Mixplorer: Scaffolding Design Space Exploration through Genetic Recombination of Multiple Peoples' Designs to Support Novices' Creativity

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ABSTRACT

The ability to consider a wide range of solutions to a design problem is a crucial skill for designers, and is a major differentiator between experts and novices. One reason for this is that novices are unaware of the full extent of the design space in which solutions are situated. To support novice designers with design space exploration, we introduce Mixplorer, a system that allows designers to take an initial design and mix it with other designs. Mixplorer differs from existing tools by supporting the exploration of ill-defined design spaces through *social design space exploration*. To evaluate Mixplorer, we conducted (1) an interview study with design instructors who reported that Mixplorer would "help to open the minds" of novice designers and (2) a controlled experiment with novices, finding that the design-mixing functionality of Mixplorer provided significantly better support for creativity, and that participants who mixed designs produced more novel designs.

CCS CONCEPTS

• **Applied computing → Interactive learning environments**; • **Human-centered computing → Empirical studies in HCI**.

KEYWORDS

design exploration, design support system, creativity support

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1 INTRODUCTION

The process of finding a solution to a creative design task often involves exploring alternative solutions created by other designers. These alternatives provide designers with a more complete understanding of the design space [13, 14] and comparing alternatives can help them make stronger critiques and better design decisions [8, 21, 43]. Previous studies have explored different ways to support the exploration of design alternatives and shown positive effects in terms of the quality of design outcome, collaboration, and creativity support [24, 41, 48].

A particularly effective method of exploring alternative solutions is to mix and combine them to create new ideas. People can produce better ideas if they are able to learn from recombining ideas into new ideas and iterating on new ideas to improve them [2, 7, 15]. However, for a creative design task, combining, or mixing, multiple ideas to generate a new design is not a trivial process. This can be particularly challenging for novice designers, as they can get superficially fixated on the solutions of others without being able to combine them to generate new solutions [17, 39, 40]. The ability to generate solutions to a design problem is related to the level of experience of the designers and it requires domain knowledge and expertise to maintain the quality of generated solutions [23, 26, 47].

To support novice designers with exploring and combining design alternatives we developed Mixplorer, a system to help novices generate novel designs by mixing design alternatives. The target users of Mixplorer are apprentice garden designers in the vocational education and training (VET) system at the upper secondary level. Mixplorer provides a simple interface that can be used to create an initial garden design and a second interface that can be used to generate alternative designs by performing a select-and-mix process. The design-mixing process of Mixplorer uses a genetic algorithm to breed two garden designs and generate a new one. However, rather than using a fitness function to select optimal designs, Mixplorer uses a *human-in-the-loop* approach. The user is provided with an

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interface that allows them to easily browse possible children of two designs and select the one that they prefer. This genetic exploration algorithm can be used repeatedly to generate many generations of child designs from an initial set of starting designs. Throughout this paper we use the term "design mixing" to refer to the entire process of selecting parent designs, browsing possible children, and adding children to the design space using the interface of Mixplorer. Another feature that differentiates Mixplorer from existing tools is that it enables *social* design space exploration. We describe this exploration method as social because Mixplorer is meant to be used synchronously by multiple students in a classroom setting, where each student can view and mix the designs that are simultaneously being created by their peers.

To evaluate Mixplorer, we carried out two studies. First, we conducted an interview study with expert garden designers who were also instructors in the VET system to understand the potential benefits and limitations of using Mixplorer with apprentice garden designers in the classroom. The instructors reported highly-positive experiences using the application, had few reservations about incorporating it into their teaching practices, and believed that using Mixplorer would support students' divergent thinking. In the second study, we conducted a controlled experiment to compare design space exploration with design mixing to two other conditions, one with no exploration and another with random exploration. We found that design mixing with Mixplorer provided significantly more support for novices' creative practices, particularly for exploration and collaboration. We also found that after using the design-mixing interface, participants produced designs that were more novel (i.e., more different from their initial designs) than participants in the other two groups. Finally, we showed that making it easier for novices to explore and keep track of many ideas directly affects the novelty of the designs they produce.

2 BACKGROUND

Creative thinking is defined as a cognitive ability to generate a large number of original ideas or solutions to a problem [1]. One of the barriers to creative thinking in a design task is *design fixation*, a blind adherence to a set of ideas or concepts limiting the output of design [17]. A way to overcome design fixation is to explore alternative designs in the design space. In creative work, the design outcome is not necessarily known at the outset, and designers are encouraged to first explore the space before deciding on a solution [11, 31]. However, design space exploration for a creative design problem is not a simple task, particularly for novice designers. Expert designers are more capable of generating alternative designs based on their domain knowledge and previous experience [23, 47]. On the other hand, novice designers, without the expertise and the level of experience required for this process, can benefit more from technological support for design space exploration. These creativity support tools [37] are capable of supporting novices in rapidly generating multiple design alternatives and exploring the implications of those designs.

