ExquiMo: An Exquisite Corpse Tool for Co-creative 3D Shape Modeling

by

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Abstract

We introduce a shape modeling tool, ExquiMo, which is guided by the idea of improving the creativity of 3D shape designs through collaboration. Inspired by the game of Exquisite Corpse, our tool allocates distinct parts of a shape to multiple players who model the assigned parts in a sequence. Our approach is motivated by the understanding that effective surprise leads to creative outcomes. Hence, to maintain the surprise factor of the output, we conceal the previously modeled parts from the most recent player. Part designs from individual players are fused together to produce an often unexpected, hence creative, end result. We demonstrate the effectiveness of collaborative modeling for both man-made and natural shapes. Our results show that, when compared to models designed by individual users, multi-user collaborative modeling via ExquiMo tends to lead to more creative designs in terms of the most common criteria used to identify creative artifacts.

Keywords: 3D Shape Modeling; Creative Design; Human Computer Interaction

To my parents, my sister, and the rest of the creative souls out there...

Acknowledgements

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Chapter 1

Introduction

*"The generation of really new ideas is in the depths of human nature... It is
deep in the ground. You have to struggle to get at it through surface layers"*

- Abraham Maslow, *Emotional blocks to creativity*

Creativity is a wonder of the brain. It broadens the human imagination, thereby spawning innovations ranging from surreal paintings to unheard melodies. Due to the competitive edge it provides, the interest for promoting creativity within leading organizations, product markets, and academia is rapidly growing. Hence, there is an increasing need to stimulate human creativity through computational means such as Creativity Support Tools [48].

In the field of computer graphics, with the predicted ubiquity of virtual reality, game development, and 3D printing applications [34], the demand for compelling 3D content is rapidly growing. Casual users are willing to create their own compelling designs without having to gain expertise in 3D modeling. However, standard shape modeling tools such as AutoCAD require some level of training due to their complexities. A novice user may find it difficult to model a shape from its geometric primitives and low level editing operations, which may also affect the quality of the end design. As a result, the tools that allow even the most inexperienced users to build their own creative three-dimensional content are gaining more attention.

Focusing on this aspect, the most recent advancements in modeling software have attempted to make the shape creation and modeling process a pleasant experience for both novice and expert users alike. Most of such tools focus on utilizing existing models to reduce the complexity of modeling from the scratch [1]. Combining parts from multiple existing shapes extracted from current repositories, or blending existing models together have become the state-of-the-art in modern computer-aided design tools. However, in the context of achieving higher levels of creativity, deriving inspiration from existing content may not be the optimal solution, as it only relies on the tool's ability to find the most interesting combination, without exploiting the creativity of the human user.

Although the idea of computational support to enhance creativity is not completely new to computer graphics, only a handful of attempts have been made to develop creativity support tools to stimulate human creativity [9]. Inspired modeling methods such as explorative modeling [36], example-driven synthesis [9], and evolutionary design [59] have attempted to develop computational tools to assist creative design. However, the creativity level of the output produced by these inspired-modeling approaches is limited.

To address the limitations of the existing tools, it is important to understand what *creativity* is. Although there is no commonly agreed definition, creativity can be considered as "the ability to come up with ideas or artifacts that are new, surprising, and valuable" [5]. On a related note, Jerome Bruner [6] terms effective surprise as the hallmark of a creative enterprise. Oftentimes, the output produced by the inspired modeling methods resembles the models taken as inspirations; hence limiting the effective surprise. Our approach to creative modeling builds upon the idea that *collaboration* plays an important role in providing the "effective surprise" for a creative endeavor [43].

1.1 Overview of our approach

In this thesis, we introduce the idea of *co-creativity* for 3D shape modeling, with the goal of producing effectively surprising geometric forms. Co-creativity is guided by the collaboration of multiple individuals who contribute to a creative endeavor [14]. During this collaboration, ideas from each individual are fused together to produce unexpected results [14]. Our realization of co-creative modeling is inspired by the tabletop game "Exquisite Corpse" [20], which exploits human collaboration to produce a creative sketch or poem. In an Exquisite Corpse game, each player draws a particular part of a sketch in sequence, such that previous drawings are concealed from the current player to stimulate unexpectedness of the final outcome. However, a sufficient level of coherence should be maintained between each drawing. Hence, the overall goal is conveyed to all the players at the beginning of the game, e.g., the category of the object drawn, and vague hints of others' drawings may be revealed to the current player.

1.2 Contributions

Our main contribution is the development of *ExquiMo*, an Exquisite Corpse tool for co-creative 3D shape modeling. The tool draws inspiration from an Exquisite Corpse gameplay which provides the potential to contribute to the unexpected, interesting, and uncommon attributes [5] of the end design, which in-turn leads to creative geometric forms. A sketch-based modeling paradigm is used to enable casual users to participate in the gameplay. We demonstrate the creative potential enabled by ExquiMo with visual examples of man-made
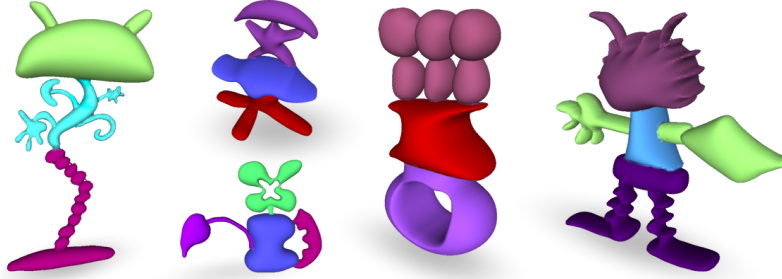
Figure 1.1: Collaboratively designed 3D shapes via ExquiMo, our modeling tool inspired by the Exquisite Corpse game, exhibiting an appreciable level of creativity. Different colors in each shape correspond to parts designed by different users.

and organic 3D shapes produced through collaborative efforts between multiple players (Figure 1.1).

Furthermore, we provide a comprehensive evaluation of our approach through a user study that is conducted to compare shapes designed by single users to shapes designed collaboratively by multiple users. Under both scenarios, the users completed their designs using ExquiMo and they were provided with the same instructions and goals for the design: to be creative while ensuring that the produced final object would function as expected. For the comparison, a different set of users were asked to judge the creativity of the final designs while keeping in mind their functionality. We further demonstrate the results of the user study which are supportive of our hypothesis that multi-user collaborative 3D modeling via ExquiMo tends to lead to more creative designs.

1.3 Organization

This thesis is organized as follows. In chapter 2, we survey the most closely related work in the domains of 3D shape modeling and computer-assisted creativity. In chapter 3, we introduce our tool (ExquiMo) which draws inspiration from a table-top game to enhance the creativity of non-expert users. In chapter 4, we provide a comprehensive evaluation of our tool's ability to enhance the interestingness of the 3D shape designs with respect to the concepts in creativity and cognition. We conclude our thesis in chapter 5, and introduce possible avenues for future work.

Chapter 2

Background and Related Work

> *"They create or they seek to create, and this in itself endows the process with dignity."*
>
> - Jerome Bruner, *On Knowing: Essays for the Left Hand*

In this chapter, we first outline the common theories of creativity to provide a general idea of a creative process. Then we provide an introduction to creativity in 3D shape modeling, and survey existing techniques that attempt to stimulate or inspire creativity in both domains of general artistic design and 3D shape design. We discuss these techniques under two main categories; *creativity support tools*, in which computational tools are merely a guidance to the user to achieve creativity, and *generative systems*, in which the computational tools are creative by themselves. Finally, we provide an introduction to the idea of collaboration as a means of stimulating creativity, and survey current techniques that utilize this idea to achieve creativity in design.

2.1 Creativity in design

Prior to building tools that stimulate, support, or produce creative geometric forms, it is vital to understand the general criteria for creativity and how creative ideas are formed. In the following sections, we present common theories of creativity, provide criteria to identify a creative idea or a product, describe creative processes, and provide an introduction to creativity in the domain of shape modeling and design. The theories and criteria presented in the following sections are used in chapter 4 as evaluation criteria for our tool.

2.1.1 Theories of creativity

The notion of creativity is intuitive to humans. Although a generally agreed definition for creativity has not been established in the literature to the best of our knowledge, in the field of cognitive science and artificial intelligence, different opinions have been discussed

on the general criteria to identify creativity [27, 54, 5].

Combination of ideas. One of the most prominent understandings of creativity is the *combination* of existing information in an unfamiliar manner. "Creativity, it has been said, consists largely of rearranging what we know in order to find out what we do not know", argues Kneller [30]. In one study that introduces five stages of ideation [61], creative ideas are referred to as "nothing more less than a combination of the old". Such combinations can be either intentional or unintentional; however they should be less probable, and the final output should "make sense" [5]. In order to combine ideas, there should be a rich knowledge base, and a process that helps making the combinations.

Conceptual spaces. Boden identifies conceptual spaces as "structured styles of thought" [5], which is merely a *way of thinking* that is valued within a particular social group. For example, different artistic styles, scientific theories, recipes, or color palettes can be considered a conceptual space, within which a person can come up with a new idea by *exploring* this space. Depending on the size of the space, a large number of ways to explore the space may exist, however it will be finite and would enable the creators to see new possibilities they had not seen before. This conceptual space can be *transformed* by altering the existing knowledge, which may cause a change in the style of thinking, leading to highly surprising or impossible ideas. Hence, the transformation helps generating new possibilities that would not have been possible in the untransformed space.

Input and output creativity. By its definition, "input creativity involves the analysis of incoming data, whereas output creativity involves the production of something new" [41]. Input creativity is used when solving an existing problem, whereas output creativity helps devising new problems or ideas. Hence, the more interesting type from the two is the output creativity. However, input creativity is essential to account for the role of evaluation, sensibility, and aesthetic judgment [60] of output creativity.

Exploration and exploitation. In the context of adaptive learning, exploration, as introduced by March [35], refers to learning and innovation (i.e., explore new possibilities), and exploitation refers to the use of past knowledge. Exploring involves searching, creating, and discovering new ideas and innovations. Exploitation involves refining, applying and using existing knowledge. Albeit the differences between the two ideas, March [35] argues the essentiality of both exploration and exploitation, hence gaining a balance between the two concepts.

2.1.2 Creativity criteria

In the artistic domain, some ideas may be considered merely new, while some ideas are more than new; they are creative. Hence a question arises as to "what factors determine the creativity?" Among the many theories of creativity, common criteria can be found which have been widely accepted in the cognitive science community. One such theory identifies creativity as the ability to produce work that is both "novel" (i.e., original, unexpected) and appropriate (i.e. useful) [53]. Boden's view of creativity presents three criteria to identify a creative idea or an artifact: *novel*, *surprising*, and *valuable*. In this section, we discuss these three criteria in detail.

Novelty. The first criterion commonly discussed in the literature is *novelty* or *originality*. Originality and creativity go hand in hand. Harding's view of originality depends on "new and striking combinations of ideas" [22]. Any act, idea, or product that changes an existing domain is defined as creativity by Csikszentmihalyi [13], where the *novelty* is highlighted as an important factor. In one of the works by Koestler, *originality* was identified as a factor in creativity, and four metrics for originality are presented as, *1)* bisociation, *2)* activation of potentials, *3)* flexibility, and *4)* novelty.

