the design

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

**Help the design process**

Most participants found the tool useful, as it can help with the design-thinking process as well as iterating and generating new design ideas. P11 exemplifies how the sketching tool helped their design process, "*The sketches presented after I did my initial sketch, change the creative process, making me think of different object and using that design philosophy and then the second object to affect the first."* This participant described how the system's output sketch helped them think of different design ideas and iterate on their initial design sketch. This demonstrates that the tool generally supports the iterative nature of the early design process. Additionally, P14 comments: "*it sort of help[ed] me to see how I think about design, like they teach us just to design, I never really thought about how I go about that process of designing and so having this sort of precedent to work with is more useful to me."* This participant shows the role such a tool could play in design education. It helps to provide precedents that can inform the design process and inspire additional thinking on the topic.

P4 described how helpful the system is when they say, *"I think the system's response is very helpful, because it gives me a leverage on adding to my initial design or just give me some clue or hint to change my design to make it better."* Here, the participant comments about how the tool helps them iterate on their design by adding or changing different elements of the initial sketch based on the 'clues' or 'hints' provided by the system's output. P5 agrees with this sentiment when they said, *"the way that we communicate is great because you add something and I am going to redesign it and so it's great."* This participant focused on the communication channel established between the user and system, and described how this channel helped in the redesign process. In a similar vein, P25 describes how *"it kind of guided me through some conventional ways of improving my design"* which shows how the tool serves to shepherd users through the design process by providing new avenues to explore and inspiration to change the user's initial design.

**High novelty conceptual shift designs**

We found that high novelty conceptual shifts inspire participants to change the overall shape of their design by adding new features from another design space related to the target sketch. In this condition, 21/24 reported that it is more inspiring when the system's response is less similar to their initial design. P11 commented: *"I think to create an interesting result it was more helpful to have a dissimilar object as opposed to a similar, because it allows you to change the form and different ideas instead of just kind of a similar shape affecting it."* This participant indicates that when the system's response is less similar to their initial design (high novelty condition), it helps to change the structure, such that it is possible to incorporate different ideas from the target sketch. Similarly, P10 commented: *"It was easier to make changes when it was more different. I think when something is already similar sometimes my brain already has a same set of ideas, but when I am presented with something different the contrast helps me to generate a new idea."* This participant was able to come with a new idea when he/she was presented with a sketch that was less similar to the initial drawing.

When P16 was presented with a sketch of an aircraft-carrier after designing a chair, they described how the system's sketch opened up new possibilities for them, *"The aircraft-carrier may have chairs but it doesn't elicit specific form especially giving the prompt that is going to be at the kitchen table. Thinking about new possibilities that can happen definitely opens the new design criteria."* This example shows that the chairs of the aircraft-carrier introduced new design criteria that inspired the participant to sketch a new kitchen chair with the features of aircraft-carrier seats, such as more comfort. Additionally, when P21 was presented with a sketch of a speedboat after designing a chair, they also found new possibilities in the design space, *"The relationship between the two, even though they are used both in the same task or* *same function because of the difference that one is on water, one needs to be outdoor, the different needs and purposes between the two was influencing me better to create something new between them."* Similarly, P22 used the features of the system's response to reason about their initial sketch, *"The aircraft, because of its curves and the materiality, so thinking about the skin of the material, maybe thinking about its curves so that led me to think about the curves which maybe helped me to think of armrest."* In this example both the structure and the concept of the target sketch inspired the participant to change the shape to be curvy as well as adding new functionalities such as armrests.

**Low novelty conceptual shift designs**

Overall, 3/24 participants commented that it is more helpful when the sketch that is presented to them is more similar to their initial drawing (low novelty condition). P4 explains why the sketch of fence that was highly similar to their initial drawing of bridge was more helpful, *"because there were clear features and structures that could help by adding, mainly the similar features."* In this case, the participant preferred to finalize the original drawing by adding more details and structures rather than changing the existing features. Similarly, P9 commented: *"I like the product of end results when stuff [is] more similar. Because I could pull from the profile of fence and add to the bridge...So, you take something from it and add it to your design."* From both P4 and P9, we can conclude that when the system is in low novelty mode the designer mainly adds more details to the initial drawing rather than transforming the shape or adding new features to the drawing. Most participants found the low novelty condition less helpful. For instance, P12 described how they liked less similar designs, *"I would say it was more helpful when it was less similar because then you are not just copying the instances from the other design."* P8 agreed with this sentiment when they said: *"high similarity is kind of within my expectation."*

In both cases of P8 and P12, the low novelty conceptual shift designs do not help to significantly change the original drawing. Instead, they are used to combine some elements of the two sketches. P13 echoes this general viewpoint when they said: *"I think if you are presenting something that is almost exactly the same, you are going to introduce the same idea again."* Similar to P8, this participant also emphasizes the fact that low novelty conceptual shifts are within their expectation. P22 also commented: *"I feel that similar designs didn't give me as much creative freedom."* These examples demonstrate that low novelty conceptual shifts may help to combine the elements of the two sketches, rather than encouraging the user's creative thoughts. Both likely have a role in co-creative design systems, serving different purposes.

## 6.3 Quantitative Analysis

We compared the results from the user's feedback on the three design tasks associated with high, intermediate, and low novelty conditions. We grouped the responses into high, neutral, and low ratings: 4 and 5 are considered high, 3 is neutral, and 1 and 2 are low. For each condition we count the number of ratings based on this grouping.

### Analysis of creative ideas

Participants were asked to rate the responses provided by the system after each design session. With this question, we aimed to understand whether increasing the novelty of the system's response inspired their creative thoughts. We found that 91.66% of the participants thought that the system's response inspired creativity when the system was in the high novelty condition (HNC) compared to 29.16% in the low novelty condition (LNC). These results indicate that when the system's response is more novel with respect to the user's sketch (HNC), it is associated with more creative outcomes, which may encourage the user to come up with new design ideas for their initial drawing. When the system was in intermediate novelty condition (INC), 54.16% of the participants were highly inspired by the system's response. Figure 6.13-a shows the distribution of the ratings for the three conditions.

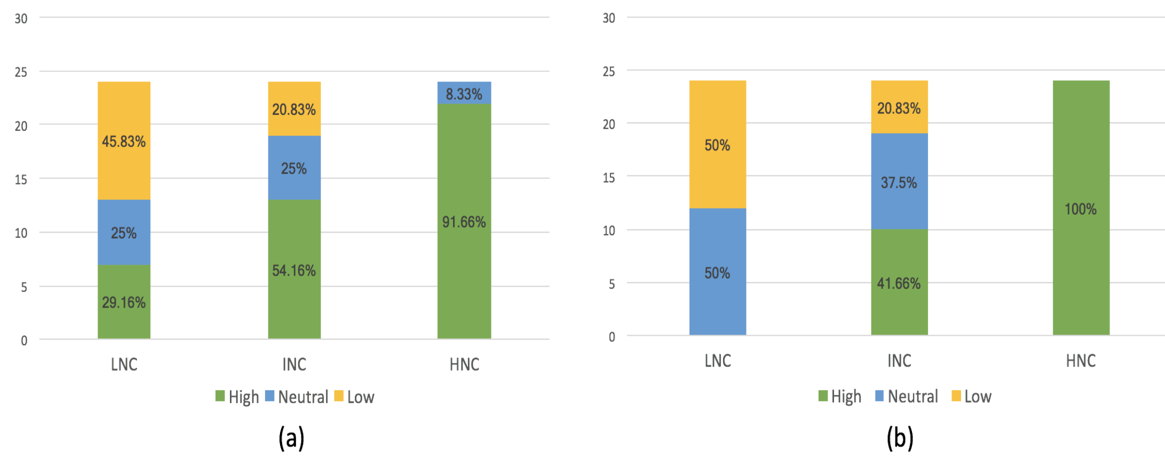


Figure 6.13: The total percentage of high, intermediate, and low survey responses for (a) inspired creative ideas, and (b) led to different design.

### Analysis of design object inspiration

Transformational creativity happens when a designer changes one or more structural variables of the current design object to produce new variables [16]. This implies that the system's response has the potential to inspire the user to transform some features of a design concept by adding new features from another design space related to the system's response. We explored whether increasing the novelty of the system's response can lead to transformational creativity in which the participant's designed object significantly deviates from their initial sketch. All participants rated high in response to changing their design when the system was in HNC. This indicates that when the system's response was less similar to the participant's input (HNC), they were able to transform their initial sketch. By contrast, when the system was in LNC, none of the participants reported that the system helped them come up with a different type of design object. when the system was in INC, 41.66% of the participants rated high in response to changing their design and 58.33% rated low or neutral (see Figure 6.13-b).

# CHAPTER 7: CREATIVE SKETCHING PARTNER USER STUDY

In this section we describe our co-creative sketching tool, creative sketching partner or CSP. We first introduce the interface of the tool followed by different user scenarios. We then describe the user study and the results of the study to investigate our hypothesis and research questions.

## 7.1 User Experience Design

We developed the CSP system to inspire the design creativity of users for a given design task, and to study different cognitive models of creativity associated with the users' responses. The interface of the tool is shown in Figure 7.1. There are two main design principles for the CSP system, 1) provide a sketch response to the user, and 2) enable users to manually 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 7.1. The visual similarity slider controls the amount of structural characteristics shared with the user's input. 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 design task is displayed on the top-left side of the interface (section A of Figure 7.1), and it includes the target object to be drawn 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 7.1) to complete their sketch. Once the user finishes their drawing, they can click on the "inspire me" icon (section C of Figure 7.1) to see the system's response. The system's response is displayed as a sketch on

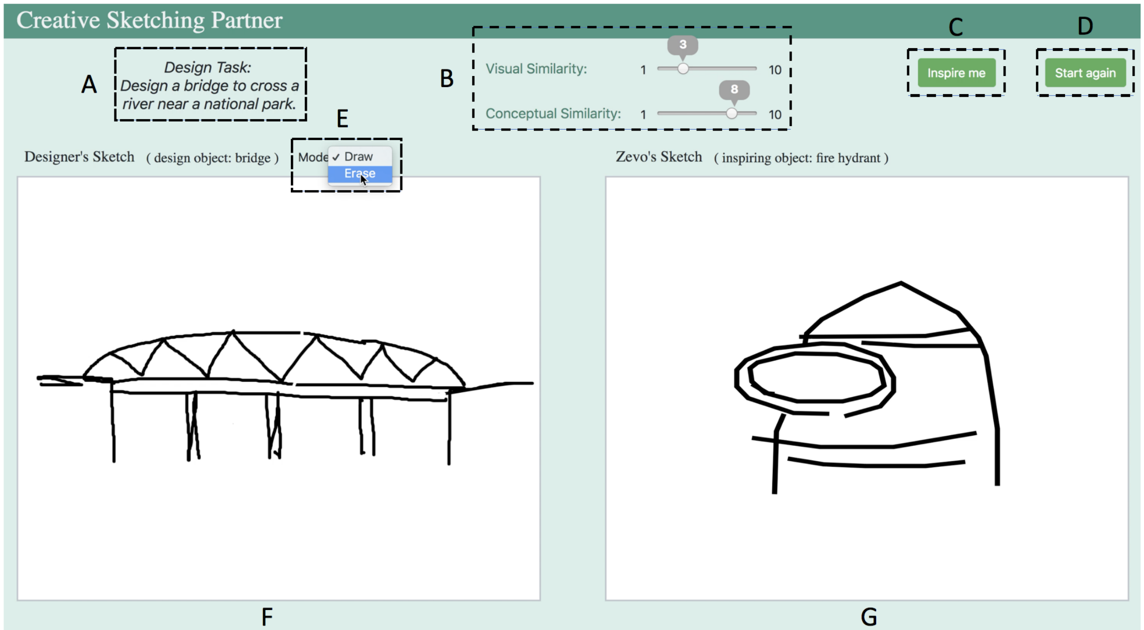


Figure 7.1: Creative Sketching Partner user interface.