Computer-supported techniques for design space exploration can be categorized into four types: parametric exploration, history-based exploration, rule-based exploration, and genetic exploration [36]. Parametric exploration allows generating variations of a design by changing values of parameterized variables [14, 48]; systems with history-based exploration provide a mechanism to keep the history of design changes and to go back in time when needed [19]; rule-based exploration helps the designers explore related examples by suggesting them based on their designs [3, 24]; and genetic exploration involves generating new solutions by combining components of existing designs.

For the purpose of supporting designers with exploring a large volume of a design space, the genetic exploration approach is an attractive choice [36, 46]. This approach is capable of developing an initial set of starting designs into a much richer set of solutions for the users to explore [6], and has been used in 3D shape modeling [6, 30, 46], 2D graphics [42, 48], visual arts [9], architecture [12, 44], and even music [33]. However, despite the wide range of the applied domains, there are challenges and limitations in applying genetic exploration to creative design.

The first challenge is that genetic algorithms require a fitness function that evaluates the performance of a solution. For this reason, existing tools tend to be in domains where the requirements are well-specified and the performance can be measurable (i.e., engineering or architecture). For creative design, the problem is often ill-defined and it is difficult or impossible to define a fitness function that can measure the performance objectively. The problem of poorly-defined or undefined optimization functions is one that affects all types of generative design tools, not just those that use genetic algorithms. One solution to this problem is to involve humans in the generation loop [22, 34]. By having users perform the evaluation and selection processes, the generative algorithm can be used for a preference-based exploration tailored to each user [36]. Different approaches of integrating user preferences in generative design exploration have been demonstrated in previous research such as using user-created sketches [4], optimizing for high-level goals specified by users [16, 27], and learning users' intent [35]. In Mixplorer, we opted to replace the fitness function in the selection process entirely with the user's evaluation of the generated designs. Mixplorer provides a collection of novel interfaces and visualizations that are designed to support novices in (a) choosing which designs they'd like to breed, (b) efficiently generating and browsing a wide variety of possible children, and (c) selecting a child design and adding it to the set of designs that can be combined together.

However, the choice to use a human-in-the-loop instead of a fitness function gives rise to a second challenge, which is that this type of system requires a set of existing designs to be used as the source of genetic operations. For example, consider the domain of garden design. A typical genetic exploration system would not be able to support outdoor spaces which are uploaded by the user, since it would not contain any example gardens for that space. While the system could produce random designs and use these as the initial set, the chance that any of these random designs would be judged as suitable for the space is extremely low, which would make the process of using these designs to produce children fruitless. This is not only a challenge for garden design, but for any open-ended, creative domain where each task presents a new problem with different requirements and constraints. Hence, the majority of existing systems that utilize this approach are limited to solving a generic problem (e.g., abstract 2D graphics) or a single problem (e.g., solar panel design for a specific roof) [42, 48].

We propose a solution to this problem that we call *social design space exploration*. In social design space exploration, the initial set of examples used in the genetic mixing process is created by a group of designers working on the problem. Mixplorer contains a Garden Design Interface that can be used to quickly design gardens for any outdoor space, and uses a real-time, cloud-based database to collect these examples as they are created and present them to all of the users working on a common problem, where they can be used as the source designs in the genetic mixing algorithm as soon as they appear. This means that Mixplorer is not limited to a small set of designs, but can support meaningful genetic exploration on any outdoor space that a user uploads. This makes Mixplorer more than a demonstration of an exploration system, but rather a usable tool for real design tasks.

Social design space exploration may also be useful in helping novices explore a larger volume of the design space. While each individual may only be aware of a small part of the design space, collectively they can show each other parts of the space they were not considering [38]. However, merely seeing other examples from the larger design space may not support or scaffold students in design space exploration. During the learning process, it is often not enough to provide a resource to learners; scaffolds are regularly needed to support the integration of the resource into the learning process [10, 18, 20]. Exposure to examples in a design space without a scaffolding mechanism can be similar to reading a map that shows places to visit without any streets to follow. We hypothesize that the design-mixing functionality of Mixplorer may serve as a scaffold that provides additional support for design space exploration.

2.1 Research Questions

The design of Mixplorer aims to address the challenges described above and support novice designers with exploring a broader design space for creative design. To evaluate Mixplorer, we conducted two studies where each of them tried to answer a set of research questions.