However, an idea or an artifact that is new to the creator, may not be universally novel. For example, a student who does not have any domain knowledge may come up with an idea that has been already introduced to that domain. The concept of P-creativity and H-creativity are introduced by Boden [5] to distinguish between these two types of creativity. P-creativity is to come up with an idea that is new, valuable and surprising to the person who comes up with it, whereas H-creativity involves ideas that no one else has ever thought of before. H-creativity is in this sense a special case of P-creativity, which provides better contributions to the domain in which the ideas are initiated.

Surprise factor. The second criterion that is highlighted as a contributing factor to creativity in many of the early studies in cognitive science is the *element of surprise* [30, 5]. Depending on the context or the output, unpredictability or the element of surprise has been given three different meanings in the literature [5]. Firstly, *unfamiliarity* may contribute to the surprise factor, where the idea is unlikely to occur, hence not familiar. Secondly, the surprise factor may occur due to the *unexpectedness* it brings. The idea may not be unfamiliar (i.e., it fits into the general familiar style), however it has not been realized before. The third kind of surprise may occur due to the *astonishment* caused by an impossible idea. All three different types of surprise can be utilized when building tools to enhance human creativity.

Value. The third, less common, criterion used to identify a creative idea or a product is the *value* of the output. Robert Weisberg [57], for instance, introduces a creative work as "a novel product of *value*". The term "value" is used to represent something useful, beneficial, or profitable. However, the aesthetic value of a novel creation may be difficult to recognize or to state clearly. The value of an idea or a product changes across cultures, domain and within peer groups [5]. However, if the value is properly defined, a creation without value will not make sense.

2.1.3   The creative process

A creative process transforms input raw material (i.e. knowledge, experience, data) into a creative output [39]. Hence, a creative process can be considered as the thought process that results in a creative idea. According to the multiple theories of creativity that were discussed, this thought process involves exploring existing information and making novel combinations to solve a particular problem [5, 37]. A creative mind can re-organize the existing information and combine them in previously unknown manners. Therefore, any techniques to assist creativity should provide relevant triggers during the creative process to provide new ways of combining existing items, which, according to Sternberg [53] provides a "combinatorial leap" [39].

2.2   Creativity in shape modeling

Due to the ubiquity of applications that use 3D graphics, effective geometric modeling techniques to generate creative content have gained much attention. Many interactive geometric modeling tools have been developed with a motivation of enabling non-expert users to create 3D models efficiently. In the domain of computer graphics, creativity involves designing new models that are both surprising or unexpected [12] and valuable [5] to the modeler. Similar to other domains, two types of computational tools exist to ensure creativity of the output designs. The first kind is *generative systems*. Shape modeling tools belonging to this category are thriving to achieve creativity levels comparable to humans [12] during the shape design and modeling process. These tools attempt to be creative by themselves without having any human assistance. The second kind belongs to the category of creativity support [48], which is less ambitious than generative systems. The tools under this category are not necessarily self-creative, however they are capable of enhancing or stimulating human creativity. In the following sections, we survey existing methods in both geometric modeling domain and in the general artistic domain under these two categories.

2.2.1 Generative systems

One of the possible approaches to computational creativity is a generative system, a term used to identify computational tools that automatically generate novel, surprising and valuable ideas or products [12]. A starting point may be provided to the tool which can go beyond the mere possibilities of combining and exploring the conceptual space. Autonomous creativity, as termed in some domains, is more prominent in artistic domains such as music and art [3]. One of the pioneering work is the art-creating program AARON [11]. Recent adaptations to machine learning and evolutionary computing approaches have been helpful in creating such autonomous systems [46], although they are not advanced enough to be compared to human creativity. In the shape modeling and design domain, few tools have been introduced that self-generate novel three-dimensional shapes. In the following, we survey the existing tools under two common categories: *shape synthesis* and *evolutionary design*.

Shape synthesis. When building large repositories of 3D models, it is helpful to use data-driven approaches, such as probabilistic models [8, 28] or template-based learning approaches [29] to synthesize novel shapes. A starting point is given in the form of three-dimensional shapes, and computational models are applied on the input to generate novel content. Novelty here refers to producing shapes that are, up to some extent, different from the query shapes topologically or geometrically. Nevertheless, it does not directly target "creativity", which is the focus on our pursuit.

Evolutionary design. Early works by Karl Sims [51] apply evolutionary computing to produce novel virtual creatures with some desired functionality. Input shapes are evolved in batches, and a fitness function is provided to evaluate the output. Several follow-up works [10, 59] in computer graphics have applied similar concepts to synthesize a set of "fit and diverse" shapes. Here, the focus on "diversity" attempts to stimulate creativity. In our work, we achieve creativity in shape modeling by combining the ideas of multiple users. The fitness or the functional plausibility is achieved by defining an end goal that encourages a coherent end result. Although the tool itself is creative, the creativity of the modeler is not considered in any of the generative systems.

2.2.2 Creativity support tools

The term *Creativity Support Tools* (CSTs) has gained much attention over the past few years as the domains in which such tools are used have expanded. The goal of creativity support tools is to empower users to be innovative [49] by stimulating the idea generation process. According to the theories presented in the preceding sections, creativity support tools can enable combination, exploration and transformation of conceptual spaces, and at

the same time guide the user to achieve novel, surprising and valuable content. An example of creativity support is visualization tools that present existing domain knowledge to the user who can explore, combine, or transform this space to discover valuable information. Creativity support tools are arguably the most prominent kind in the domain of creative shape modeling and design. In this sub-section, we survey the computational tools in 3D shape modeling which can be identified as "creativity support" under 3 main categories.

Part-based modeling One of the predominant modeling paradigms, part-based modeling [18, 31], allows a novice user to combine a set of parts taken from an existing shape repository to produce a new geometric form. Such tools facilitate the *exploration* of the conceptual space (i.e., existing parts of 3D shapes), and helps user in making interesting combinations. However, these tools may not allow the user to transform the design space, which may limit the new possibilities.

Data-driven modeling Recent work by Chaudhuri, et al. [9] is the first of its kind that uses the term *creative modeling*. Their 3D modeling tool provides data-driven suggestions for suitable shape parts to the users so as to "stimulate" their creativity. With all the data-driven techniques, the conceptual design of the shapes comes from the user [18] or is possibly stimulated by machine suggestions [9], yet the parts themselves are obtained from existing models, limiting the imaginative capabilities of the users.

Shape blending. Another possible approach to creating novel shapes from a given set of geometrically and topologically varying query shapes is via blending [2, 25]. The blending could be controlled by a user [25], or the user can select the desired shapes from the resulting set [2]. A more recent work [63] introduces a low-dimensional procedural model for an object category to facilitate exploring the space of novel shapes by varying different parameters. More relevant to our work is the recent attempt to automatically design Zoomorphic shapes through deforming and merging a man-made object and an animal model to suggest unusual, yet viable, designs to the user [15]. The above methods focus on exploring the conceptual space, whereas more focus should be given for the transformation that allows the user to discover more possibilities that leads to more creative designs.

2.3   Collaborative design

Collaboration is one of the influencing factors for creativity [42]. During a creative process, ideas can be formed by collaboration, which stimulates novel combinations, or triggers the transformation of the conceptual space [5]. Collaborating towards a creative outcome is termed as "co-creation", which brings several individuals together to jointly produce a

creative output [12]. Our work identifies collaboration as a means of stimulating, supporting, or inspiring the thought process for increased creativity.

To the best of our knowledge, our work is the first to introduce collaboration into the geometric modeling domain. However, the idea of collaboration is unintentionally used by some previous work through crowd-sourcing methods. PicBreeder [46] and EndlessForms [10], are two applications that provide multiple users to collaborate (or contribute) in generating novel images and 3D shapes by evolving a set of shapes produced by other users. In the work of Talton, et al. [56], the modeling activity of individual users can be learned as a distribution to construct high-quality alternative 3D models through exploring in a space of various models [56]. Although these systems offer collaborative environments, the users can only interact with already generated shapes. Conversely, we concentrate on providing the participants with more control on what they desire to create.

Interestingly, in the domain of human computer interaction, a number of methods have been developed to incorporate a machine as a colleague for collaborative design. Davis et al. [14] introduce Drawing Apprentice, a co-creative agent which co-operates with users in real-time on abstract drawings. We apply a similar concept into the geometric modeling domain. In contrast to their tool, the collaboration is performed between multiple human users in our approach and involving a computer partner in the framework is left for future work.

2.4   Discussion

In our work, we are interested in exploring how human creativity can be supported by the underlying modeling tool. Although the works discussed under this section facilitate some levels of creativity, most of the existing works in the shape modeling and design domain do not explicitly target the creativity of the output shapes; hence the domain of creative modeling is relatively unexplored. One of the few works on creative shape modeling comes from evolutionary computing [51, 59] as discussed under generative systems. However, to the best of our knowledge, none of the previous works exploit co-creativity to model creative and functionally plausible shapes. In the upcoming chapters, we present our collaborative shape modeling tool, ExquiMo, which is designed to support creativity of the modeler according to the many theories and criteria for creativity which were discussed in this chapter.

Chapter 3

Co-Creative Shape Modeling

"Ideas rose in crowds; I felt them collide until pairs interlocked so to speak, making a stable combination."

- Henri Poincaré, *The Foundations of Science*

In this chapter, we introduce our shape modeling tool, ExquiMo, which draws inspiration from collaborative design to support creativity. First, we discuss the idea of collaboration and its association to creativity. Next we introduce the game of Exquisite Corpse which harnesses collaboration to design creative art. Then we describe the implementation details of ExquiMo including the high-level design pipeline and the underlying sketch-based modeling paradigm used. Finally, we present the output designs collaboratively modeled with ExquiMo, which are evaluated in detail in the succeeding chapters.

3.1   Creativity and collaboration

As described in chapter 2, during a creative process creativity can arise through novel combinations of concepts [5]. However, these novel combinations should provide an *element of surprise* and be of value at the same time. Jerome Bruner, for instance, terms this "effective surprise" as "the hallmark of a creative enterprise" [7]. One possible technique of incorporating the surprise factor is to facilitate collaboration among a group of people [43] who are either experts or non-experts in a particular domain. Collaboration can jointly produce an outcome that is both surprising and mutually valued [12]. Our tool, ExquiMo, is inspired by the idea that collaboration can facilitate creativity during the 3D shape modeling process. One approach used in the domain of human-computer interaction to inherently support collaboration during a creative process is *collaborative games*.

3.1.1 Collaborative games

Games are means of providing enjoyable experiences to the players, at the same time making players work towards a common goal. In both cognitive science and human computer interaction domains, games have been introduced as a means of increasing creativity of the players [60], enhancing their thinking patterns [19, 17], making mundane and tedious tasks more enjoyable [16], and to support several other cognitive processes [44]. These games generally follow a set of rules, including the manner in which the game proceeds, and a set of constraints that comply with the original goal of the game. Following the lead of the previous works on game-based tools for creativity support [60], our collaborative modeling tool draws inspiration from the tabletop game "Exquisite Corpse" [20] to facilitate human collaboration with a goal of producing a creative sketch-based design.

3.2 Shape modeling via Exquisite Corpse

In this section, we provide an overview of the Exquisite Corpse (EC) game-play, and we describe in detail the design and implementation of ExquiMo which draws inspiration from the game of EC for the task of collaborative modeling of 3D shapes.