the right drawing panel (section G of Figure 7.1). An object label is included 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 7.1) 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 design. 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

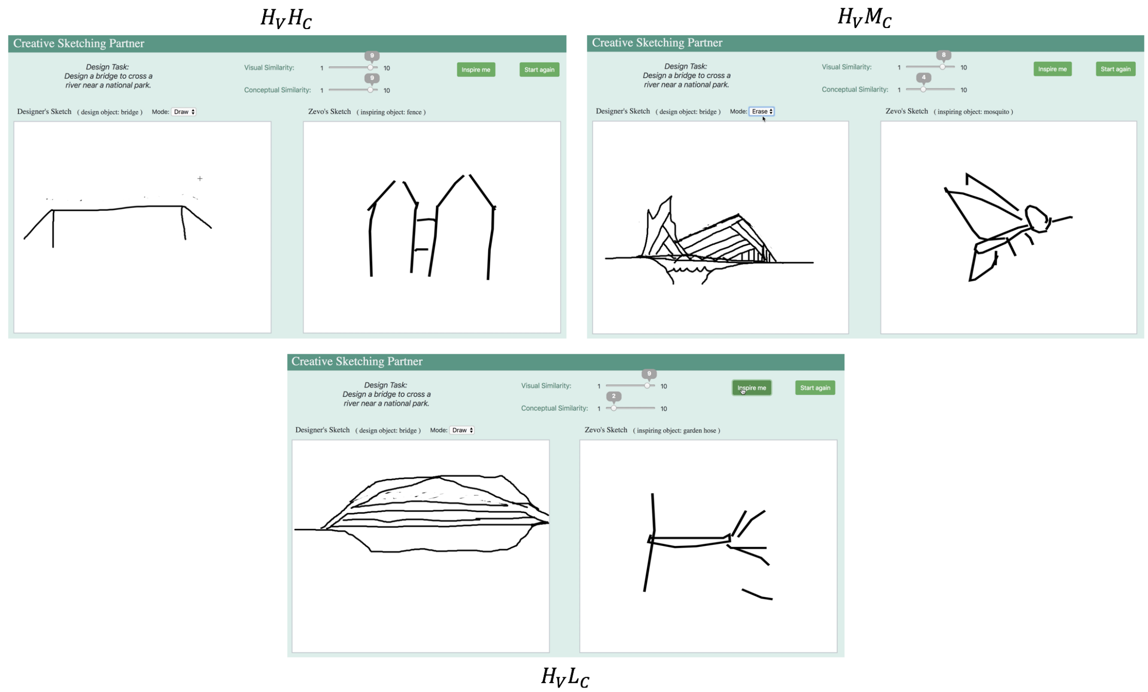


Figure 7.2: Examples for high visual similarity condition.

Erase mode (section E of Figure 7.1). Once the erasing is completed the user can switch to Draw mode to continue drawing.

**User scenarios for high visual similarity condition.** In this condition, the visual similarity slider is set to 7 or higher and the conceptual similarity slider can range from low to high (1 to 10). This leads to three different conditions, such that in all conditions the visual similarity is high and the conceptual similarity can be either low, medium, or high. Figure 7.3 shows some samples of user scenarios that happened throughout our design session for these three conditions. $H_v$ represents the high visual similarity condition, and $H_c$, $M_c$, and $L_c$ are high, medium, and low conceptual similarity conditions.

**User scenarios for medium visual similarity condition.** In this condition, the visual similarity slider is set from 4 to 6, and the conceptual similarity slider can range from low to high (1 to 10). This corresponds to three different conditions, such that in all conditions the visual similarity is medium and the conceptual similarity

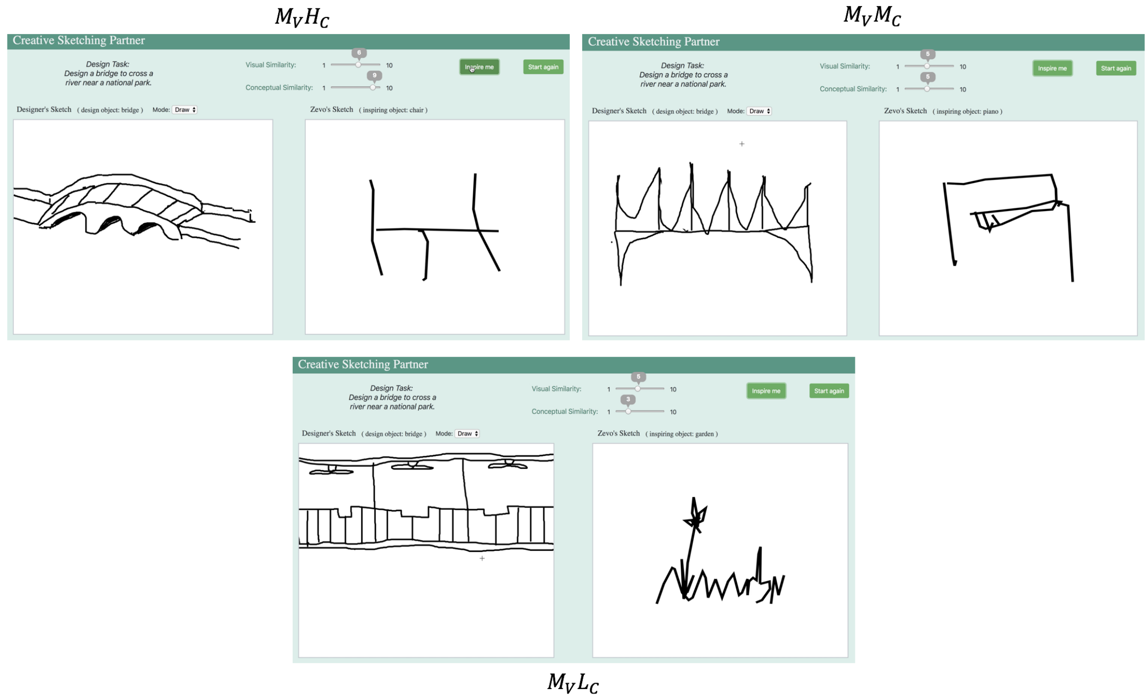


Figure 7.3: Examples for medium visual similarity condition.

can be either low, medium, or high. Figure 7.4 shows examples of user scenarios for these conditions.

**User scenarios for low visual similarity condition.** In this condition, the visual similarity slider is set between 1 and 3, and the conceptual similarity can range from low to high (1 to 10). This leads to three distinct conditions, in which all conditions have the visual similarity set to high and the conceptual similarity ranges from low to high. Figure 7.5 shows examples of user scenarios for these conditions.

## 7.2 System Design

In this section, we describe the two phases of the system design for both visual and conceptual similarity modules. In preparation to determine candidates based on visual similarity, we have two phases: offline and online. The offline phase divides the sketches of each category into clusters and selects a random sketch as a representative for that cluster. This corresponds to 345 $\times$ 10 sketches (number of categories $\times$ number of clusters per category), from which the AI agent can select. We then

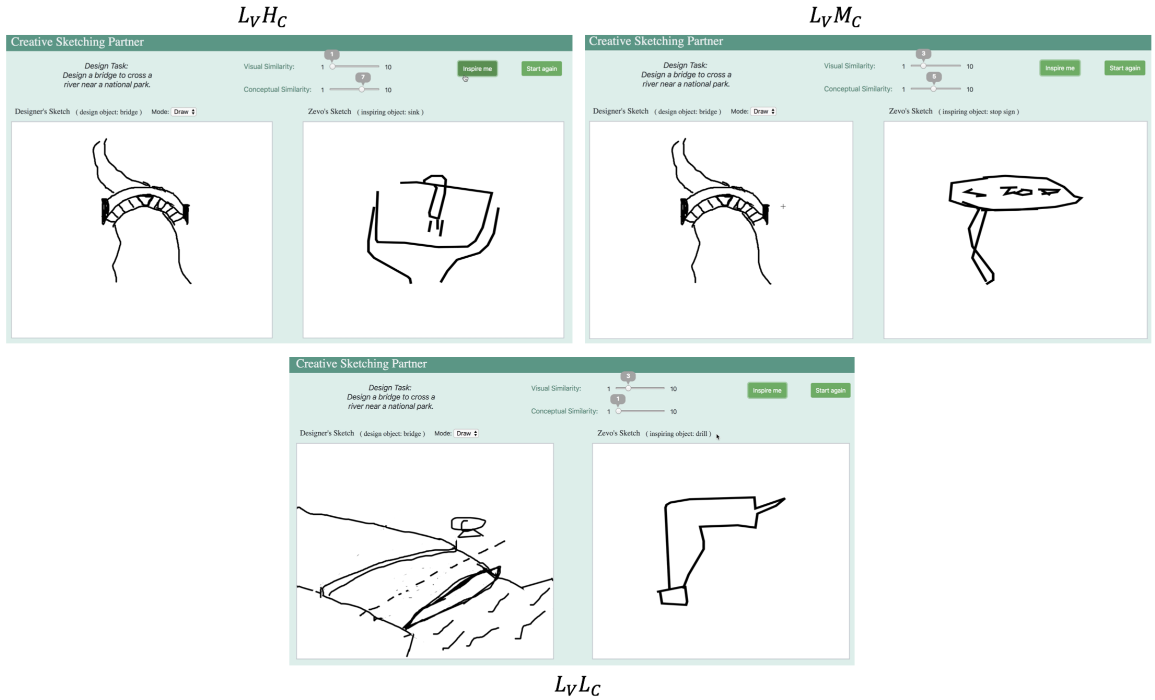


Figure 7.4: Examples for low visual similarity condition.

compute visual similarities between all cluster centroids of distinct categories. For more implementation details refer to section 4.2.

The online phase maps the user's input sketch into a sketch of another category with a measure of visual similarity. To do so, the visual features are extracted from the user's sketch input, which is assigned to the closest representative cluster within its category. The L2 distance is then computed between the identified centroid and cluster centroids of distinct categories obtained from the offline phase. We then identify the top 100 visual similar categories, such that the first 10 candidates are selected when the user sets the visual similarity slider (Section B of Figure 7.1) to 1, the second 10 candidates are selected when the visual similarity slider is set to 2, and so on (Figure 7.5).