The first study was designed to learn more about the feasibility of using Mixplorer in an authentic educational setting with novice designers. In particular, we were interested in answering the following questions:

- How can Mixplorer be incorporated into design teaching and how well does it fit into their existing practices?
- What are the potential benefits of Mixplorer for novice designers in creative practices?

The second study was built on the findings of the first study and had a more specific focus on the design-mixing functionality of Mixplorer. In particular, we were interested in learning more about the specific ways that the activity of design mixing might support novices' creative practices. We designed an experiment to answer the following research questions:

- To what degree does the design-mixing functionality of Mixplorer support novices' creative practices during the garden design activity?
- Do novice designers produce more novel designs after working with the design-mixing interface of Mixplorer?

3 MIXPLORER

Mixplorer is a web application for creating a garden design and exploring the design space by mixing it with other designs. It has two phases—a design phase where users can design a new garden and an exploration phase where they can mix the designs. Users start the exploration with the design that they created in the design phase. In this section, we describe the interfaces for the two phases and explain the algorithm we developed for the design-mixing process.

3.1 The Garden Design Interface

The Garden Design Interface in Mixplorer allows users to design a garden by dragging and dropping different elements into a 3D rendering of an outdoor space. In the two studies reported in this paper the outdoor space was a 3D rendering of the backyard of a Roman Catholic diocese which we reconstructed using a photogrammetry tool. We chose this site because it was an actual work site for training apprentice gardeners in a local vocational school, though in principle any 3D model of an outdoor space could be used. As shown in Figure 1a, this interface shows the birds-eye view of the outdoor space and an inventory that includes trees, bushes, walls, benches, and stone plates. Once an item is selected from the interface, it follows the mouse and can be stamped multiple times in the garden by clicking the mouse. Items can be rotated using arrow keys on the keyboard and deleted with a right-click.

3.2 The Garden Exploration Interface

Once a user has created a design, they can generate and explore other designs by mixing their creation with others in the Garden Exploration Interface (Figure 1b). Each design is represented as a node in the *Design Space Graph* on the lower left. When the mouse pointer hovers over a node, a 3D rendering of the design is visualized on the top right. In the lower center of the screen, the *Design Mixing Generator* panel is shown. After selecting two 'parent' designs from the Design Space Graph, users can generate child designs using Design Mixing Generator. This is done by moving a slider back and forth between each of the parent designs. The position of the slider affects the probability of sampling genes from one parent or the other. For example, the further the slider is placed to the left, the higher the probability that genes from the left parent will be sampled and the lower the probability that genes from the right parent will be sampled. By moving the slider back and forth, the user can quickly explore a large number of children that could be produced by the two parent designs. Once a user finds a child design that they like, they can add it to Design Space Graph where it appears as a new node and becomes available for the next iteration of mixing. Each design created in this way is visually linked to its parents using edges. As more nodes are added, the Design Space Graph tracks the history of node creation and maps which regions of the design space have and have not been explored. The process of design mixing using the Garden Exploration Interface is demonstrated in Figure 2.

3.3 Design Mixing Algorithm

We used a genetic algorithm approach to enable the ability to mix garden designs and generate multiple variations from the design

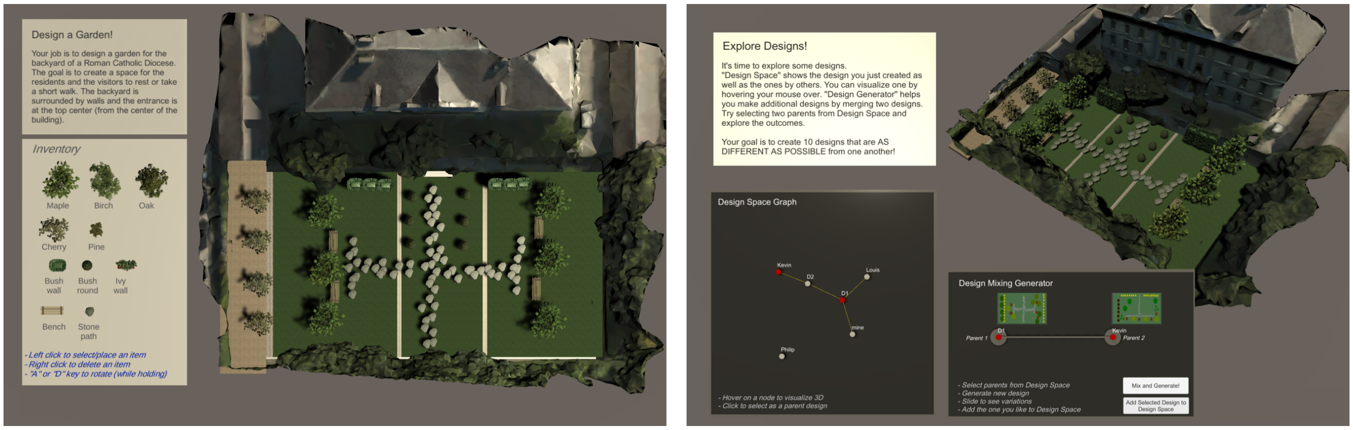

Figure 1: Garden Design Interface (*left*) and Garden Exploration Interface (*right*) of Mixplorer