3.2.1 The game of Exquisite Corpse

"Exquisite Corpse" [52] is a multi-player game that showcases collective creativity by producing an extremely creative end result [20], let it be a poem, a drawing (see Figure 3.1), or a prose. In the poetic domain, the game proceeds as follows. First, an image of a scenario is shown to all the participants. The first player writes the first verse about the scenery in a piece of paper, and passes it on to the next player in line. All the players can only view the last word of the verse written by their predecessors, which ensures unexpectedness of each input. The lines of the poem are written in a sequence so that, once all the players have contributed, the end result would be a complete poem. The creativity of each person, and the fact that they are unaware of the input of the other players, contribute to the humorous juxtapositions, hence creative end results.

We follow a similar technique to Exquisite Corpse when modeling a 3D shape in parts as a collaboration between two or more players, while ensuring that the end result is creative and functionally coherent.

3.2.2 Design and implementation

Our shape modeling tool follows the rules and constraints imposed during an Exquisite Corpse game-play, and adapts them to fit the shape modeling process (see the design pipeline provided in Figure 3.3). The underlying shape modeling process should enable

Figure 3.1: Three interesting sketches produced by the 2D Exquisite Corpse drawing game.
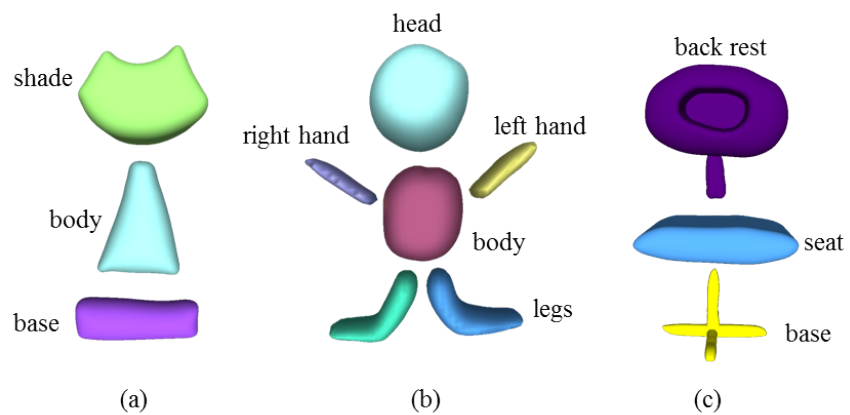
Figure 3.2: Examples of predefined shape templates, (a) a lamp, (b) a creature, and (c) a swivel chair.

even the most inexperienced users to collaborate during the game-play. Hence, a sketch-based modeling approach is used as the underlying modeling paradigm when designing ExquiMo.

End goal definition. Analogous to showing an image containing a scenario in an Exquisite Corpse game-play, we first define an end goal to encourage a certain level of coherence between the users (Figure 3.3(a)). The goal can be the exact type of a chair (e.g., a swivel chair), a shape category (e.g., an animal), or an abstract shape (e.g., an upright shape with 3 parts). The number of players required to draw one shape is predefined and varies according to each shape category.

Part allocation. For each shape category, we predefine a template that provides a placeholder for each member from the set of semantic components that compose a given shape. An example of a template is given in Figure 3.2(a), where the lamp is decomposed into three semantic parts - the shade, body, and base. When a target has been selected, we retrieve its template and players are each allocated one part therefrom; each player will then use the modeling tool to produce their assigned part, taking turns according to a predefined part insertion sequence (see Figure 3.3).

The modeling tool. Once each user is allocated a part, the game is started by the player who is allocated the first part. Each player draws a contour or a sketch of the allocated part during their turn, including the boundaries and less detailed interiors, which is immediately converted to 3D prior to switching players (Figure 3.3(b)). Since our goal is to encourage creativity while providing a simple tool that even novice players can use, we use ShapeShop [45] as the foundation for our modeling tool, and make modifications in order for it to fit to our collaborative modeling workflow (as described under the subsequent steps). ShapeShop provides a sketch-based, 2D interface that then applies CSG-based cutting and blending operations to produce interesting 3D shapes with arbitrary topology, hence aligning with our stated goal of creative modeling. Few of the operations provided by ShapeShop, which were utilized by our modeling tool, are shown in Figure 3.4.

Co-creative modeling. We term the use of collaboration in the shape modeling domain as *co-creative shape modeling*. When the first player draws the allocated part in 3D, our collaborative modeling tool provides an option to "change the user", which conceals the currently drawn parts from the next player (Figure 3.3(b)). This technique of hiding the current design from the players contributes to the surprise factor of the output shape. However, parts designed by different players may not align properly, resulting in implausible or non-functional shapes. Therefore, to encourage coherency, hints are provided in the form of small portions of the connecting regions of the adjacent parts, which are revealed to the

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Collaborative modeling stage

Spout   Handle
Body

Sequence 1: First player   Sequence 2: Second player   Sequence 3: Third player

(a) Part allocation   (b) Sequentially modeled spout (left), body (middle), and handle (right) of a teapot   (c) Final merged result
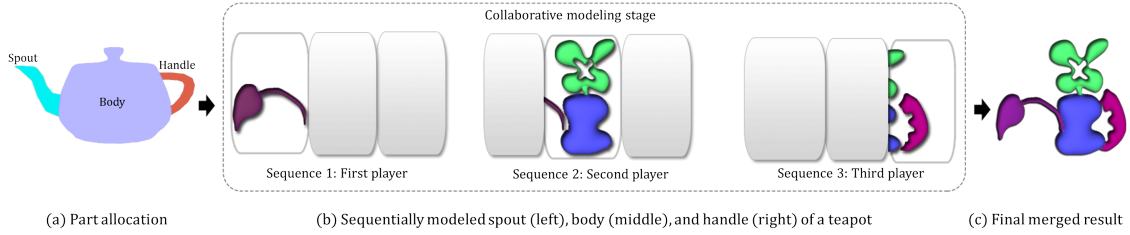
Figure 3.3: Design pipeline of ExquiMo. Initially, an object category is given and the parts are allocated to players (a). Sequentially, each player designs the allocated part in the form of a 2D sketch, which is then converted to a 3D part (b). Note that a player may receive a small hint for the previously designed part. Finally, the parts are translated, scaled, and merged to produce the final shape (c).
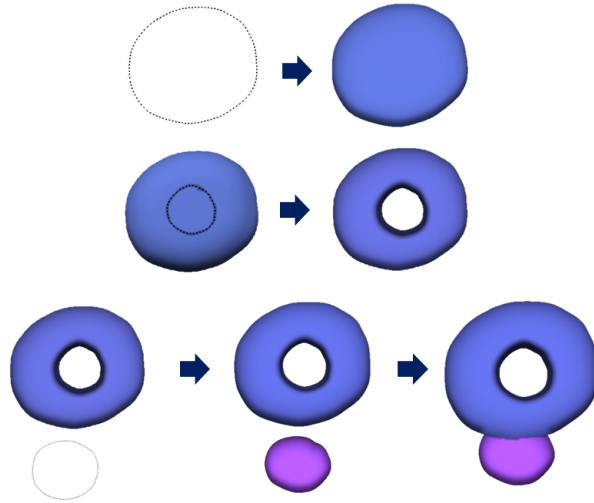
Figure 3.4: Three examples of the editing operators provided by ShapeShop that allows the players to model creative shapes. The operations are, from top to bottom in order, sketch to 3D conversion, CSG-based cutting, and part merging.

player when necessary. Each player can adjust the percentage of the adjacent part which is visible to them during the game-play.

Part merging. At the very end of the game, once all the players complete their turns in designing the corresponding parts, the entire shape is unveiled, and a merge operation is performed by the last player to fusion the parts together. This merge operation consists of two key steps: (i) proper *alignment* of the two parts to be merged, and (ii) *blending* the aligned parts into one complete shape [24]. During the alignment step, our tool simply aligns the reflection symmetry planes of the two parts. The 3D parts which were created from the scratch almost always have the reflectional symmetry property; hence alignment by symmetry planes between two adjoining parts is natural and ubiquitous. If the user deems that a further alignment is necessary, the system then allows the user to manually

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perform the alignment by means of simple translation, rotation, and scaling operations. When the parts are properly aligned, our tool utilizes the blending operations facilitated by ShapeShop, which implements parameterized Hyperblend [45] via a hierarchical BlobTree structure [58] to combine multiple parts into one shape.

The problem of part merging has been previously studied in the shape composition literature, such as the commonly used field based approaches [62, 24], part snapping [50] based on Soft-ICP registration [47], and boundary interpolation [33], those of which could be feasibly adapted by our work. However, owing to our focus on high-level creative modeling, as opposed to low-level part composition, we chose to implement a much simpler scheme as described.

3.3   Results

In this section, we present results obtained by co-creatively modeling 3D shapes using ExquiMo. Studies were conducted in two stages. In the first stage, we conducted experiments using a set of participants who utilized the tool for collaborative shape modeling. In the second stage, we conducted three user studies to evaluate the designs produced in the first stage, which are discussed in chapter 4.

Object categories. In the current work, as a proof of concept, we limit ourselves to seven object categories: teapots, lamps, vases, swivel chairs, perfume bottles, and watering cans as man-made shapes, and creatures as an organic shape category. These object categories were chosen due to their common usage in the literature [59, 21, 2], as well as the possibility of decomposing them into less than six parts. As future work, user studies can be conducted with more categories of shapes that require a larger number of players to collaborate during a single game-play. Note that creatures are the most frequently played forms in conventional Exquisite Corpse drawing games. For these target shape categories, we predefined a template consisting of three to five parts. The players are provided with the list of target categories to model, from which they make their selection.

Collaborative modeling. During the first stage of our study, we conducted experiments with 10 participants, who were asked to play the game of Exquisite Corpse in 3D using our collaborative modeling tool ExquiMo. The participants are graduate students in computer science and engineering who had a negligible level of experience in design (i.e., novice users). We now discuss the process we followed when conducting the experiments.