Likewise, for the conceptual similarity module, we have two phases: offline and online. The offline phase computes the conceptual similarity between any two labels in the QD dataset. The implantation details are described in section 4.2. The online

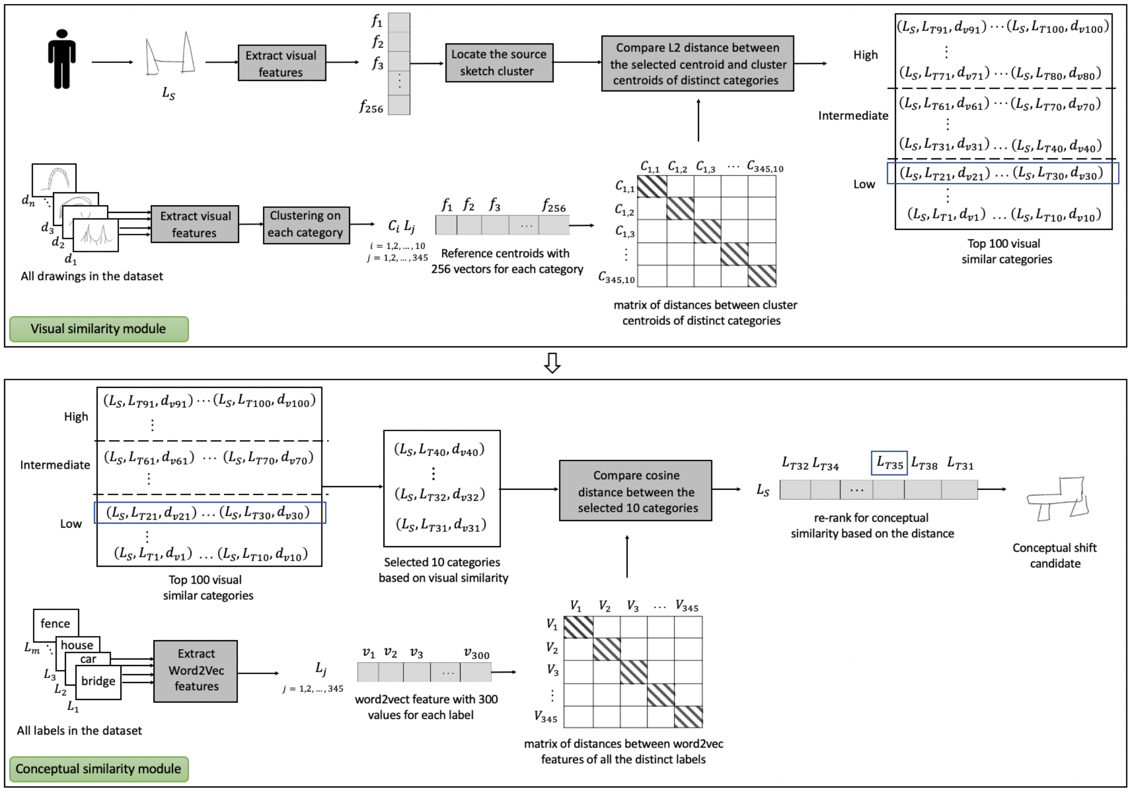


Figure 7.5: Computational steps to identify a conceptual shift for the system's response.

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 (Section B of Figure 7.1) to a specific value, the system will choose a sketch based on the ordered pairs position.

## 7.3 Study Design

We conducted a user study to assess whether the CSP tool can effectively collaborate with designers on a shared design task to inspire their creative thoughts and leads to different cognitive models of design creativity in the user's response.

For this study, we had 50 participants, 25 females, and 25 males recruited from the college of Architecture at a large public university in North America. The study included a single design task where the participant is asked to design a bridge to cross a river near a national park. Participants are asked to iterate their bridge design three times during the course of the study. They are free to seek inspiration from the system as many times as they would like to help find a suitable design from the system to aid in their sketch. While participants are working to find an inspiring design from the system, they can modify the visual and conceptual similarity sliders as many times as they would like to help tune the system's suggestions. The design task is not timed since different designers work at different paces, but on average, the design tasks lasted approximately 15-20 minutes. The entire session for each participant was screen-recorded.

After the design task, participants are asked to engage in a retrospective protocol where the researcher shows a video of the participant engaging in the design task and asks the participant to describe what they were thinking throughout the study. Then, the researcher conducted a structured interview with the participants about their experience during the design task. 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?
- 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?

The entire session for the retrospective protocol and interview were audio recorded and transcribed for analysis. Participants were provided with a $5 gift card as compensation for their involvement.

## 7.4 Qualitative Analysis

We divide each participant session into three different phases. Each phase is delineated when the participant starts making changes to their current object based on the system's design sketch output. At each phase, we collect the user's sketch, the system's sketch, and the settings of the visual and conceptual similarity sliders. 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 different conditions as discussed in Section 4.2.4. We then analyzed the retrospective protocol analysis transcripts, the interview transcripts, and the three different sketches that participants produced based on the CET framework.

### 7.4.1 Protocol Analysis

We collected the three sketches produced after each iteration from all 50 participants, which corresponds to a total of 150 generated sketches. Two individuals coded the retrospective protocol analysis transcripts and the three design sketches for each participant. The coders engaged in a blind coding approach where they did not know the condition for each design session. The transcripts include the thought process of each participant throughout the design session and the coders divided the transcript of each participant into three different segments. Each segment begins when the user starts explaining their thought processes for each change they made to their existing drawing and ends when they finish explaining their changes. The coders classified each segment into one of the categories of the CET ontology introduced in Chapter 5. Figure 7.5 shows the distribution of the three types of creativity for the nine conditions, and the condition of each phase is shown on the top corner, as explained in Section 4.3. The number of instances that the sliders were set to a specific condition and the user made changes to their current drawing is noted in the corner for each

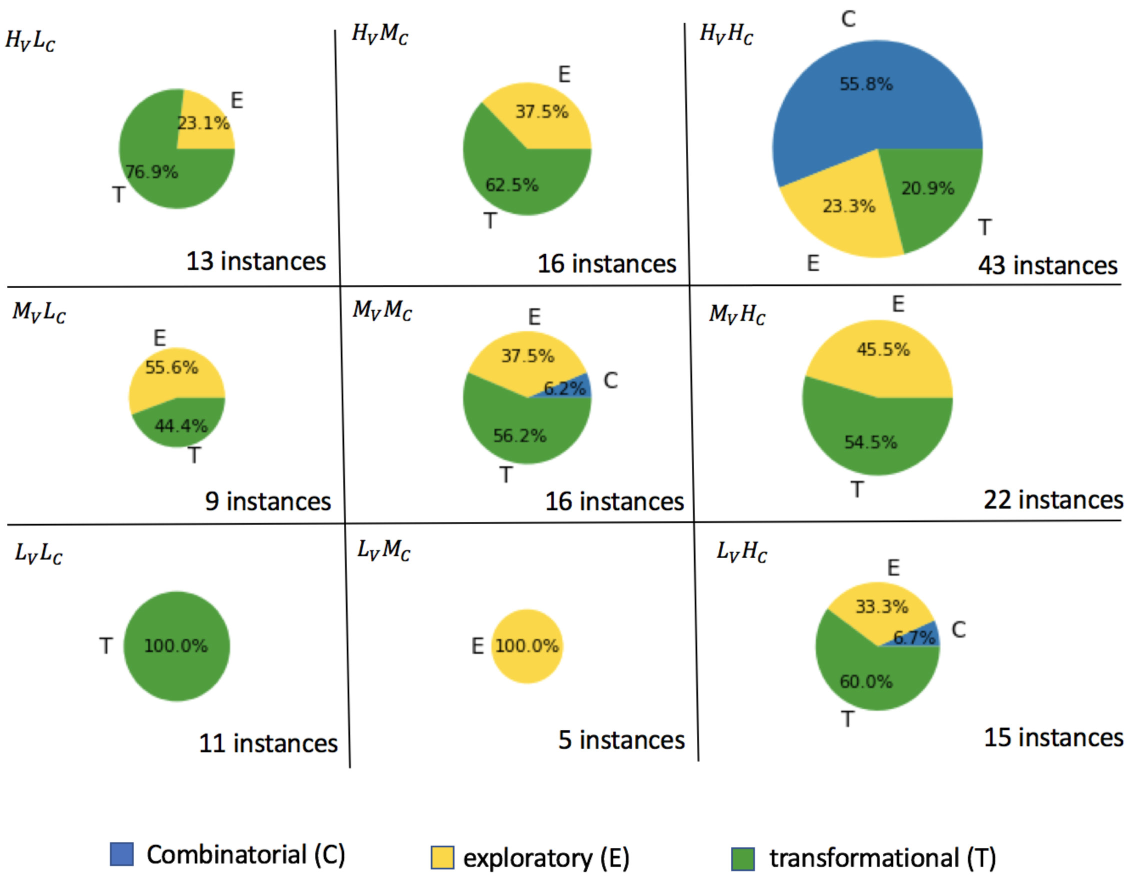


Figure 7.6: Distribution of the three types of creativity and the total number of instances for the nine conditions.

condition. As shown, the number of instances in each conditions is different because users were able to change the sliders as many times as they wished and made changes based on their preference settings.

As the results show when the slider for both visual and conceptual similarity were set to high, in most instances (24/43) 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 10 and 9 times, respectively. Our results show that exploratory creativity has two main characteristics. The first is when participants used the system's response as a context

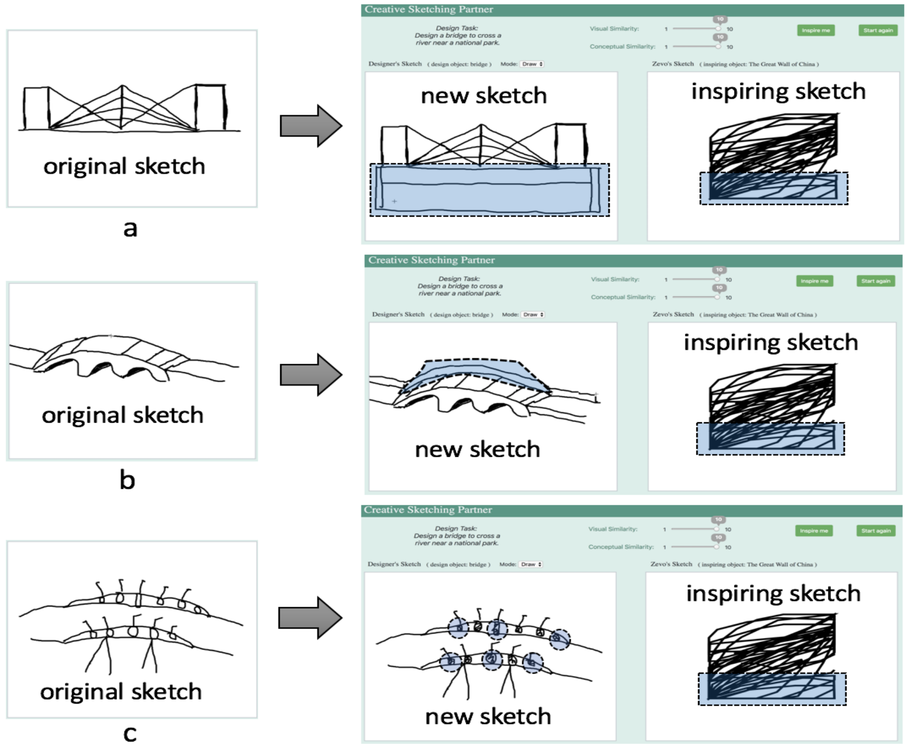


Figure 7.7: Examples of combinatorial creativity: part of the wall is added beneath the bridge (a), above the bridge (b), and to fill the holes in the bridge (c).