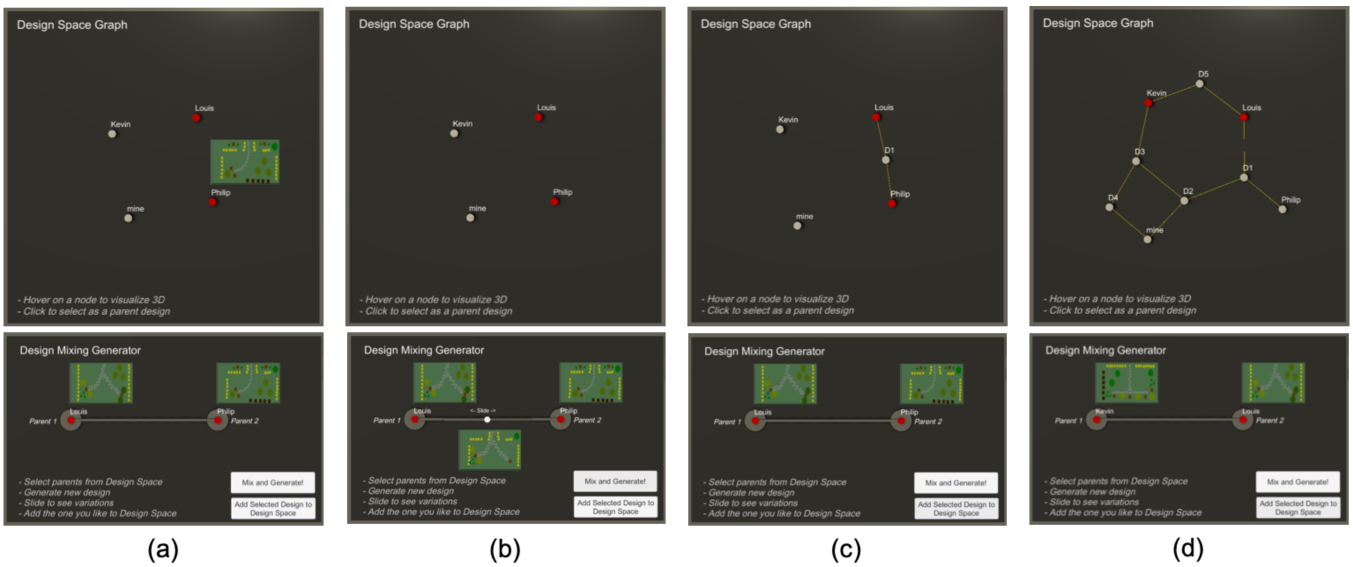

Figure 2: Zoomed-in view of the Garden Exploration Interface showing the sequence of design mixing. (a) Selecting nodes in the Design Space Graph populates the parents in the Design Mixing Generator. (b) Children can be browsed by adjusting the slider, where the position of the slider determines the probability of inheriting features from different parents. (c) Once a satisfactory child is found, clicking a button adds it to the Design Space Graph. (d) The Design Space Graph after a few generations of children have been generated.

space. A genetic algorithm is a meta-heuristic inspired by the biological natural selection process which is commonly used to generate solutions to search problems [45], and genetic exploration systems utilize these types of algorithms for the purpose of solution space exploration. We describe the details of our genetic algorithm used in the Garden Exploration Interface of Mixplorer in this section.

3.3.1 Design Representation. In order to apply a genetic algorithm to garden design generation, we needed to first define a genetic representation of a garden. When a user creates a garden using Mixplorer, the design is a set of objects that have been placed in a given space. In our genetic representation, each object, along with its position and orientation information, is called an *Item*. To capture and embed structural information of the garden, we also added another level in the representation called *Structure*. A group of Items forms a structure. Because structural information is often represented by the same type of objects (e.g., a set of bushes that form a wall or stone plates creating a path), we defined a Structure from each object type. Figure 3 shows an example genetic representation used in Mixplorer. Each design has all available object types as *Object Genes* in the first level. Under each Object Gene, there are a set of Structures defined by objects of that type. Finally, each Structure has a set of Items that belong to it.

```
Design 1
    ∟ Object Gene 1
        ∟ Structure 1
            ∟ Item 1: position, orientation
            ∟ Item 2: position, orientation
                ⋮
            ∟ Item n: position, orientation
        ∟ Structure 2
            ⋮
        ∟ Structure m
    ∟ Object Gene 2
        ⋮
    ∟ Object Gene k
```

Figure 3: Genetic representation of a garden

3.3.2 *Design Generation by Mixing.* The process of mixing the genetic representations to produce new garden designs was performed by a genetic algorithm. A typical genetic algorithm includes the following steps: selecting items from the existing population, applying genetic operators, and applying heuristics. We describe here how each step is applied in Mixplorer.