First, all the participants were conveyed the purpose of the tool, and the rules of the game (as mentioned in Section 3.2). They were asked to be "as creative as possible" when drawing the shape parts. Second, the participants were asked to choose one of the predefined target shape categories. A sketch (i.e. an outline) of an abstract shape belonging to
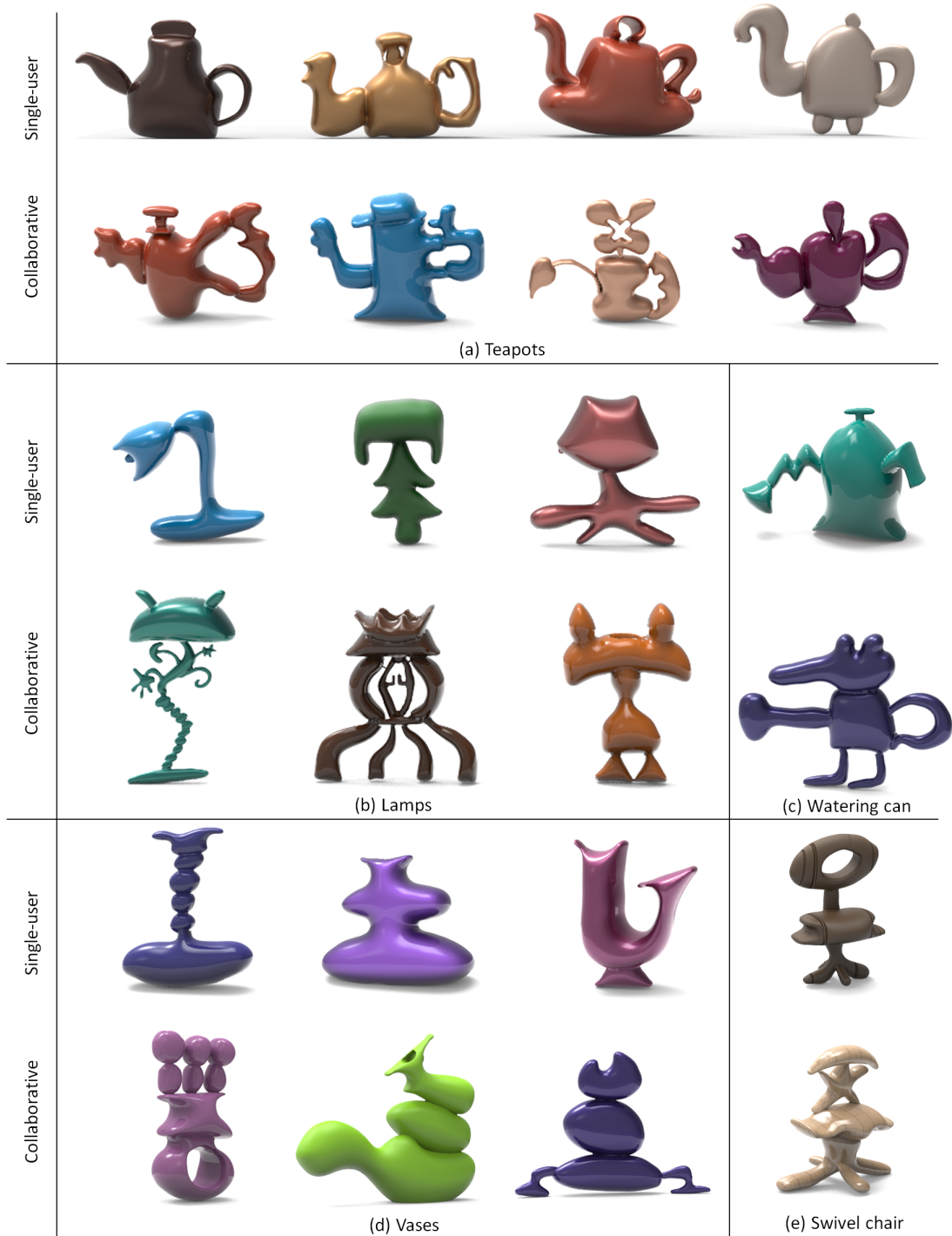
Figure 3.5: A sample of the shape categories modeled by a single user (top row), and multiple users (bottom row) using our tool, ExquiMo. Collaboratively modeled shapes were voted as "more creative, while remaining functional" by the participants of the user study.
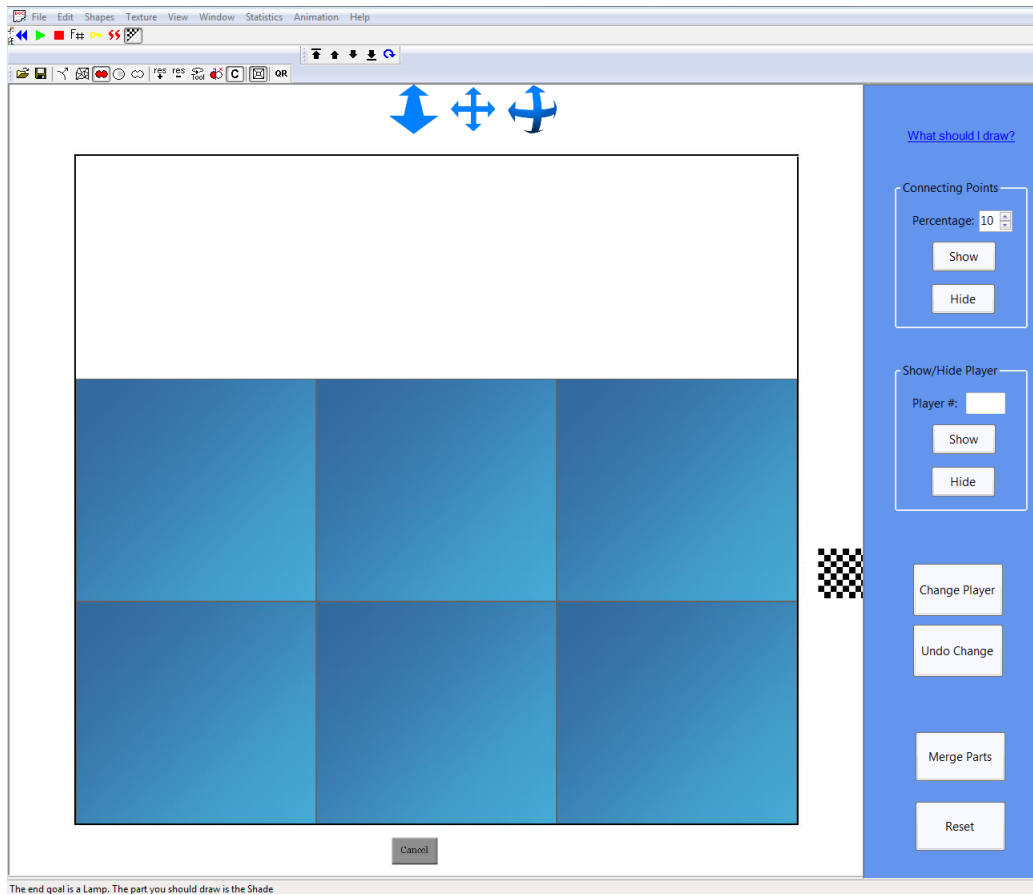
Figure 3.6: The user interface of our collaborative modeling tool ExquiMo.

the same shape category, with already labeled parts, is shown to all the players to avoid any confusion; see Figure 3.3(a). As the third step, each user was asked to *individually* model a shape from the selected category using the modeling tool, which was later utilized as the "single-user" design in our second stage. Finally, the players were asked to *collaboratively* model a shape for the selected category using our tool (see Figure 3.6). When merged, the resulting shape displayed a significant level of creativity (Figure 1.1 and Figure 3.5).

Platform and timing. Our tool can be controlled by touch-enabled devices, providing easy interaction to novice users. However, in a situation where a significant level of unease was detected with the tool, the participant was asked to sketch their idea on paper prior to drawing on the computer screen, so that the imaginative capabilities of the user would not have been hindered by the unfamiliarity with the tool. During the modeling process, each player took at most 10 minutes to draw the allocated part, leading to a total game time of 35 minutes on average.

Chapter 4

Evaluation

In this chapter, we comprehensively evaluate the output of our collaborative shape modeling tool, ExquiMo, according to the creativity criteria presented in chapter 2. We have conducted 3 separate user studies in the form of questionnaires to acquire human judgment on the level of creativity exhibited by the models produced using our tool. First we discuss the questions we are hoping to answer with the user studies, second we present the methodology we followed to conduct the studies. Finally, we summarize the results of the 3 questionnaires and discuss their implications.

4.1 Research questions

The goal of the user studies conducted is to evaluate the creativity of the models designed with ExquiMo. We formed the following research questions which were tested during the user studies to validate the usefulness of our tool in terms of creativity support.

1. According to the intuitive notion of creativity, is our collaborative modeling platform (ExquiMo) effective in *improving* the creativity of the output designs?

2. Are the three criteria for creativity (as discussed in chapter 2) met in the output of ExquiMo?

3. Do the design constraints imposed on the user affect the creativity of the output of ExquiMo?

Addressing the first research question, we hypothesize that our collaborative modeling tool is effective in improving the creativity of shape designs. To answer the second research question related to the three creativity criteria, we form the following four alternative hypotheses.

- H_1: Collaborative designs are relatively more *novel* than single-user designs.

- H_2: Collaborative designs are relatively more *surprising* than single-user designs.

- H_3: Collaborative designs are relatively more *valuable* than single-user designs.

- H_4: Single-user designs are relatively more *functional* than collaborative designs.

We set the following three alternative hypotheses to answer the third research question.

- H_5: Constrained designs (i.e. designs created under constrained conditions) are relatively more *novel* than unconstrained designs (i.e. designs created without constrained conditions).

- H_6: Constrained designs are relatively more *surprising* than unconstrained designs.

- H_7: Constrained designs are relatively more *valuable* than unconstrained designs.

In the following sections, we present the methodology we used to test the hypotheses, followed by a discussion based on the results.

4.2 Methodology

Three user studies were conducted in the form of questionnaires in the following format.

- First study: For each shape category, compare pairs to identify the more creative shapes.

- Second study: Rank each shape according to the level of creativity.

- Third study: Compare and rate the designs using an ordinal scale.

Each questionnaire lasted approximately 15 minutes, and contained two types of questions: quantitative and qualitative. A maximum time of 15 minutes was allocated to complete each questionnaire.

4.2.1 Participants

First and second user studies were completed by 39 participants each, majority of which come from a computer science or engineering background, while a minority was from non-technical disciplines. The third user study was completed by 42 participants who were acquired on the Amazon Mechanical Turk platform [40]. Users were not restricted based on demographic factors, and the acquired users represented different geographical regions; hence, essentially, different cultures.

4.2.2 First study

We designed the first user study to test whether our collaborative modeling tool is effective in improving the creativity of shape designs. The questionnaire consisted of three parts. In each part, the user was presented with a pair of shapes, where one shape was modeled by an individual user, and the other was modeled by a collaborative effort. The pairs shown were randomly shuffled to avoid any biases. In the first part of the questionnaire, the user was asked to select "the design that is more creative", given the category of the shape. At the same time, to identify the factors that deem an object creative to humans, we asked the user to reason out his/her choice. Terms or keywords were not provided during the questionnaire, so as not to limit an individual's definition of creativity. The second part required the user to choose "the design that is more functional", along with qualitative feedback to specify the reason for their choice. The third part focused on both creativity and functionality together, where the user was asked to select "the design that is more creative, while remaining functional". The shape designs shown to the user are included in Figure 3.5, and the pairing of both collaborative and single-user designs corresponds to the pairing of the questionnaire.

4.2.3 Second study

The second user study was designed to identify the designs produced by our tool that appear most *creative while remaining functional* to the user. In the questionnaire, the user was presented with 6 to 8 shapes from one shape category, where half of the shapes presented were modeled individually, while the other half were modeled collaboratively. The users were asked to select "the top three shapes (in order) that are creative, while remaining functional". Four shape categories were presented in the questionnaire, namely teapots, monsters, lamps, and vases, all of which were drawn from the shapes given in Figure 3.5.

4.2.4 Third study

The third questionnaire was designed to find out whether the output produced by our tool meets the creativity criteria discussed in chapter 2, and to explore the factors that contribute to the *effective surprise*. With regards to the three criteria, the study also focuses on testing whether the constraints imposed during the game affect the creativity of the output.

The three criteria used to identify a creative idea or an artifact (as introduced by Boden [5]) are: *novelty*, *surprise factor*, and *value*. Additionally, we also attempt to identify whether the the output shapes appear *functional* to the participants. The surprise factor can be one of three forms: *unfamiliar*, *interesting*, or *astonishing*. The definitions of the terms provided to the participants during the study are taken from the literature [4, 23, 5], and are given in Table 4.1. The shapes presented to the user during the user study are given in Figure 3.5 and Figure 4.1. The pairing of both collaborative and single-user designs, as

Table 4.1: The definitions of the terms [4, 23, 5] provided to the participants during the third questionnaire.