for the bridge design. In these cases, they explored adding landscape to their current drawing. Another characteristics 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 and the conceptual similarity was in medium or low, there is a higher percentage of transformational creativity compsred to exploratory creativity and no combinatorial creativity. This suggests that, when the concept is less related, users utilize it to re-interpret their design

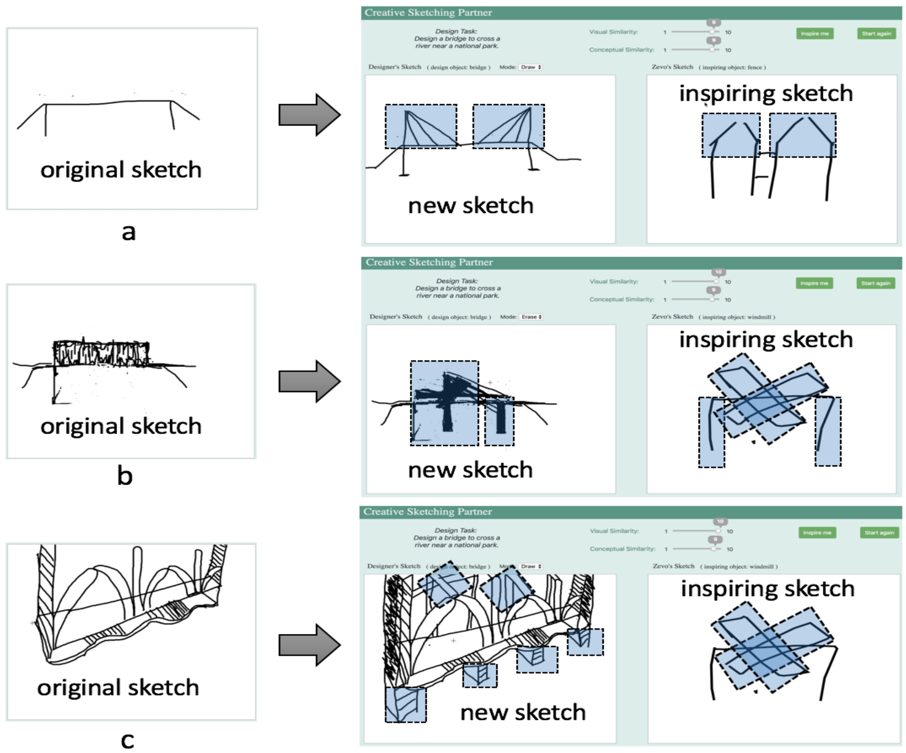


Figure 7.8: Examples of combinatorial creativity: part of the fence is added as cables above the bridge design (a), top part of the bridge is replaced with the "windmill" sketch (b), and some parts of the windmill is used for bridge design (c).

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. Moreover, 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 (no combinatorial creativity).

When the visual similarity is medium (second row Figure 7.5), the number of times that transformational or exploratory creativity is observed in the user's response is not significantly different. 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 added a new function to their existing drawing. Combinatorial creativity occurred only once when the system was in medium

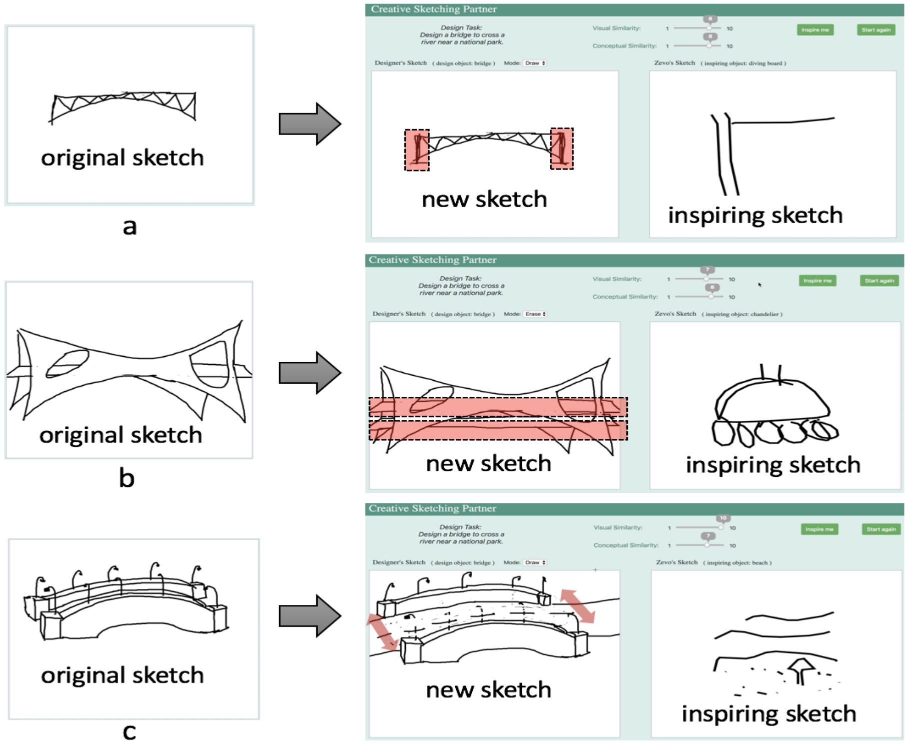


Figure 7.9: Examples of exploratory creativity: the two ends of the bridge are expanded (a), an additional path is added (b), the path between the two sides of the bridge is increased (c).

visual and conceptual similarity condition.

When the system was in the low visual and low conceptual similarity condition, all the responses fell into 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 conceptual space. However, when the concept was intermediately similar, all participants modified their drawing in the same design space, i.e. exploratory creativity.

Below, we describe the type of design thinking that happened throughout the study for the high, medium, and low visual similarity conditions.

**High Visual Similarity Condition.** Overall, we observed that 72 times participants set the visual slider to high and the conceptual slider varying from low to high.

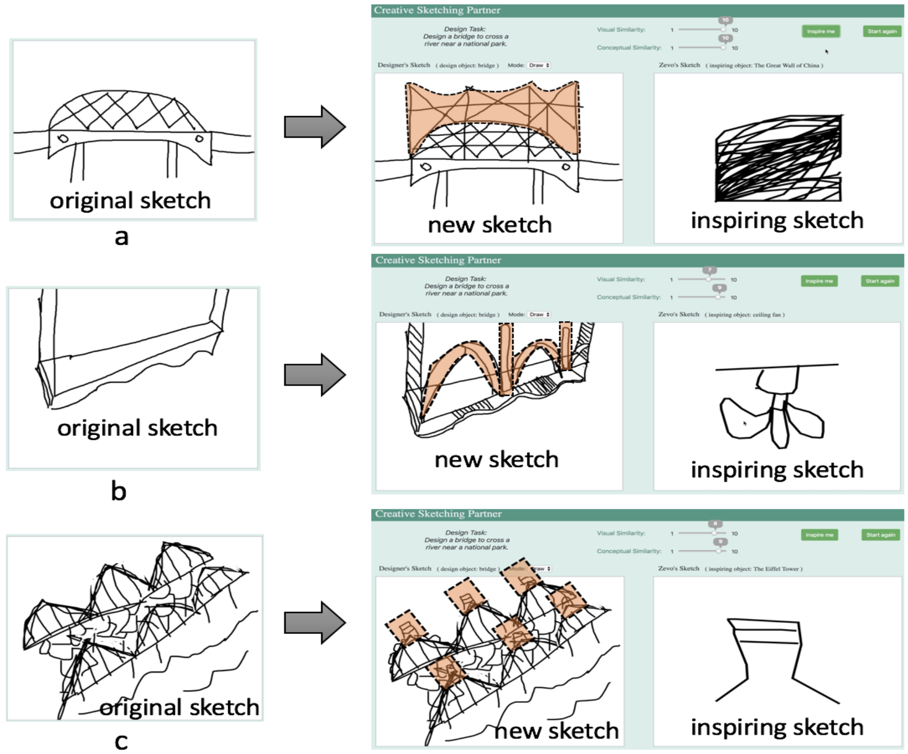


Figure 7.10: Examples of transformational creativity: the outline shape of the bridge is changed (a), the structure of the ceiling-fan is used as protection (b), the upper part of the Eiffel tower is used as decoration (c).

Based on the user's response in each iteration, combinatorial creativity occurred only when the visual and conceptual similarity were both high (24 times). In these instances participants combined eigther the whole or a subset of the system's response with their current drawing. For instance, participant P13 used the triangles of fence as cables for bridge design in order to add more structures. P2, P3, P10, P19, P23, and P32 added the wall from the "great-wall-of-china" sketch on top of the bridge to make some protection, while P35 and P47 added the wall beneath their bridge design to add more strength to their bridge. Others, such as P41 and P46 incorporated part of the grate-wall-of-china, such as the materials to fill some parts of their bridge with wall in order to make it stronger. P6 replaced the upper part of the bridge design with the "windmill" sketch after rotating some of the structure of the system's response; whereas P2 and P12 utilized parts of the windmill design, such as the blade

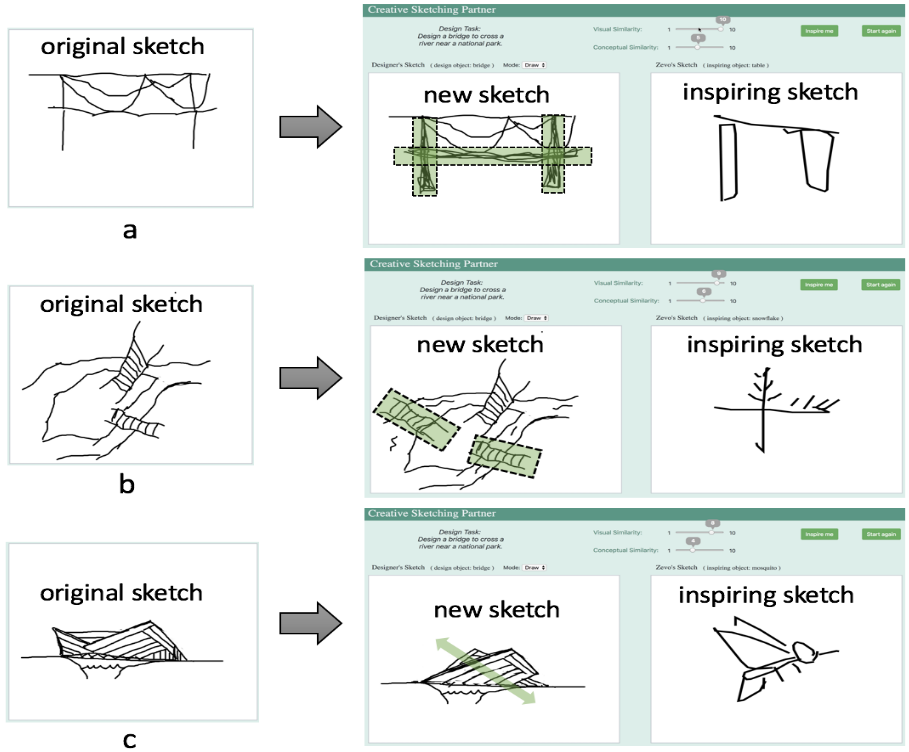


Figure 7.11: Examples of exploratory creativity: the columns and the base part of the bridge are expanded and become ticker (a), more bridges are added (b), the direction of one part of the bridge is changed (c).

to add more structure to their existing design. Figures 7.6 and 7.7 show examples for combinatorial creativity when the system was in high visual and high conceptual similarity condition.