Selection: First, a subset of an existing population must be selected to serve as 'parents' to breed a new generation. This selection process is often carried out using a fitness function that evaluates each candidate solution. However, as we have previously described, in open-ended creative domains such as garden design it can be difficult to define a function that is able to objectively evaluate a design. In Mixplorer, we adopted the human-in-the-loop approach to solve the problem [22, 34]. Instead of using a fitness function, users are asked to select candidate designs to breed. Therefore, in Mixplorer, evaluation of the designs was based on the judgment of a user, not on a pre-defined fitness function.

Genetic operators: The two main genetic operators used in the genetic algorithm were crossover and mutation. Crossover operators combine the genes of the parents to produce a child and mutation operators alter gene values to maintain diversity. We defined three types of crossover operators for Mixplorer:

- Tree vs. non-trees crossover: A child takes the tree genes from one parent and non-tree genes from another. This is the crossover at the highest level.
- Gene-level crossover: A child takes the Object Gene of each object type from one of the parents. This is a standard way of doing a crossover.
- Structure-level crossover: Each Structure from a parent can be inherited to one of its children. As a result, one Object Gene can have more than one Structure.

For mutation, we defined four types as follows:

- Change type: A Structure of an Object Gene is transferred to another Object Gene.
- Switch type: Two Structures from two Object Genes are swapped.
- Mirror: All objects are mirrored around the vertical or horizontal axis.
- Mirror half: A random half of the design is selected, copied, and mirrored to the other side.

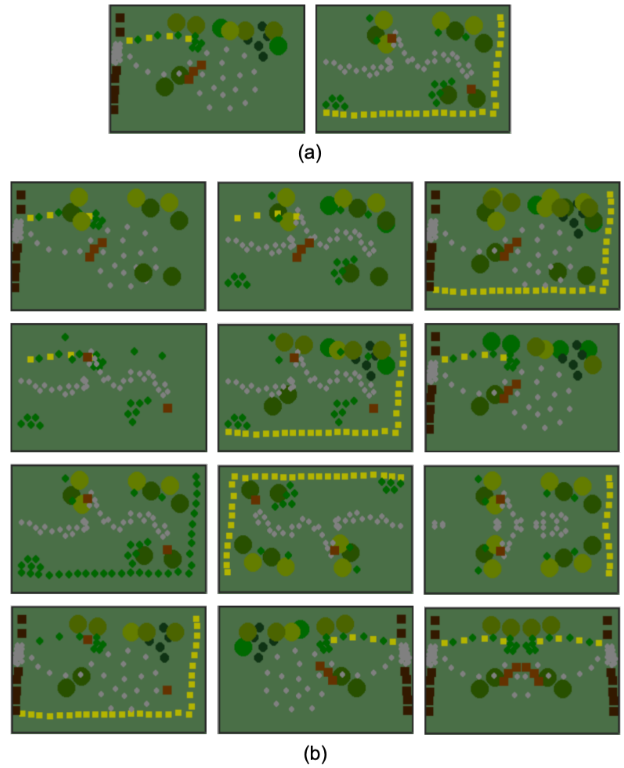

Figure 4: Example designs generated using the mixing process of Mixplorer: (a) parent designs and (b) child designs generated using different genetic operators

Each type of crossover and mutation was applied with an equal probability in the mixing process.

3.3.3 *Heuristics.* In genetic algorithms heuristics are often introduced to make the process more robust. In Mixplorer, we added two heuristics to validate the designs generated by applying the genetic operators:

- If an added Structure is superposed onto another Structure, undo the addition.
- If a generated child design is too similar to one of its parents, ignore the child.

Figure 4 shows example designs generated using the design mixing process described above.

4 STUDY 1: INTERVIEWS WITH EXPERT GARDEN DESIGN INSTRUCTORS

Based on our previous experiences working with garden-design instructors, we knew that Mixplorer was unlike other tools being used in the garden design curriculum. This meant there was a valid threat of Mixplorer not being adopted by instructors because of being too novel or foreign to their current practices. To address this concern, we recruited six garden-design instructors from vocational schools to take part in a semi-structured, task-based interview with the Mixplorer application. The first goal of this interview was to learn more about the feasibility of using Mixplorer in an authentic educational setting with apprentice designers. In particular, we were interested in understanding whether instructors would incorporate Mixplorer into their teaching, and if so, how they saw it fitting into their existing practices. The second goal of the interview was to see whether instructors believed that Mixplorer could be used to support their students' divergent thinking, and if so, how much of this support could be attributed to the design-mixing functionality.