Term	Definition used
Novel	Completely new, and as far as you know, no similar design exists
Surprising	Unfamiliar, interesting or astonishing
Valuable	Useful, beneficial, or profitable
Functional	Capable of accomplishing the purpose of the object represented by the design
Unfamiliar	The design is not known to you before, or unrecognizable
Interesting	Captivates your attention, or arouses your curiosity
Astonishing	Extremely impressive
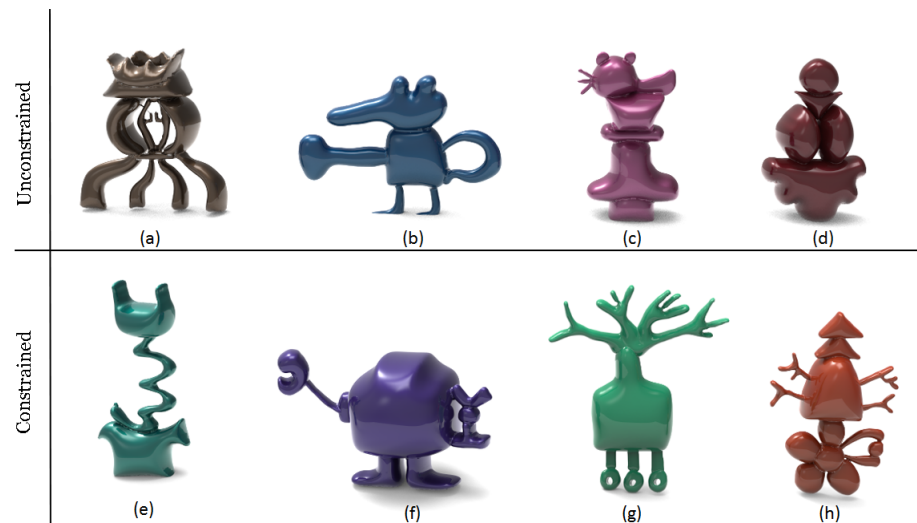
Figure 4.1: A sample of the shapes modeled under no constraints (top row), and with multiple constraints (bottom row) using our tool, ExquiMo.

well as constrained and unconstrained designs correspond to the pairing given in the questionnaire. A Likert scale was used in the questionnaire to avoid subjectivity towards the intuitive notions of creativity of each individual.

Likert scale. Likert scale [32] is an ordinal scale with 5 or 7 points [55]. The respondents were required to provide a rating according to the degree to which they agree or disagree with a statement given. During the third questionnaire, we asked the user to select the option that best represents how they feel about the designs given according to the criteria shown in Table 4.1. The five options available to the user were: *not at all*, *slightly*, *moderately*, *very*, and *extremely*.

The reasons behind our choice for a Likert scale are to minimize the subjectivity of the participants, and to provide them flexibility when choosing the designs that meet the creativity criteria. When a participant is asked to choose the "most creative design", they may have to make a choice between the two designs given in a pair. If the participant identifies both designs as creative, with one design slightly more creative than the other, Likert scale allows them to voice their opinion using the ordinal scale.

The meaning of an ordinal scale is that the order given in the options is relevant, however the options cannot be considered equi-distanced (i.e., the distance between "not at all" and "slightly" is not necessarily equal to the distance between "slightly" and "moderately"). Hence there is a strong disagreement in the literature regarding the summarization of results acquired from a Likert scale [38, 26]. For the statistical analysis of the results, non-parametric tests can be used [55]. The use of parametric tests or descriptive statistics, such as mean and standard deviation, has been recommended in the literature only if the following criteria are satisfied.

- Sample size (n) is greater than 30; or n<30 and the sampling distribution is normally distributed.

- At least 5 options are provided in the ordinal scale.

- No extreme scores are present.

- If n<30, the variance of the two samples being compared is approximately equal.

Even if the above criteria are not satisfied, the *median* has been proposed as the "measure of central tendency" [55] or, more commonly, the percentage agreement for each category.

Design constraints. Several design constraints were introduced to the users during the modeling process to observe the variation of creativity of the output designs. First, the end goal was restricted in all the cases, except for designs (c) and (g) depicted in Figure 4.1 , for which we asked the participants of the questionnaire to identify the shape represented by the design. The conflicting responses provided by the users confirms the need of an end goal that specifies the category of the shape being designed. Second, we constrained the appearance of the designs. For instance, one group of players were instructed to design animal-like parts (Figure 4.1 (f)), while another group was instructed to draw inspiration from "tree-like structures" (Figure 4.1 (h)).

4.3   Summary of findings

The findings of each user study are summarized in the following subsections.

Table 4.2: Statistics from the first questionnaire, which provide the percentage of votes received for all shape categories with respect to the level of collaboration. The three aspects considered for each shape pair were, creativity, functionality, and both creativity and functionality together.

Aspect	Single-user	Collaborative
Creativity	28.57%	71.43%
Functionality	64.89%	35.11%
Creative while functioning (C & F)	46.28%	53.72%

Table 4.3: Detailed statistics from the first questionnaire indicating the percentage of votes received for individually and collaboratively designed models belonging to each shape category.

Category	Aspect	Single-user	Collaborative
Lamp	Creativity	10.75%	89.25%
	Functionality	57.50%	42.50%
	C & F	39.24%	60.76%
Chair	Creativity	20.93%	79.07%
	Functionality	66.67%	33.33%
	C & F	41.03%	58.97%
Watering Can	Creativity	23.81%	76.19%
	Functionality	53.85%	46.15%
	C & F	27.91%	72.09%
Teapot	Creativity	25.19%	74.81%
	Functionality	76.92%	23.08%
	C & F	45.30%	54.70%
Creature	Creativity	38.17%	61.83%
	Functionality	53.85%	46.15%
	C & F	48.70%	51.30%
Vase	Creativity	44.32%	55.68%
	Functionality	75.64%	24.36%
	C & F	64.10%	35.90%

Table 4.4: Statistics from the second questionnaire, including the percentage of votes received for each shape category with respect to the level of collaboration.

Category	Single-user	Collaborative
Creature	28.89%	71.11%
Teapot	28.95%	71.05%
Lamp	34.21%	65.79%
Vase	57.89%	42.11%

4.3.1 Collaborative creativity

The statistics acquired from the first questionnaire (Table 4.2 and Table 4.3) show that the collaboratively modeled shape designs were found to be more "creative" by the users when compared to individually modeled shapes, over all the tested object categories. As depicted in Table 4.2, 71% of the participants chose the shapes designed by ExquiMo as more creative. The most common keywords collected from the qualitative feedback can be identified as the factors that humans used to determine the creativity of the given designs. Out of the five keywords extracted from the study, "unexpected", "less ordinary", "imaginative", "attractive", and "non-symmetrical" align with the idea of effective surprise addressed by our work. Whereas the keywords "complex" and "more detailed" which are extracted from the responses deviate towards the careful thought players have given to designing each part.

However, in the second part of the study, the collaboratively modeled shapes were not categorized as being more "functional" relative to the individually modeled shapes majority of the time. Feedback from the qualitative study reveals that the users tend to select a model designed by a single-user as more functional due to its resemblance to a common, more familiar design. Perhaps more importantly, the collaboratively designed shapes were selected as more "creative while remaining functional" by the majority of the users over all object categories except for the vases, hence revealing users' preference with the collaboratively created models overall. Vases have a relatively simpler design when compared to other shape categories. Participants of the study have reasoned out that the single-user designs for vases were "less complex", "practical", and "can stand properly on a surface". Hence they have given a preference to simplicity of the design, over creative, yet somewhat complex designs of vases, which may have been the cause for the higher percentage of votes received by the single-user designs under the vases category.

The statistics acquired from the second questionnaire (see Table 4.4) convey the participants' preference for collaboratively modeled designs in most shape categories. Moreover, out of the four shape categories presented to the user, the designs that received the most votes consist of collaboratively designed shapes, which are included in Figure 1.1. Af-

Table 4.5: Summary statistics for the third questionnaire indicating the p value obtained using the Mann-Whitney U test for each hypothesis given in section 4.1.

Hypothesis	p-value
H_1 (Novelty for collaborative vs. single-user designs)	9.64×10^{-7}
H_2 (Surprise factor for collaborative vs. single-user designs)	1.86×10^{-5}
H_3 (Value for collaborative vs. single-user designs)	0.62
H_4 (Functionality for collaborative vs. single-user designs)	1.4×10^{-4}
H_5 (Novelty for constrained vs. unconstrained designs)	0.09
H_6 (Surprise factor for constrained vs. unconstrained designs)	0.09
H_7 (Value for constrained vs. unconstrained designs)	0.77

ter combining the responses received from both studies, we conclude that our hypothesis is valid for the categories of shapes being tested; hence, the designs produced using our collaborative modeling tool is effective in improving creativity, while remaining functional compared to the designs produced by a single user.

4.3.2 Criteria for creativity and effective surprise

The summary of the results acquired from the third questionnaire is given in Tables 4.6, 4.7, 4.8, and 4.9. The results of the study supports the hypotheses related to novelty, surprise, and functionality (H_1, H_2, and H_3) of the collaborative designs. However, the results do not support our next three hypotheses (H_5, H_6, and H_7) which focus on the aspect that the constraints imposed by the tool increase the creativity of the output designs.

Detailed analysis. The second research question can be answered by validating the alternative hypotheses H_1 to H_4 (summary statistics are shown in Table 4.6 and Table 4.7). The median user ratings of single-user designs were compared with the collaborative designs for each creativity criteria. As the sample size $n > 30$, and follows an ordinal scale, the results were analyzed using the nonparametric Mann-Whitney U test. The statistics obtained (Table 4.5) suggest that the median user rating for novelty and surprise criteria of the collaborative designs are significantly higher than the single user designs, and the median user rating for the functional aspect of single-user designs is relatively higher than collaborative designs, supporting the alternative hypotheses H_1, H_2, and H_4 ($p < 0.001$, Mann-Whitney test). However, the statistics do not support the third alternative hypothesis (H_3) related to the third criteria (i.e., value), failing to reject the null hypothesis at $p < 0.05$ ($p = 0.62$, Mann-Whitney test).

Hypotheses H_5 to H_7 can be validated to answer the third research question: *does restrictions affect creativity?* The statistics obtained (Table 4.5, Table 4.8, and Table 4.9)

Table 4.6: Detailed statistics from the third questionnaire indicating the mean and the median for each criterion tested using the Likert scale for models designed collaboratively and by a single user.

Group	Criterion	Mean	Median
Collaborative	Novel	3.37	4.0
	Surprising	3.29	4.0
	Valuable	2.80	3.0
	Functional	3.00	3.0
Single-user	Novel	2.88	3.0
	Surprising	2.88	3.0
	Valuable	2.82	3.0
	Functional	3.38	4.0

Table 4.7: Detailed statistics from the third questionnaire indicating the mean and the median for each criterion tested using the Likert scale for models designed with and without constraints.