Exploratory creativity was noted 10 times when the two sliders were set to high. Within this phase, some participants explored altering some parameters of their current sketch or adding context around their bridge design. For instance, P1 added thickness to both ends of the bridge to create a stronger bases inspired by the lower structure of the diving-board. P21 and P40 explored adding another layer for car passage to their bridge design inspired by the concept of the ceiling-fan and the structure of the chandelier sketch, respectively. P11 expanded the path between the two sides of the bridge based on the space observed between the lines in the “beach” sketch. Other participants explored adding landscape to their existing design. P30 added

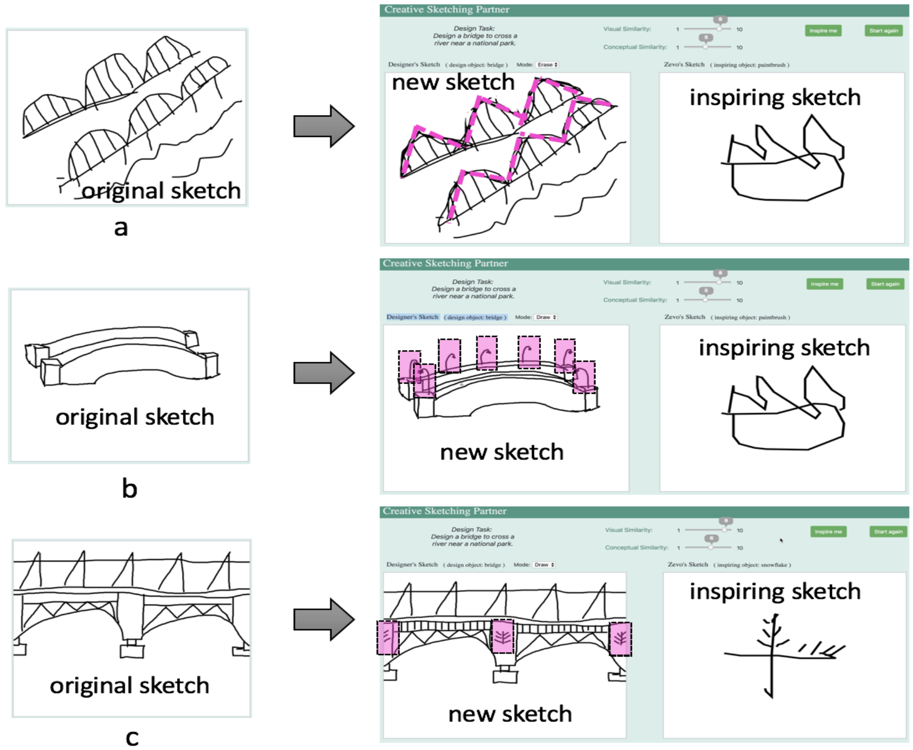


Figure 7.12: Examples of transformational creativity: the outline shape of the bridge is changed (a), the light posts are added to the bridge (b), the snowflake is added to the base of the bridge as decoration (c).

sand beneath the bridge as a context inspired by the ocean. P41 added water below the bridge inspired by the ocean. Figure 7.8 shows examples for exploratory creativity when the system was in high visual and high conceptual similarity condition.

Finally, within this phase, transofrmational creativity happened 9 times. When the visual and conceptual similarity were high, some participants changed the outline shape of their bridge design or added a new function to their existing design. P9 changed the outline shape of the top part of the bridge design inspired by the massive size of the great-wall-of-china in order to emphasize verticality. P12 added protection to its current drawing inspired by the structure of the ceiling-fan. The new added structure mimics the shape of the fans. P13 added an introduction at the start and at the end of the bridge design inspired by the concept of the speedboat, such as the space and how it embraces people. When the visual and conceptual similarity

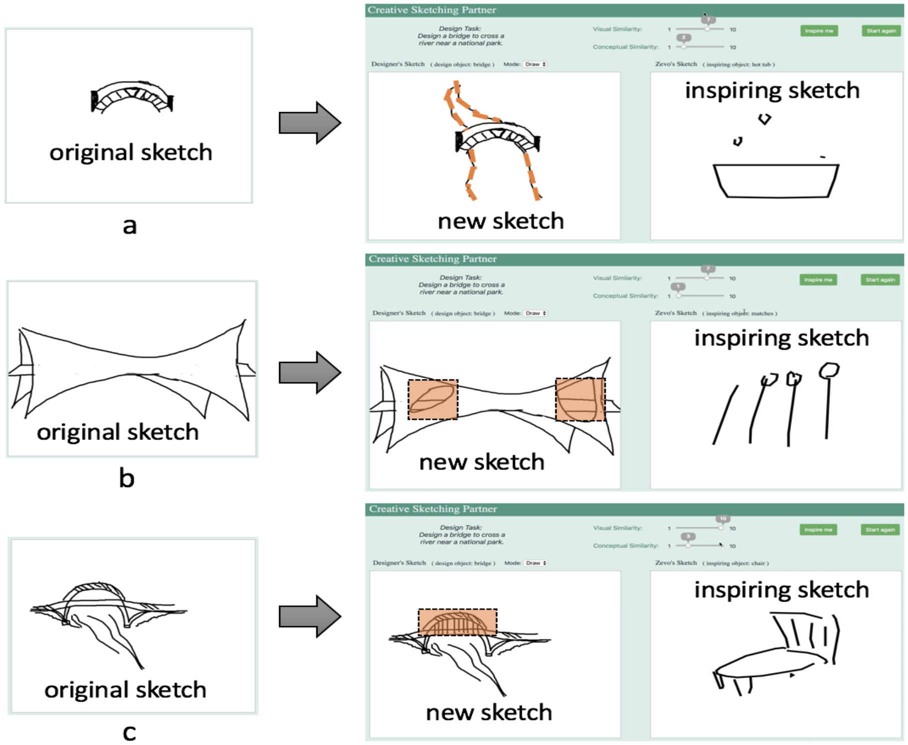


Figure 7.13: Example of exploratory creativity: a context is added to the bridge design (a). Examples of transforamtional creativity: holes are created to the bridge to make more light (b), suspensions are added to the bridge based on the lines in the chair (c).

were both high, some participants added some or part of the system's response as a decoration to their existing design. For example, P25 added the upper structure of the "Eiffel Tower" on top of each arch in the bridge in order to adorn the current design. P41 used the circles observed in the "chandelior" sketch to create some holes in the bridge design. Figure 7.9 shows examples for transformational creativity when the system was in high visual and high conceptual similarity condition.

Our data showed that 16 times participants set the visual slider to high and the conceptual slider to medium. Out of which 6 is associated with exploratory creativity and 10 is associated with transformational creativity. P4 increased the base size for both sides of the bridge design as well as the base of the bridge inspired by the thickness observed in the legs of the "table" sketch. P17 actively expanded both ends of

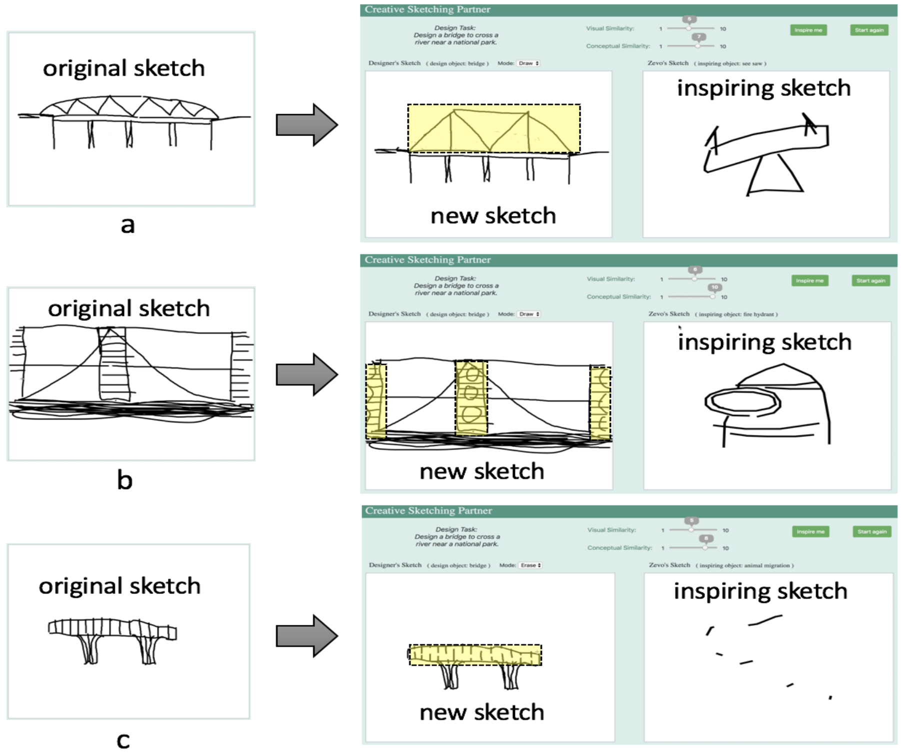


Figure 7.14: Examples of exploratory creativity: a symmetrical structure is applied to the bridge design (a), the same pattern is applied to the bridge based on the lines and circle observed in the fire hydrant (b), and the randomness observed in the "animal migration" sketch (c).

the bridge after seeing the continues lines in the legs of the "table" sketch. P5 changed the orientation of one side of the bridge inspired by the wings of the "mosquito". P48 explored adding more bridges based on the structure of the "snowflake". Examples are shown in Figure 7.10.