4.1 Methods

4.1.1 Participants. We recruited six garden-design instructors from vocational training schools in the Ticino region of Switzerland. The average age of the instructors was 48 years (SD = 10.28). The instructors had a combined 83 years of teaching experience, and as a group were currently responsible for teaching over 400 apprentices per year in the upper secondary level education.

4.1.2 Procedure. Instructors were interviewed one-at-a-time using the Zoom videoconferencing platform, and audio, video, and screen recordings of each interview were recorded using the built-in capabilities of Zoom. After a short introduction to the study which included filling out a consent form, instructors were provided with a web link to Mixplorer and asked to open the website on their browser.

Once the application was loaded, the instructors were guided through three phases of using the application. In the first phase, the instructors were given the Garden Design Interface of Mixplorer and prompted to "design a garden for the backyard of a Roman Catholic Diocese, [where the] goal is to create a space for the residents and visitors to rest or take a short walk." The interface contained an inventory of garden design elements such as trees, bushes, stones, and benches which could be dragged and placed into a three-dimensional model of the backyard of the Diocese (Figure 1a).

After completing their design, the instructors moved onto the second, design exploration phase. In this phase, they were presented with the Garden Exploration Interface of Mixplorer for mixing and exploring garden designs. They were asked to use the interface to "generate new designs that are as different as possible from one another." Once they were satisfied with their designs, they moved on to the third and final phase.

In this third phase, the instructors were first presented with all of the designs from the second phase and asked to choose the three designs they liked most. After selecting three designs, they were brought back to the design interface from the first phase. With the three selected designs displayed at the top of the screen, the instructors were asked to re-design the garden for the Catholic Diocese. Once they were satisfied with their design, they exited the application.

Instructors were then asked questions from a semi-structured interview protocol which is described in the next section. After answering the questions, the instructors were given a link to an online version of the Creativity Support Index [5] and asked to spend a few minutes filling it out. Finally, the instructors were thanked for their participation and the interview ended.

4.1.3 Interview Protocol. The semi-structured interview protocol covered four topics: experience using the application, instructors' thoughts about how they might use Mixplorer in the classroom, instructors' beliefs about the importance of divergent thinking in garden design, and the instructors' beliefs about how Mixplorer might support students' divergent thinking skills.

4.2 Results

4.2.1 Experience Using the Application. Overall, the instructors reported highly-positive experiences using the Mixplorer application. Regarding usability, five of the six instructors said that the application was intuitive and easy to use. One instructor commented that "Compared to [other applications] that I've tried in the past I found it very easy and responsive." Another said that "It is very simple. Although I was skeptical at first, it's very easy to understand." A third said "For someone like me who doesn't use a computer it becomes really easy and sharable." When asked about whether he enjoyed using the application, the lone instructor with doubts about its usability said "It's difficult to say... I'm better at drawing on paper," though he later admitted that the application "seems very intuitive and easy."

4.2.2 Feasibility of Using Mixplorer in the Classroom. All of the instructors were open to using Mixplorer with their students, and most were enthusiastic about its potential. One instructor commented "I'd really like to try it with the apprentices," and another said "I put myself into the shoes of the pupils who, after explanation and testing, I'm sure will be able to use it to great effect." Most felt that the tool was appropriate for novices (i.e., first-year apprentices). However, one instructor expressed doubts about whether Mixplorer could be used by true novices, saying "I think it's a more suitable tool in the third year where you can already open up a little bit to the students and show them what they can do after the certificate at a professional level."

This openness to using the tool was somewhat surprising because of our original assumptions. As previously mentioned, one of our concerns about Mixplorer was that it would be too different from the tools that instructors were currently using in their teaching. The instructors confirmed that this was the case. One said "I have never seen a similar application that had this functionality," and another said "It's definitely an interesting tool and it's not the usual piece of paper that is typically used while drawing." However, these differences were generally seen as a good thing: not as reasons to avoid using the tool, but as improvements over existing tools and methods. Mixplorer was perceived as fitting into instructors' current practices better than other software tools, which were described as overly complex and difficult to use. One said "In general, [other] applications get complex before they got to a stage like this with a rendering, and for people like me who are not architects [these other tools] are difficult." In contrast, Mixplorer was perceived as less complex and easier to use. One instructor commented that "Compared to [other applications] that I've tried in the past I found it very easy and responsive."