Group	Criterion	Mean	Median
Constrained	Novel	3.84	4.0
	Surprising	3.81	4.0
	Valuable	2.93	3.0
	Functional	2.90	3.0
Unconstrained	Novel	3.67	4.0
	Surprising	3.63	4.0
	Valuable	2.88	3.0
	Functional	2.93	3.0

Table 4.8: Detailed statistics from the third questionnaire indicating the mean and the median for each criterion related to the surprise factor tested using the Likert scale for models designed collaboratively and by a single user.

Group	Criterion	Mean	Median
	Unfamiliar	3.19	3.0
Collaborative	Interesting	3.22	3.0
	Astonishing	2.75	3.0
	Unfamiliar	2.62	2.0
Single-user	Interesting	2.85	3.0
	Astonishing	2.43	2.0

Table 4.9: Detailed statistics from the third questionnaire indicating the mean and the median for each criterion for the "surprise factor" tested using the Likert scale for models designed with and without constraints.

Group	Criterion	Mean	Median
	Unfamiliar	3.65	4.0
Constrained	Interesting	3.57	4.0
	Valuable	3.07	3.0
	Unfamiliar	3.52	4.0
Unconstrained	Interesting	3.52	4.0
	Astonishing	2.96	3.0

do not support the alternative hypotheses H_5 to H_7 failing to reject all the null hypotheses at $p < 0.05$. The p values obtained from Mann-Whitney U test for each hypothesis H_5, H_6, and H_7 are 0.09, 0.09, and 0.07 respectively. Hence, it cannot be concluded that the constraints imposed on the user affect the creativity of the output designs.

4.4   Discussion

The results obtained from the three questionnaires succinctly provides answers to our three research questions posed in this chapter. According to the first two questionnaires, a majority of the participants found collaboratively modeled shape designs more "creative", hence verifying that our collaborative modeling platform is effective in improving the creativity of the output designs. The third questionnaire compares the median value of the ratings received for designs modeled collaboratively and by an individual user, providing the insight that collaborative designs have a higher median value in the *novel* and *surprising* criteria, whereas collaborative designs have a lower median value for the *functional* aspect. This result answers the second research question by concluding that *novelty* and *surprise* criteria for creativity which are commonly discussed in the literature are successfully satisfied by the output of our tool. The third questionnaire also provides the insight that there is no significant difference in the level of creativity exhibited by shapes modeled under design constraints when compared to shapes modeled without any design constraints. Hence, we can conclude that the design constraints imposed by the tool do not necessarily affect the creativity of the output of our collaborative modeling tool.

Chapter 5

Conclusion and Future Work

In this thesis, we present a modeling tool, ExquiMo, which assists users in designing creative 3D shapes. We build upon the game of Exquisite Corpse, which is based on the idea of collaboration. It combines the creative capabilities of multiple players by allowing them to *co-creatively* design distinct parts of a given shape. We increase the unexpectedness of the end result by concealing the parts already being modeled, whereas the coherency is maintained by revealing small portions of any adjacent parts to the part being currently modeled.

We attempt to answer three main research questions related to co-creative shape modeling. From the key insights acquired by our user studies, we conclude that our collaborative modeling platform is effective in improving the creativity in terms of *novelty* and the *surprise* factor. We also conclude that the design constraints imposed on the user do not affect the creativity of the output of our collaborative modeling tool.

Limitations. As a proof of concept, our tool was tested with only six shape categories. When defining shape templates, the complexity of the shapes should be limited in order to guarantee that the given shape can be collaboratively modeled. Our tool is also limited by the underlying sketch-based modeling paradigm. Users tend to sketch complex designs, for example parts of the shapes that span in multiple directions. However, the conversion of such complex designs from 2D to 3D limits the efficiency and the effectiveness of our tool. The requirement for smooth and closed 2D contours [45] is another limitation faced during sketch to 3D conversion.

Future work. The approach we have introduced in this paper is a preliminary attempt to bring in collaborative design to the creative modeling domain. Hence, there are many potential areas to be explored when extending our modeling paradigm. First, our current rudimentary part merging scheme can certainly be improved with a more sophisticated state-of-the-art alignment and merging scheme, which may require less interaction from the

user. Furthermore, a more detailed analysis of shapes can be carried out as future work to identify the aspects of the models that define the designs as creative. Our work attempts to gain a certain level of functional stability by means of hints (i.e. connecting points). However, it may be helpful to study the impact of hints on both functional stability and creativity alike. It is also important to compare the effectiveness of parallel modeling, as opposed to the sequential modeling approach used during the collaborative modeling stage of ExquiMo. Finally, our work can be potentially improved to have an online community of players collaborating in real-time to design creative three-dimensional content via ExquiMo.

Bibliography

[1] Ibraheem Alhashim. *Topology-Varying Shape Matching and Modeling.* PhD thesis, Simon Fraser University, 2015.

[2] Ibraheem Alhashim, Honghua Li, Kai Xu, Junjie Cao, Rui Ma, and Hao Zhang. Topology-varying 3D shape creation via structural blending. *ACM Transactions on Graphics (TOG)*, 33(4):158–158, 2014.

[3] Kim Binsted. Machine humour: An implemented model of puns. 1996.

[4] Margaret Boden. Creativity and unpredictability. *Stanford Humanities Review*, 4(2):123–139, 1995.

[5] Margaret A Boden. *The creative mind: Myths and mechanisms.* Psychology Press, 2004.

[6] Jerome Seymour Bruner. *On knowing: Essays for the left hand.* Harvard University Press, eighth edition, 1979.

[7] Jerome Seymour Bruner. *On knowing: Essays for the left hand.* Harvard University Press, 1979.

[8] Siddhartha Chaudhuri, Evangelos Kalogerakis, Leonidas Guibas, and Vladlen Koltun. Probabilistic reasoning for assembly-based 3D modeling. In *ACM Transactions on Graphics (TOG)*, volume 30, pages 35–35. ACM, 2011.

[9] Siddhartha Chaudhuri and Vladlen Koltun. Data-driven suggestions for creativity support in 3D modeling. In *ACM Transactions on Graphics (TOG)*, volume 29, pages 183–183. ACM, 2010.

[10] Jeff Clune and Hod Lipson. Evolving 3D objects with a generative encoding inspired by developmental biology. *ACM SIGEVOlution*, 5(4):2–12, 2011.

[11] Harold Cohen. The further exploits of aaron, painter. *Stanford Humanities Review*, 4(2):141–158, 1995.

[12] Daniel Cohen-Or and Hao Zhang. From inspired modeling to creative modeling. *The Visual Computer*, 32(1):7–14, 2016.

[13] Mihaly Csikszentmihalyi. Flow and the psychology of discovery and invention. *New Yprk: Harper Collins*, 1996.

[14] Nicholas Davis, Chih-PIn Hsiao, Kunwar Yashraj Singh, Lisa Li, Sanat Moningi, and Brian Magerko. Drawing apprentice: An enactive co-creative agent for artistic collaboration. In *Proceedings of the 2015 ACM SIGCHI Conference on Creativity and Cognition*, pages 185–186, 2015.

[15] Noah Duncan, Lap-Fai Yu, Sai-Kit Yeung, and Demetri Terzopoulos. Zoomorphic design. *ACM Transactions on Graphics (TOG)*, 34(4):95–95, 2015.

[16] David R Flatla, Carl Gutwin, Lennart E Nacke, Scott Bateman, and Regan L Mandryk. Calibration games: making calibration tasks enjoyable by adding motivating game elements. In *Proceedings of the 24th annual ACM symposium on User interface software and technology*, pages 403–412. ACM, 2011.

[17] Harry E Foundalis. *PHAEACO: a cognitive architecture inspired by Bongard's problems*. PhD thesis, Indiana University, Bloomington, 2006.

[18] Thomas Funkhouser, Michael Kazhdan, Philip Shilane, Patrick Min, William Kiefer, Ayellet Tal, Szymon Rusinkiewicz, and David Dobkin. Modeling by example. *ACM Transactions on Graphics (TOG)*, 23(3):652–663, 2004.

[19] Martin Gardner. Playing new-eleusis, game that simulates search for truth. *Scientific American*, 237(4):18, 1977.

[20] Olivia Gude. Playing, creativity, possibility. *Art Education*, 63(2):25–25, 2010.

[21] Xuekun Guo, Juncong Lin, Kai Xu, and Xiaogang Jin. Creature grammar for creative modeling of 3D monsters. *Graphical Models*, 76(5):376–389, 2014.

[22] Rosamond EM Harding. *Anatomy of Inspiration*. Routledge, 2012.

[23] Ruizhen Hu, Chenyang Zhu, Oliver van Kaick, Ligang Liu, Ariel Shamir, and Hao Zhang. Interaction context (icon): towards a geometric functionality descriptor. *ACM Transactions on Graphics (TOG)*, 34(4):83, 2015.

[24] Hui Huang, Minglun Gong, Daniel Cohen-Or, Yaobin Ouyang, Fuwen Tan, and Hao Zhang. Field-guided registration for feature-conforming shape composition. *ACM Transactions on Graphics (TOG)*, 31(6):179–179, 2012.

[25] Arjun Jain, Thorsten Thormählen, Tobias Ritschel, and Hans-Peter Seidel. Exploring shape variations by 3D-model decomposition and part-based recombination. In *Computer Graphics Forum*, volume 31, pages 631–640. Wiley Online Library, 2012.

[26] Susan Jamieson et al. Likert scales: how to (ab) use them. *Medical education*, 38(12):1217–1218, 2004.

[27] Kyle E Jennings. Developing creativity: Artificial barriers in artificial intelligence. *Minds and Machines*, 20(4):489–501, 2010.

[28] Evangelos Kalogerakis, Siddhartha Chaudhuri, Daphne Koller, and Vladlen Koltun. A probabilistic model for component-based shape synthesis. *ACM Transactions on Graphics (TOG)*, 31(4):55–55, 2012.

[29] Vladimir G Kim, Wilmot Li, Niloy J Mitra, Siddhartha Chaudhuri, Stephen DiVerdi, and Thomas Funkhouser. Learning part-based templates from large collections of 3D shapes. *ACM Transactions on Graphics (TOG)*, 32(4):70–70, 2013.

[30] George Frederick Kneller. *The art and science of creativity.* Holt, Rinehart and Winston, 1965.

[31] V Kraevoy, D Julius, and A Sheffer. Shuffler: Modeling with interchangeable parts. *The Visual Computer*, 2007.

[32] Rensis Likert. A technique for the measurement of attitudes. *Archives of psychology*, 1932.

[33] Juncong Lin, Xiaogang Jin, Charlie CL Wang, and Kin-Chuen Hui. Mesh composition on models with arbitrary boundary topology. *IEEE Transactions on Visualization and Computer Graphics*, 14(3):653–665, 2008.

[34] Hod Lipson and Melba Kurman. *Fabricated: The new world of 3D printing.* John Wiley & Sons, 2013.

[35] James G March. Exploration and exploitation in organizational learning. *Organization science*, 2(1):71–87, 1991.

[36] Joe Marks, Brad Andalman, Paul A Beardsley, William Freeman, Sarah Gibson, Jessica Hodgins, Thomas Kang, Brian Mirtich, Hanspeter Pfister, Wheeler Ruml, et al. Design galleries: A general approach to setting parameters for computer graphics and animation. In *Proceedings of the 24th annual conference on Computer graphics and interactive techniques*, pages 389–400, 1997.

[37] Peter Brian Medawar. The art of the soluble creativity and originality in science. 1967.