In the case of transformational creativity, P24 changed the outline shape of the two ends for the bridge design inspired by the sharpness of the "lightning" sketch. P25 transformed the outline shape of the upper part for the bridge design from curvy to a rigid structure based on the sharpness observed in the "paintbrush" sketch. Other participants added a new function to the bridge design based on the function or the structure of the system's response. P11 added light post on top of the bridge inspired by the upper structure of the "paintbrush" sketch. P18 added the structure of the

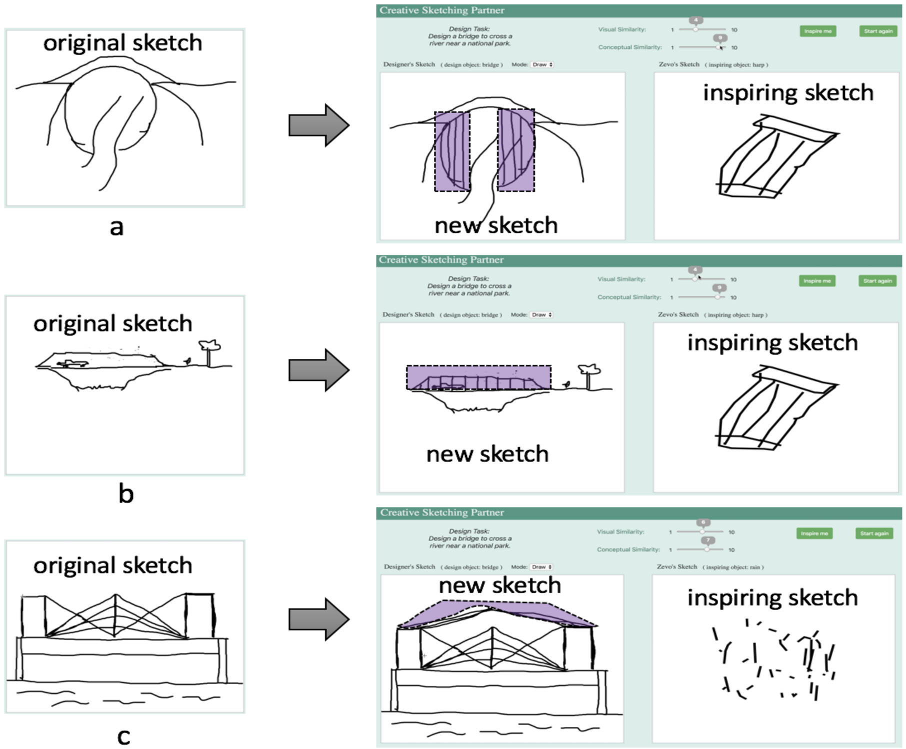


Figure 7.15: Examples of transformational creativity: a suspension is added to the bridge design based on the straight lines in the harp (a,b), a shell is added on top of the bridge based on the features of the rain (c).

snowflakes to the base of the bridge design as a decoration after seeing the "snowflake" sketch.

Finally, within this condition, 13 times participants set the visual similarity to high and the conceptual similarity to low. In this case, exploratory creativity was observed 3 times in the user's response, while transformational creativity happened 10 times (Figure 7.12). P19 explored adding a river beneath the bridge inspired by the "hot tub" sketch. P36 expanded the path between the two sides of the bridge and connected it to the path before the bridge entrance based on the space and the connections observed between the lines in the "spreadsheet" sketch. P48 explored closing the system of the bridge design by connecting the two parts of the bridge inspired by the closeness of the hot top.

In the case of transformational creativity, P31 added a shelter as a new function on

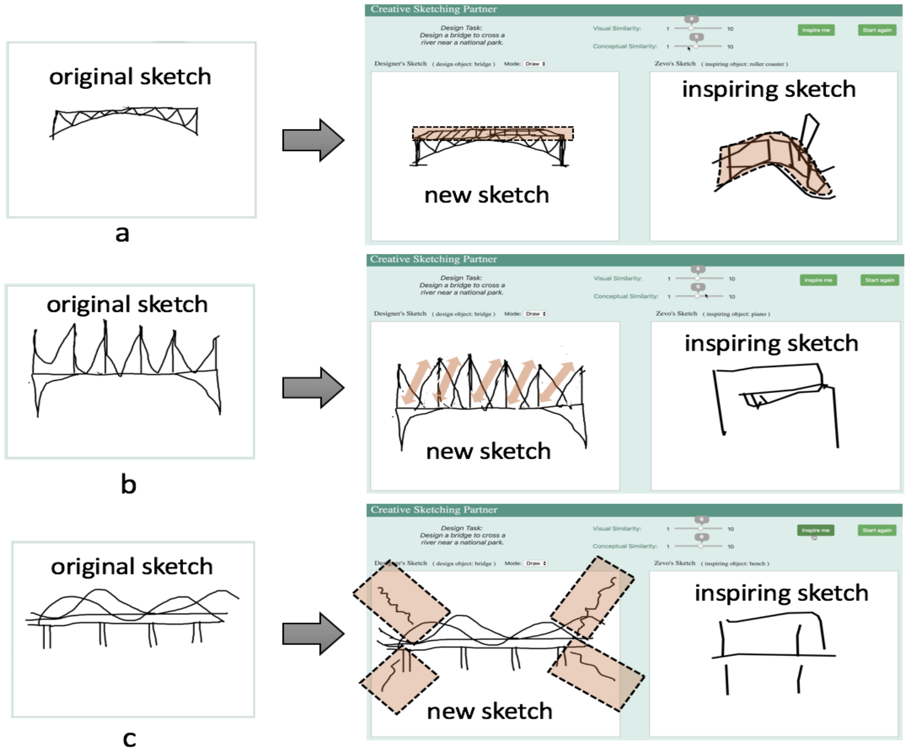


Figure 7.16: Example of combinatorial creativity: a rail is added on top of the bridge for passage (a). Examples of exploratory creativity: the orientation of some elements in the bridge design is changed (b), a context is added around the bridge sketch (c).

top of the bridge based on the structure of the bench. P33 added a suspension as a new function for the bridge design inspired by the lines observed in the chair design. Likewise, P37 added suspension to the bridge design inspired by the lines observed in the "toaster" sketch. P40 added holes to the current bridge design in order to create some light inspired by the concept of matches. Other participants changed the outline shape of some or all parts of their bridge design. For instance, P42 changed the shape of the lower part of the bridge design by giving elevation to the legs of the bridge. The changes in the new design mimics the structure of the "bench" sketch.

**Medium Visual Similarity Condition.** Our data showed that 47 times participants set the visual slider to medium and the conceptual varying from low to high. Among these instances exploratory creativity occurred 10 times and transformational creativity 12 times when the conceptual similarity slider was set to high. P3 explored

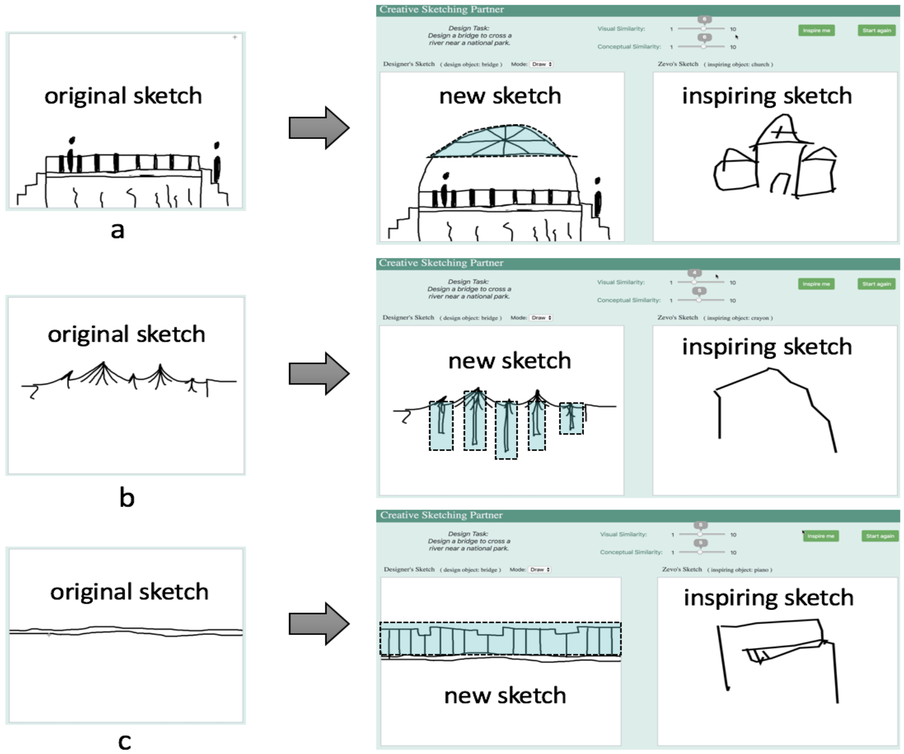


Figure 7.17: Examples of transformational creativity: a shelter is added inspired by the dome structure on top of the church (a), bases are added to the bridge design that mimics the same shape as a crayon (b), a new structure is added on top of the base of the bridge inspired by the keys in a piano (c).

creating a symmetric structure for the bridge design based on the symmetries observed in the “see saw” sketch. Some participants explored creating the same pattern for their current drawing based on the pattern being observed in the system’s response. P6 created an irregular pattern in the upper part of the bridge inspired by the randomness pattern in the “rain” sketch. In this case, the user creates the same pattern observed in the system’s response. P8 created holes between the lines of the base part of the bridge. The new design mimics the same pattern as the “fire hydrant” sketch. Likewise, P23 removed some parts of the lines in the bridge design to create a random pattern in one part of the bridge inspired by the randomness observed in the “animal migration” sketch.

In the case of transformational creativity, P34, P37, and P46 added vertical beams

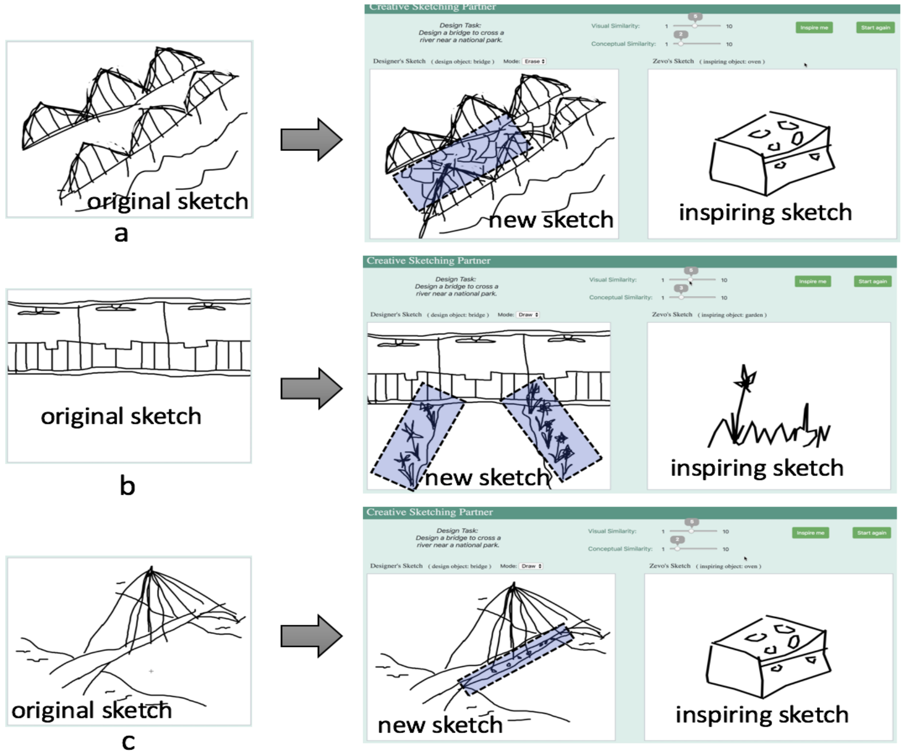


Figure 7.18: Examples of exploratory creativity: a new pattern is added in the middle of the bridge inspired by the circles on the stove (a), a context is added to the bridge design (b). Example of transformational creativity: a new structure is added to the bridge design inspired by the circles on the stove(c).

to the bridge design as a protection based on the strings observed in the "harp" sketch. P43 added light to the bridge inspired by the function of the "lantern" sketch. P27 added bases to the current drawing after seeing the "bed" sketch. The adding bases mimic the structure of the base in the "bed" design. P35 added a shelter on top of the bridge as a protection after seeing the "rain" sketch. Figures 7.13 and 7.14 show examples for exploratory and transformational creativity for medium visual and high conceptual similarity condition, respectively.