Though the instructors were not asked specifically about Mixplorer's potential for supporting collaboration, four of the six instructors spontaneously mentioned this as a reason to use the tool. These instructors explained how collaborating on design problems often resulted in better solutions, and liked how Mixplorer offered a means for students to "work with two heads and two ideas." Unexpectedly, multiple instructors described a way of using Mixplorer to support collaboration that we had not considered: Mixplorer could help multiple people, each with their own solution to a design problem, converge on a single satisfactory solution. One said "At some point we can take the groups' projects and put them together and see, by mixing ideas, what comes out. Surely, with these four ideas mixed together, you come up with one that is very similar, acceptable to everyone and also easily achievable." Another that "It could help having the design coming from different designers since, I think, it's more useful because you can take the best things from different drawings." Two instructors felt that Mixplorer could also be used in professional settings as a way to support collaboration between professional designers and clients. One explained how the application might help reconcile the work of multiple landscape architects, describing a situation where he had worked with "a more practical and a more theoretical collaborator." Another hypothesized that "It could be interesting to do in the profession with the gardener mixing and then showing it to the client or ask the client to mix and the discuss possible changes."

4.2.3 Supporting Students' Divergent Thinking with Mixplorer. Four of the six instructors believed that the design-mixing functionality of Mixplorer would support divergent thinking. One instructor said "the mixing of two projects was useful because it made me see a situation I hadn't planned... From a technical point of view, the scenario with the mix [when compared to simply seeing other examples] gives more insights. Apprentices who do not have an overview because they lack experience could benefit... The divergence between the projects and the mixing certainly opens up different visions than what was planned at the beginning with the first design." Another echoes this sentiment, saying "I find [design mixing] very creative as a function and it can also help to open the minds of those who may be struggling a little more. It can help to visualize and get out of the box but then it also depends on the apprentice."

However, two instructors raised doubts about the value of design mixing. One felt that it was enough to present novel examples to apprentices, and that the mixing part of the application was unnecessary. This instructor said "Surely seeing the other design is helpful but I don't know about mixing... The idea of showing the drawings of one's classmates is a good one, while I don't know about mixing." The other instructor with doubts felt that the design mixing functionality did too much of the work for the apprentice, saying "Of course seeing all the designs and then having the apprentice manually mix [could] be more interesting. In this case the apprentice is the one who has to actively work, instead of here [where the system does the mixing]."

4.3 Discussion

The interviews with garden-design instructors gave us more confidence about the feasibility of using Mixplorer in the classroom with apprentices. Our concerns about Mixplorer being too foreign to instructors current teaching practices were largely unfounded. All of the instructors reported that Mixplorer was intuitive and easy to use, and all were open to incorporating it into their courses. Not only did most instructors feel that Mixplorer would be able to support students' divergent thinking, but they also suggested using Mixplorer as a collaborative design tool, which was a use that we had not considered. However, two of the instructors raised doubts about the value of the design-mixing functionality of Mixplorer. One felt that the design-mixing algorithm was doing too much of the work, and that students would benefit more from manually mixing the example designs. Another felt that design mixing was unnecessary, and that it would provide no additional benefits over simply showing students each others' designs. Given their many years of experience we took these instructors' doubts seriously, and designed Study 2 to more closely investigate the value of design mixing as a method for supporting novices' creative practices.

5 STUDY 2: A CONTROLLED EXPERIMENT TO ASSESS THE VALUE OF DESIGN MIXING

Motivated by the results of the first study, the second study was designed to more closely investigate the effect of the design-mixing process of Mixplorer. Through a controlled experiment with novice designers, we compared the design-mixing functionality with two other conditions—a baseline condition with no exploration interface and a random-exploration condition that could only explore the design space by observing random examples. By comparing these groups, it was possible to determine whether design-mixing provided extra support for novices' creative practices, or whether it was no better than simply providing examples.

5.1 Methods

5.1.1 Participants. We recruited 66 paid participants (47 female and 17 male) on the Prolific recruiting platform [29] aged between 18 and 35 years ($M = 21.59$, $SD = 3.54$). The majority of the participants were students (63 students, 3 non-student), and we excluded art and design majors in the study as the target users of Mixplorer were people without any prior design experience.

5.1.2 Experimental Design. In order to study the effect of exploring the design space using Mixplorer, we designed a between-subjects experiment with three conditions: (1) no exploration, (2) random exploration, and (3) mixing exploration. Each participant was randomly assigned to one of the three conditions for the exploration activity. The first condition served as a baseline for the comparison. To further investigate the effect of the process of mixing in design exploration, we added the second condition where the participants were provided with randomly generated designs. Participants in this condition could see a new design in the design space simply by clicking a button rather than performing the select-and-mix process of Mixplorer. The random designs were generated using the same algorithm used for mixing but with two randomly selected parents, but the relationship between the designs in the space was not visualized (i.e., no lines connecting the design nodes). And in the third condition, we provided the full functionality of Mixplorer.