[38] Geoff Norman. Likert scales, levels of measurement and the "laws" of statistics. *Advances in health sciences education*, 15(5):625–632, 2010.

[39] Tommi Opas. *An investigation into the development of a Creativity Support Tool for advertising.* PhD thesis, Auckland University of Technology, 2008.

[40] Gabriele Paolacci, Jesse Chandler, and Panagiotis G Ipeirotis. Running experiments on amazon mechanical turk. *Judgment and Decision making*, 5(5):411–419, 2010.

[41] Derek Partridge and Jon Rowe. Creativity: A computational modeling approach. *Creativity, cognition, and knowledge: An interaction*, pages 211–238, 2002.

[42] Paul Paulus. Groups, teams, and creativity: The creative potential of idea-generating groups. *Applied psychology*, 49(2):237–262, 2000.

[43] Keith Sawyer. *Group genius: The creative power of collaboration.* Basic Books, 2007.

[44] Jonathan Schaeffer. A gamut of games. *AI Magazine*, 22(3):29, 2001.

[45] Ryan Schmidt, Brian Wyvill, Mario Costa Sousa, and Joaquim A Jorge. Shapeshop: Sketch-based solid modeling with blobtrees. In *ACM SIGGRAPH 2007 courses*, pages 43–43. ACM, 2007.

[46] Jimmy Secretan, Nicholas Beato, David B D Ambrosio, Adelein Rodriguez, Adam Campbell, and Kenneth O Stanley. Picbreeder: evolving pictures collaboratively online. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pages 1759–1768. ACM, 2008.

[47] Andrei Sharf, Marina Blumenkrants, Ariel Shamir, and Daniel Cohen-Or. Snappaste: An interactive technique for easy mesh composition. *The Visual Computer*, 22(9):835–844, September 2006.

[48] Ben Shneiderman. Creativity support tools: Accelerating discovery and innovation. *Communications of the ACM*, 50(12):20–32, 2007.

[49] Ben Shneiderman, Gerhard Fischer, Mary Czerwinski, Brad Myers, and Mitch Resnick. Creativity support tools: A workshop sponsored by the national science foundation, 2005.

[50] Alex Shtof, Alexander Agathos, Yotam Gingold, Ariel Shamir, and Daniel Cohen-Or. Geosemantic snapping for sketch-based modeling. *Computer Graphics Forum*, 32(2):245–253, 2013.

[51] Karl Sims. Evolving virtual creatures. In *Proceedings of the 21st annual conference on Computer graphics and interactive techniques*, pages 15–22. ACM, 1994.

[52] Michael Sorkin. *Exquisite Corpse: Writing on Buildings*. Verso, 1991.

[53] Robert J Sternberg. *Handbook of creativity*. Cambridge University Press, 1999.

[54] Robert J Sternberg. The nature of creativity. *Creativity research journal*, 18(1):87–98, 2006.

[55] Gail M Sullivan and Anthony R Artino Jr. Analyzing and interpreting data from likert-type scales. *Journal of graduate medical education*, 5(4):541–542, 2013.

[56] Jerry O Talton, Daniel Gibson, Lingfeng Yang, Pat Hanrahan, and Vladlen Koltun. Exploratory modeling with collaborative design spaces. *ACM Transactions on Graphics-TOG*, 28(5):167–167, 2009.

[57] Robert W Weisberg. *Creativity: Beyond the myth of genius*. WH Freeman New York, 1993.

[58] Brian Wyvill, Andrew Guy, and Eric Galin. Extending the csg tree. warping, blending and boolean operations in an implicit surface modeling system. In *Computer Graphics Forum*, volume 18, pages 149–158. Wiley Online Library, 1999.

[59] Kai Xu, Hao Zhang, Daniel Cohen-Or, and Baoquan Chen. Fit and diverse: set evolution for inspiring 3D shape galleries. *ACM Transactions on Graphics (TOG)*, 31(4):57–57, 2012.

[60] William W York and David C Bender. Perception, insight, and creativity in paradigm, a game of pattern exploration. In *Proceedings of the 8th ACM conference on Creativity and cognition*, pages 403–404. ACM, 2011.

[61] James Young. *A technique for producing ideas*. McGraw Hill Professional, 2003.

[62] Yizhou Yu, Kun Zhou, Dong Xu, Xiaohan Shi, Hujun Bao, Baining Guo, and Heung-Yeung Shum. Mesh editing with poisson-based gradient field manipulation. *ACM Transactions on Graphics (TOG)*, 23(3):644–651, 2004.

[63] Mehmet Ersin Yumer, Paul Asente, Radomir Mech, and Levent Burak Kara. Procedural modeling using autoencoder networks. In *Proceedings of the 28th Annual ACM Symposium on User Interface Software & Technology*, pages 109–118. ACM, 2015.

Appendix A

Summary of the Questionnaires

Interesting answers provided by participants for the question "In your opinion, what attributes determine the creativity of a design?"

- How far from the norm it is.

- How unique or different it is compared to similar items.

- Both the functionality and the novelty. While novel, it still needs to be able to function. Too novel isn't worth anything.

- Functionality and form.

- Has different colors and good design of attributes to determine the creativity of a design.

- Uniqueness, and overall "wow" factor when you see it.

- Different shapes than usual, unique use of an item, easy to use and understand how it works

- Designs that are very different, but still functional are creative.

- In my view creativity of a design is uniqueness. We have to think different and create own design.

- New design, functionality.

- Structure of design are well made.

- Novelty, originality, uniqueness.

- Originality, functionality and good looking.

- How unfamiliar it in comparison to prototypical objects of the category, and whether I could imagine its functionality.

- Simplicity, symmetry, function.

- It combines utility with novelty.

- To look different from other designs, to look beautiful and to be practical.

- Simplicity.

- Need for originality , ambition.

- Shape, color, and functionality

- Whether it is unique in design and also functional.

- Unbounded by rules.

- Whether it is novel and functional.

- Make a creativity design in a symbolic shape , a new imaginative picture design, mixed with nature, and casual things .

- The unusual aspects of the design.

- Novelty, attractiveness, simplicity.

- How unique it is when it comes to its uses.

- Whether they are interesting or make you see the product in a new light.

- Uniqueness, maintaining functionality, unexpectedness, surprise that it's never been thought of before, originality.

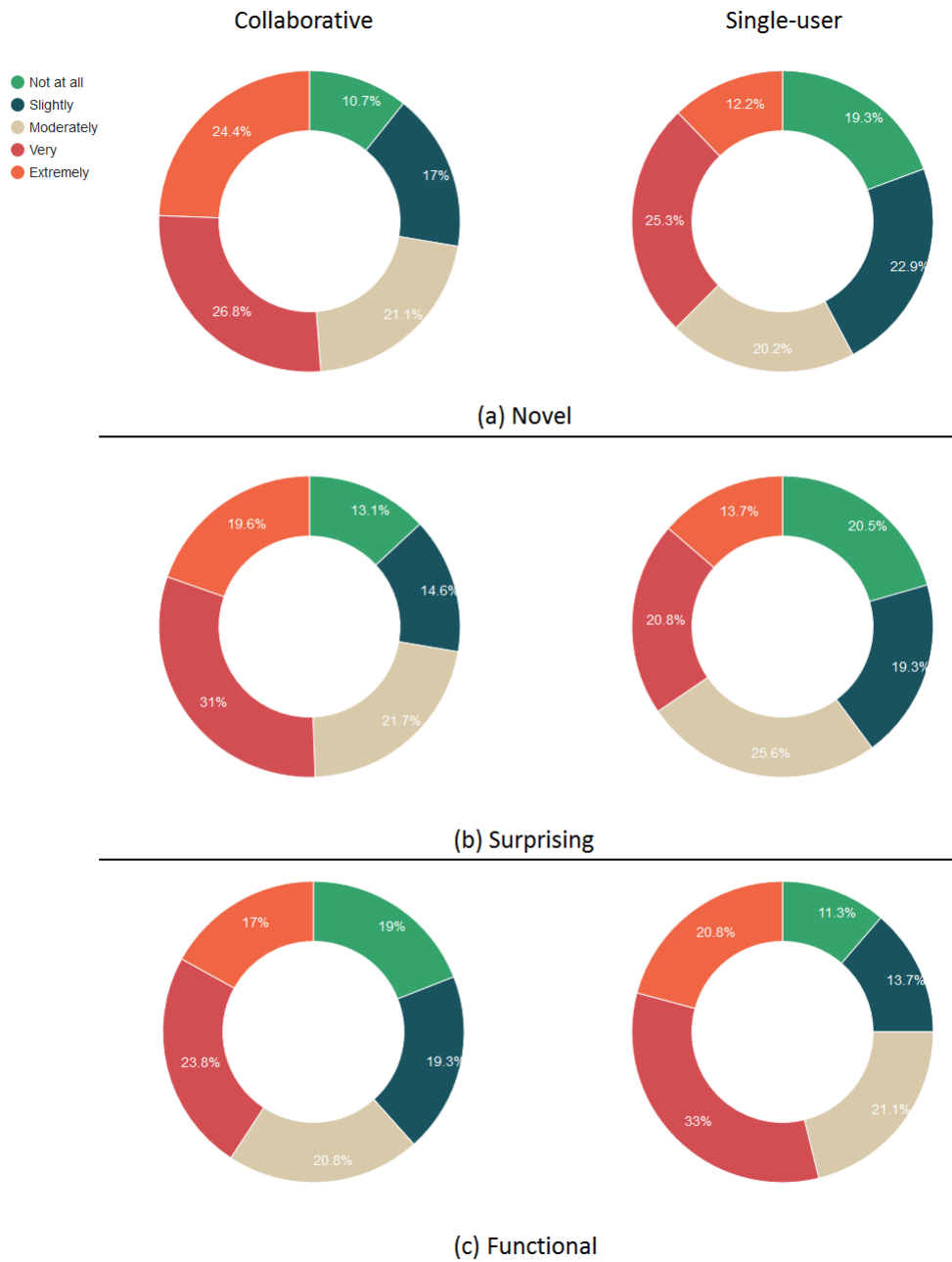- Features that I have not encountered before.