Overall, 16 times the visual and conceptual similarly was set to medium. Out of which 9 was transformational, 6 was exploratory, and 1 was combinatorial. P1 combined the rail of the roller coaster with the top part of the bridge design as a passage (Figure 7.15-a). In the case of exploratory creativity, P7 actively raised

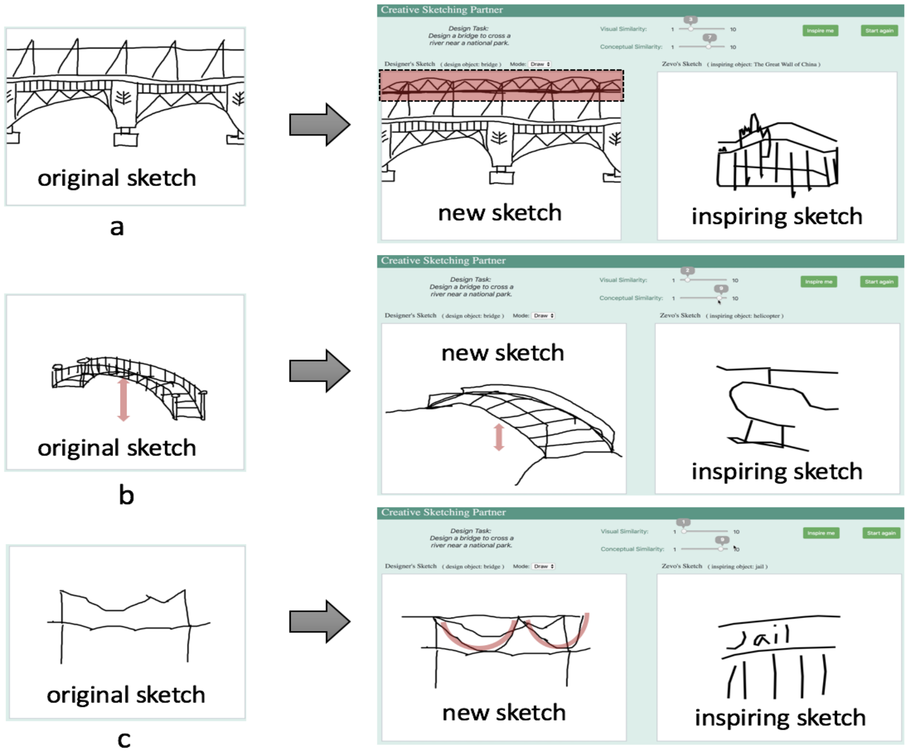


Figure 7.19: Example of combinatorial creativity: a wall is added on top of the bridge (a). Examples of exploratory creativity: the bridge is became flatter (b), more suspension is added inspired by the concept of the jail (c).

arches in his/her bridge design and changed their orientation inspired by the position of the strings in the piano. P14 divided the upper part of the bridge into two and created a triangular shape based on the up and down structure of the roller-coaster. P22 created a zigzag pattern on the top portion of the bridge after seeing the "feather" sketch. P45 explored adding landscape, such as mountains to the current drawing based on the features of the "bench" sketch (see Figures 7.15-b,c).

For transformational creativity, P16 added a new structure above the base of the bridge design inspired by the structure of the keys in a piano. In this case, the user is adding a new structure to the bridge design inspired by the features of the system's response. P20 added a shelter on top of the bridge inspired by the dome structure on top of the church. P39 added a top piece to the current design after observing the "speaker" sketch in order to reduce noise. P30 and P32 added bases to their existing

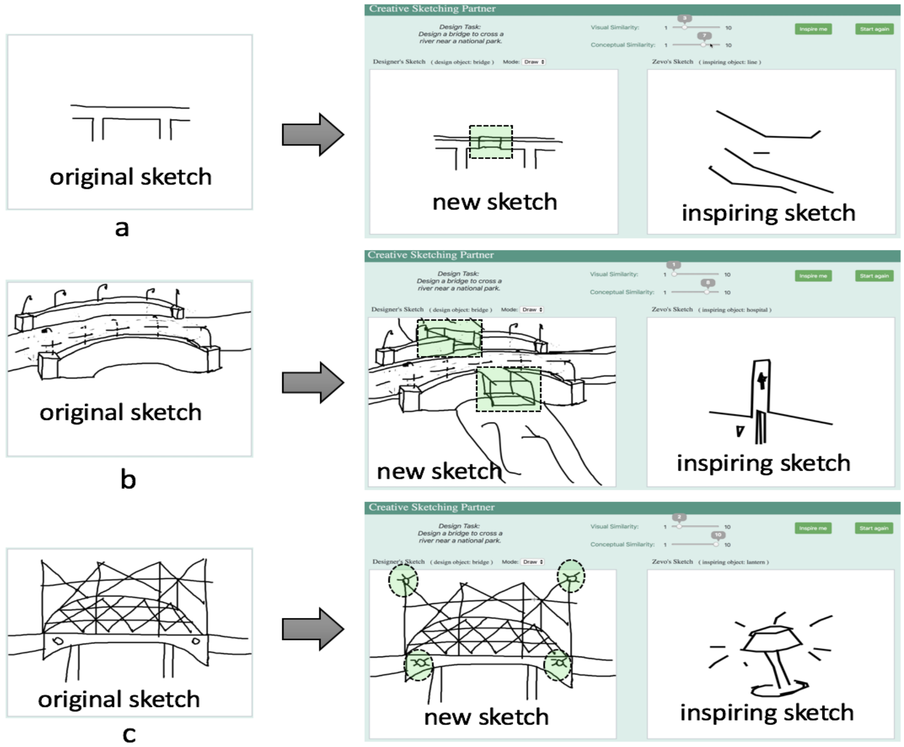


Figure 7.20: Examples of transformational creativity: a contour is added to the bridge (a), an entrance and an exit are created for the bridge design (b), lights are added to the bridge inspired by the concept of the lantern (c).

design after seeing the “crayon” and “table” sketch, respectively. The adding new bases mimics the structure of the proposed sketch. Figure 7.16 shows examples for transformational creativity for medium visual and conceptual similarity condition.

Our results showed that 9 times the visual similarity was set to medium and conceptual similarity to low. Within this condition, exploratory creativity occurred 5 times (Figure 7.17-a,b) and transformational creativity 4 times (Figure 7.17-c). In the case of P25, the user explored creating circular patterns between the two sides of the bridge, inspired by the circles observed in the “stove” sketch. P16 and P27 explored creating landscape as a context on both sides of the bridge inspired by the “garden” sketch.

In the case of transformational creativity, P2 created a new structure on top of the bridge as attraction inspired by the irregularity pattern in camouflage. P23 added

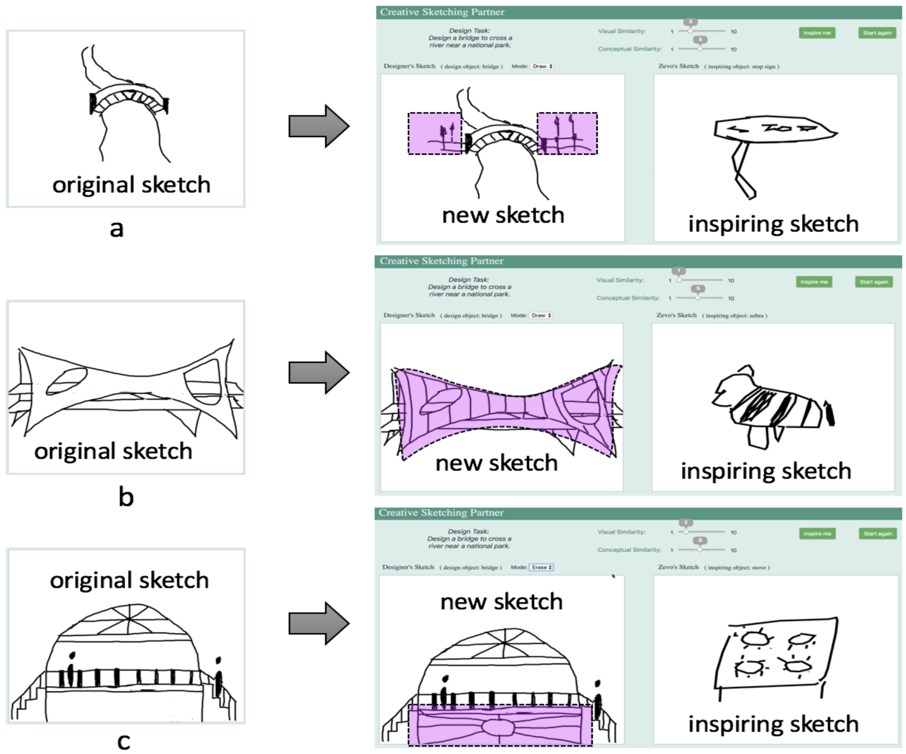


Figure 7.21: Examples of exploratory creativity: a context is added to the bridge (a), the same pattern is created on the bridge design (b), and beneath the bridge (c).

ridges to the top and bottom of the bridge after seeing the ridges in a "bottlecap" sketch. P27 added steel structure to the bridge after seeing the "oven" sketch.

**Low Visual Similarity Condition.** We observed, overall, that 31 times participants set the visual slider to low and the conceptual varying from low to high. Among these instances combinatorial creativity occurred 1 time, exploratory creativity 5 times, and transformational creativity 9 times when the conceptual similarity slider was set to high. P18 added walls on top of the bridge design after seeing the "great-wall-of-china" sketch (Figure 7.18-a). P4 explored adding more suspension to the current drawing inspired by the enclosure concept of "jail" sketch. P31 changed the amount of bending for the bridge to be flatter and more condense inspired by the concept of "helicopter" sketch that needs a lot of space when landing (Figure 7.18-b,c).

In the case of transformational creativity, P47 added contours to the middle of

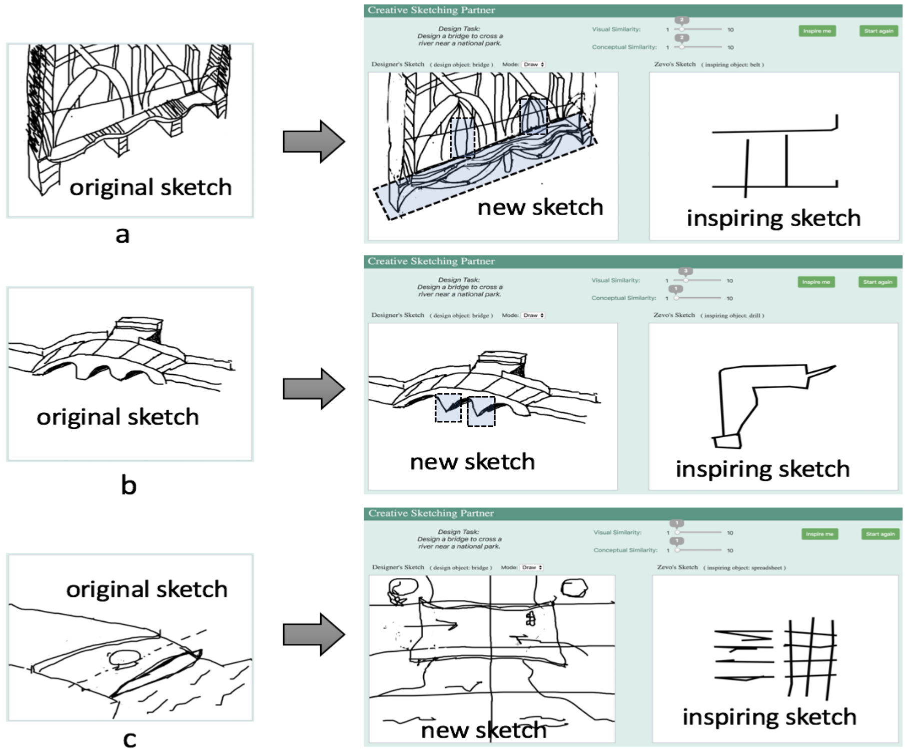


Figure 7.22: Examples of transformational creativity: the outline shape of the bridge is changed from rigid to curvy (a), the curvy structure of the base is transformed to a rigid structure (b), the bridge design is completely changed and transformed to a new design (c).

the bridge after seeing the “line” sketch. P9 added lights to the bridge design after seeing the “lantern” sketch. P11 changed the shape of a part of the current drawing by introducing an entrance and an exit inspired by the concept of a “hospital” sketch that has a door for entering and exiting. P6 transformed the outline shape of the bridge design from triangular form to a rectangular form inspired by the function of the water in the “pool” sketch, such as fluidity. Figure 7.19 shows examples of transformational creativity for low visual and high conceptual similarity condition.

Our data showed that 5 times participants set the visual slider to low and the conceptual slider to medium. In this case, all the responses were associated with exploratory creativity (Figure 7.20). P19 explored adding light posts at the entrance and exit of the bridge inspired by the “stoplight” sketch. P40 explored creating a repetition pattern of lines on the bridge design inspired by the lines in the "zebra" sketch. Likewise, P20 explored creating the same pattern observed on top of the "stove" sketch for the lower part of the bridge design.

Finally, within this condition, 11 times participants set the visual and conceptual similarity to low. In this case, all the responses were associated with transformational creativity (Figure 7.21). P3 changed the shape counter of the upper part of the bridge from two separate triangular shapes to a continues triangular while adding suspensions. The shape was inspired based on the lower triangular structure and the added suspensions were based on the vertical line on top of the "broom" sketch. P12 transformed the entire shape of the bridge design from rigid to curvy shape based on the curvy and softness of the "belt" sketch. P21 and P22 added the vertical lines observed in the "belt" sketch to the bridge design as a new structure. P17 and P38 completely deviated from their original drawing after seeing the "spreadsheet" sketch. In both cases, the new sketch has more vertical elements inspired by the vertical lines in the spreadsheet. P28 used the materials and the loopy shape of the trombone to add stone to the bridge design.

### 7.4.2 Thematic analysis

To understand how the similarity of 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.

- Facilitate ideation
- overcome design fixation
- Similarity and inspiration

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

**Facilitate 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 creatives 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.

**Overcoming design 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.

**Similarity and inspiration.** 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.

P12 reports how low versus high similarity can aid with the design process, saying: *"I think it affected creativity when it was less similar. Because you are thinking about changing your concepts and it makes you think more. But when it is highly similar you can add more details to your bridge. You can still be creative and you can still think of objects or structures to add you bridge."* In this case, high similarity designs help with finalizing the design through adding more details, whereas low similarity designs are more connected to creativity, in which a different concept is being used in another context related to the design task.

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."*

P7 was able to connect two concepts and come up with new design ideas when the system's response was less similar to their current drawing, saying: *"I was able to draw connection between something you know used for one purpose can be used for another purpose."* In this case, the function of the system's response inspired the participant to add a new function to their current drawing. In other words, when two different concepts serve various functions, the purpose of one concept can guide adding a new function to another sketch concept. P5 describes why a less similar stimuli is more inspiring, saying: *"I think the less similar because it gives different perspectives on the shape you are doing. You are not doing the same shape over and over again."*

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."*

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 visual 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."* In this case, when the two sketch concepts share high amount of structural characteristics, it helps to finalize the current design.

In some cases, when the system's output was more similar to the user's sketch, participants were able to come up with new design ideas without deviating from their original idea. P32 describes how the high similar designs were more inspiring, reporting: *"When it was more. Because it related more back to what my idea was and so I was able to visually see it better."* P46 explains why high similar outputs help creativity more compare to less similar outputs, stating: *"I think when it is more similar it helps my creativity just because I see the connection right away, whereas when it is not similar I have to think about like how this could relate to my design."*

These results demonstrate that while high similar visual and conceptual designs inspire users adding more details to their existing design, less similar designs are more connected to creativity, in which users are able to draw connections between two different concepts. In these cases, the concept of one design idea guide the user to add a new function or structure to their current drawing by re-interpreting their sketch in another category or context.

## 7.5 Summary of Results

Our results from protocol analysis demonstrate that the CSP tool can support different types of design creativity, including combinatorial, exploratory, and transformational. Our findings suggest that the high visual and conceptual similarity condition helps designers combine two design concepts (i.e. combinatorial creativity), while the low visual and conceptual similarity condition inspires designers to add new features from another design space compared to their initial design (i.e. transformational creativity).

Furthermore, the analysis from the semi-structured interview questions demonstrates that the CSP tool can help designers to come up with new design ideas in the early stage of their design task as well as overcoming design fixation. The first finding shows that the concept or the structure of the proposed sketch can aid designers to perform multiple iterations by discovering previously unexplored aspects of the creative space. Another finding demonstrates that the conceptual component of the CSP tool can successfully trigger the seeing-as mode perception of the designers by allowing them to perform multiple re-interpretations. Finally, the last finding suggest that high similarity helps with adding more structures to the initial design (i.e. combinatorial creativity) whereas low similarity inspires adding new features from a completely different design space (i.e. transformational creativity).

# CHAPTER 8: SUMMARY AND FUTURE RESEARCH

An AI model of conceptual shifts in a co-creative design context has the potential to facilitate ideation, overcome design fixation, and lead to different types of design creativity. The model uses visual and conceptual similarity components to determine potential conceptual shift candidates from distinct categories, based on the user's input. Visual similarity entails identifying clusters of sketch categories that share structural characteristics to the user's input sketch. Conceptual similarity determines the degree of similarity between the user's sketch and the selected category names. We described the computational steps involved to select the target sketch based on three different conditions: high, intermediate, and low similarity.

Studying and analyzing different cognitive models of creativity can guide the evaluation of the user's design thinking processes during the co-creative task. This thesis incorporates combinatorial, exploratory, and transformational as the three main types of design creativity and provides a framework for these three classifications as a general coding scheme. The analysis of the user's response in a co-creative design system demonstrates that they fall into these different types of creativity as we change the degree of similarity between the user's sketch and the system's response.

We described the steps to quantify conceptual shifts in the visual and conceptual space. Our presumption is that the more similar the second sketch is to the first, the less novel the second item is and the less likely that it will trigger a conceptual shift. When the two items are less similar, the more novel stimulus and the more likely it will result in a conceptual shift. We have detailed the process for classifying potential response sketches as low, intermediate, or high novelty with respect to the designer's sketch. A user study is presented in which the participants are given a design task and then experience three different versions of the tool: low, intermediate, and high novelty responses. Both quantitative and qualitative results from the user study demonstrate that the high novelty conceptual shift designs inspire creative thinking more than the low novelty condition.

To study the correlation between the degree of similarity and the user's response during a co-creative design session, we performed a Wizard-of-Oz study, in which a human wizard utilized the results of the conceptual shift algorithm for determining high, intermediate, and low similarity sketches to placed on the canvas. The findings suggest that the high visual and conceptual similarity condition may help designers combine two design concepts, the intermediate visual and conceptual similarity condition may help designers change the range of values associated with some variables of their initial design, and the low visual and conceptual similarity condition may inspire designers to add new features from another design space to their initial design.

Eventually, we developed a co-creative sketching tool called the Creative Sketching Partner or CSP. The interface has a sketching pane for both the user and system and two sliders to change the parameters of the system: one for adjusting visual similarity and the second for changing the conceptual similarity. We performed a user study with the system in order to study the correlation between the degree of similarity and cognitive models of creativity with other dimensions of similarity (e.g. high visual similarity and low conceptual similarity). Moreover, we aimed to understand how the tool can help with the design process as well as when the system's response is likely to inspire creativity. The findings demonstrate that the tool can help with the design process, facilitate ideation, and overcome design fixation. In addition, the users are more likely to produce transformational creativity when the visual and conceptual similarity are both low; wheres they are more likely to combine two concepts when the visual and conceptual similarity are both high.

Future research includes studying the user's behavior during co-creation, such as changing sliders, erasures, amount of ink used, and number of sketches created. In addition, to better understand the cognitive models of creativity, it is necessary to perform FBS coding [65] from the users' think aloud data. This will allow us to better analyze the user's design thinking process during the co-creative sketching session. Finally, we will conduct a new design experiment that uses statistical measures such as chi-squared with more participants to establish the statistical significance of the results.

## 8.1 Limitations

One limitation of the current CSP user study is having a different number of instances for each phase, which makes it difficult to establish a relationship between different cognitive models of creativity and degrees of similarity. The second limitation of the current approach is the inability of the AI agent to respond with a highly similar sketch with respect to the user's input when the system is in the high similarity condition. This occurs because the sketches produced by the designers are highly detailed and contain a high number of pen strokes, whereas the sketches from the QD dataset are abstract images with a low number of strokes. The final limitation of the current study is the qualitative nature of the current study and the lack of quantitative results.

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