Figure A.1: Percentage of votes received for each option (i.e., not at all, slightly, moderately, very and extremely), for collaborative designs (left) and designs modeled by a single user (right) under each creativity criterion discussed, (a) novel, (b) surprising, and (c) functional.
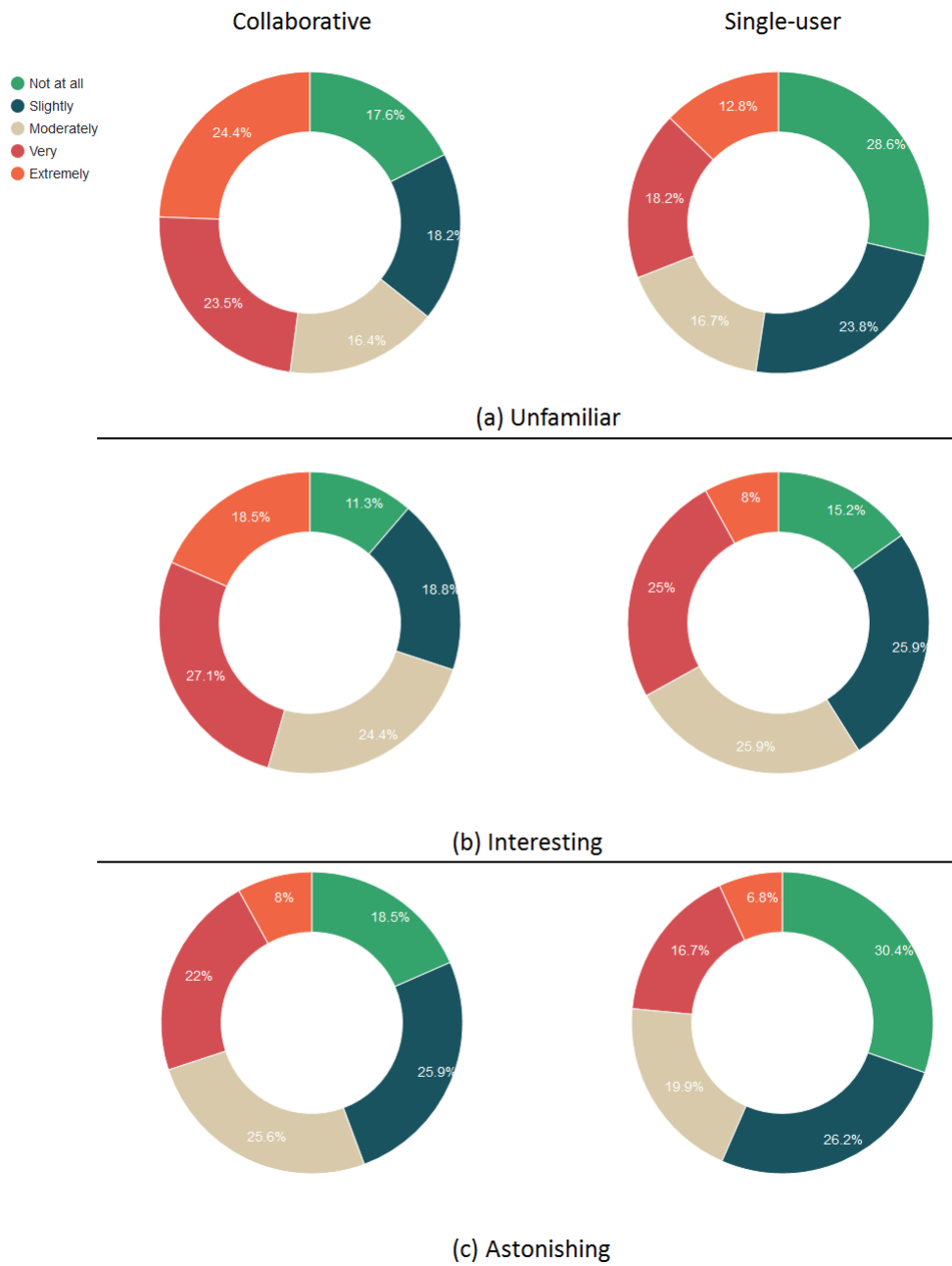
Figure A.2: Percentage of votes received for each option (i.e., not at all, slightly, moderately, very and extremely), for collaborative designs (left) and designs modeled by a single user (right) under each criterion for the *surprising factor*, (a) unfamiliar, (b) interesting, and (c) astonishing.
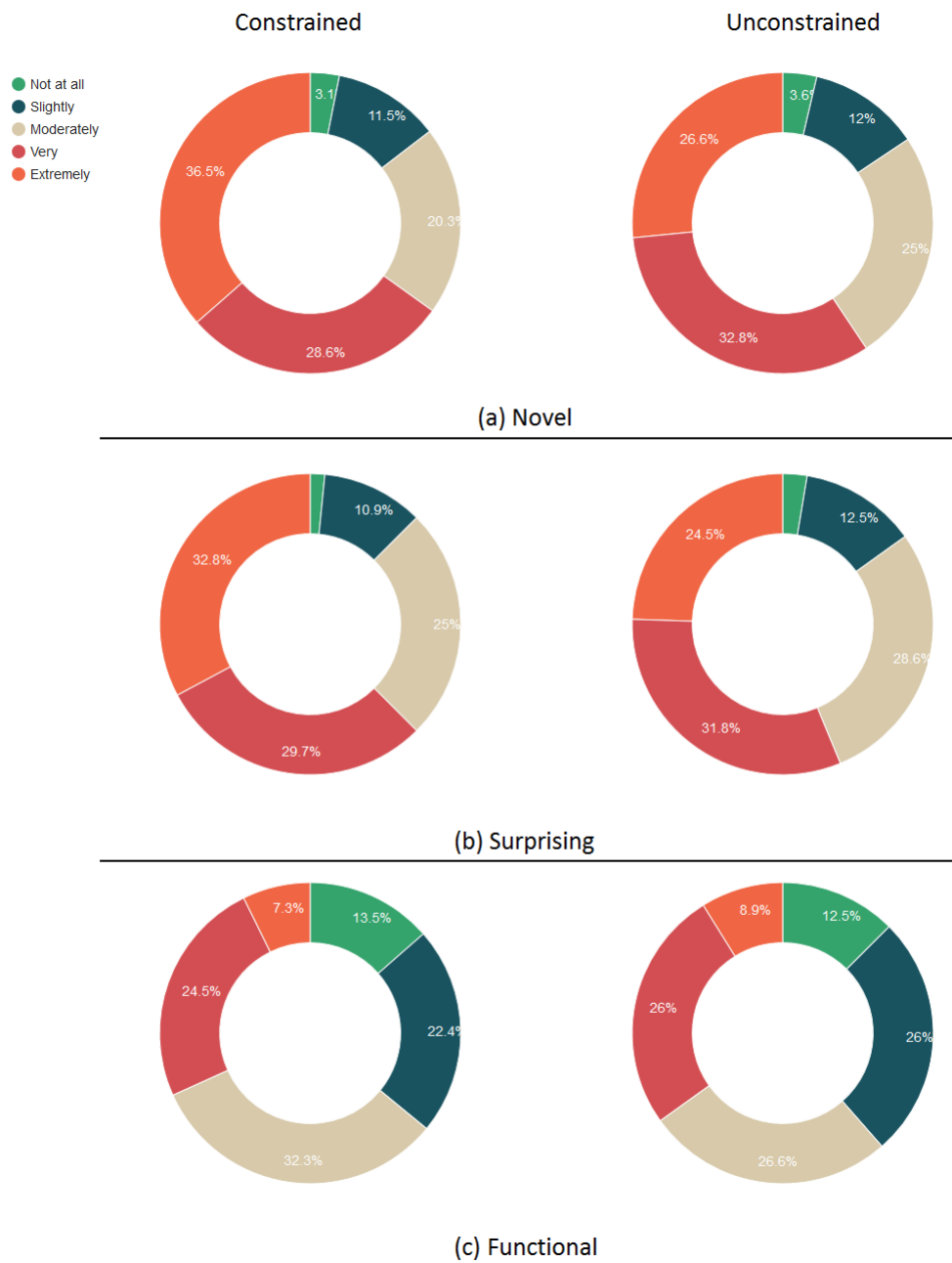
Figure A.3: Percentage of votes received for each option (i.e., not at all, slightly, moderately, very and extremely), for constrained designs (left) and unconstrained designs (right) under each creativity criterion discussed, (a) novel, (b) surprising, and (c) functional.
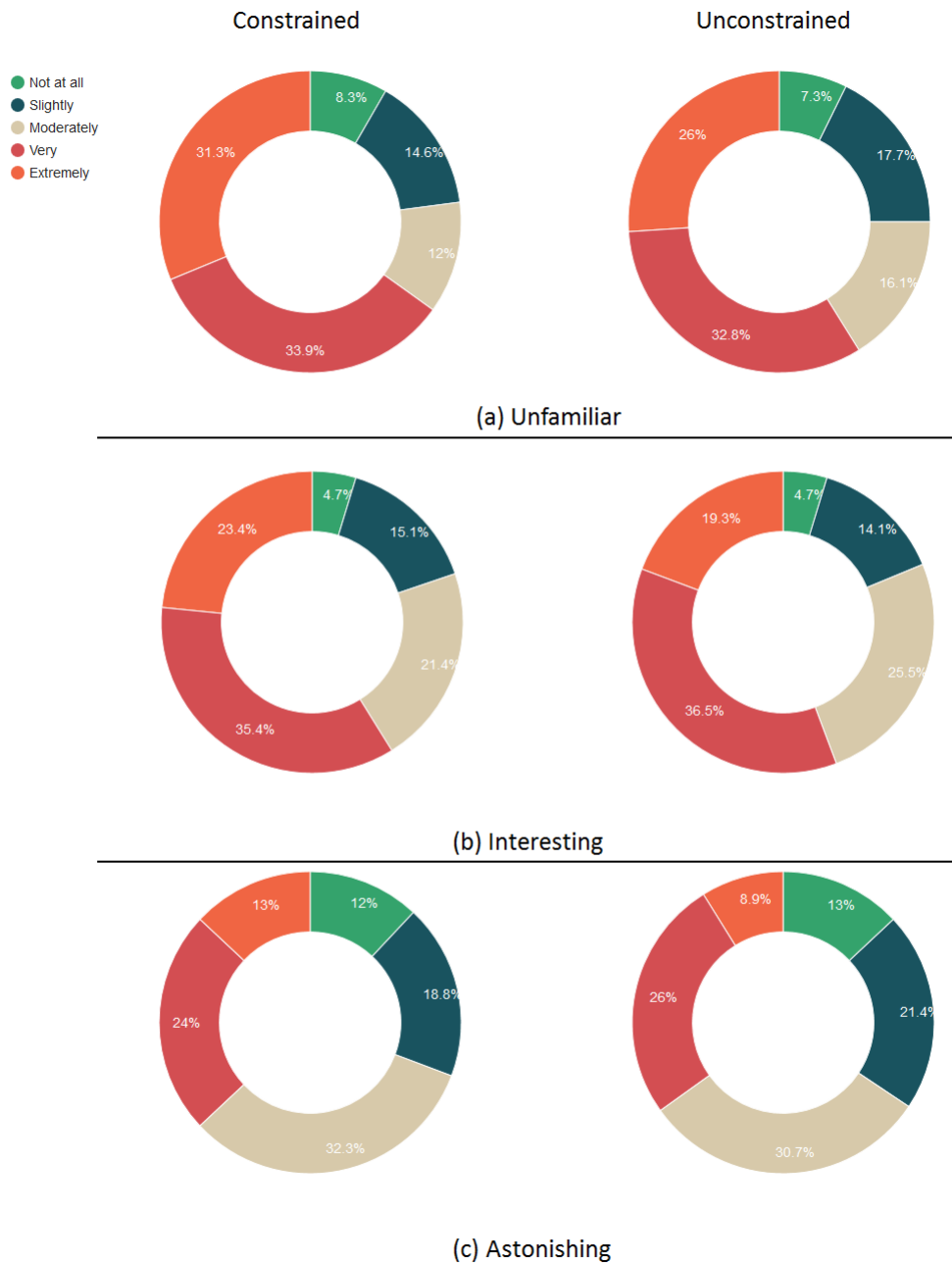
Figure A.4: Percentage of votes received for each option (i.e., not at all, slightly, moderately, very and extremely), for constrained designs (left) and unconstrained designs (right) under each criterion for the *surprising factor*, (a) unfamiliar, (b) interesting, and (c) astonishing.