5.1.3 Task and Materials. In the first phase of the study, participants in all three groups used the Garden Design Interface of Mixplorer to design a garden for the backyard of a Roman Catholic Diocese. In the second phase of the study, each group used a different version of the Garden Exploration Interface. The mixing-exploration group used the complete interface with the Design Space Graph and Design Mixing Generator. The random-exploration

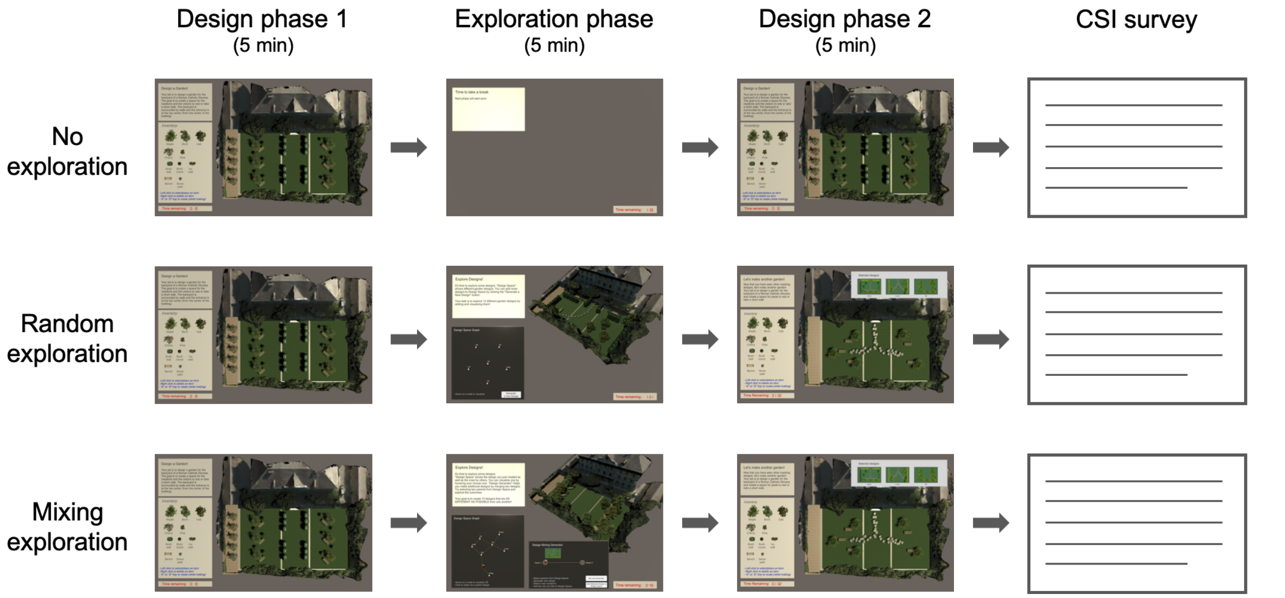

Figure 5: Experimental design of Study 2: The experiment was composed of three phases followed by the CSI survey. Each phase was controlled for time. Different exploration interface was provided for each condition as shown. For the random and mixing conditions, the participants had three designs chosen from the exploration phase displayed in the final design phase.

group was given a modified version of the Design Space Graph which did not show edges between nodes, and in place of the Design Mixing Generator they had a button that would generate random designs. The no-exploration group did not see any version of the Design Space Graph or Design Mixing Generator, and instead saw a message asking them to wait for the next step.

For the exploration phase of the experiment, participants in the mixing-exploration and random-exploration groups were provided with an initial set of three designs different from their own design. For this purpose, we selected three designs that were created by the expert garden designers in the first study. We chose the three designs that were most visibly different from one another so that participants mixing these designs would produce a wider variety of outcomes from the full design space.

5.1.4 Procedure. At the beginning of the experiment, the participants were provided with a description of the study and asked to fill out a digital consent form if they wished to participate. Afterwards, they were given a tutorial on how to use the Garden Design Interface of Mixplorer. We provided the description of the task and the inventory of the available objects described above. Once the participants were ready, they were given five minutes to complete the task using the Garden Design Interface.

After finishing their initial design the participants moved on to the exploration phase of the study. Participants in the mixing-exploration condition and random-exploration condition were given five minutes to generate 10 new designs using their respective interfaces, while participants in the no-exploration condition were asked to wait for the next phase.

After completing the exploration phase, the participants in the mixing-exploration and random-exploration conditions were presented with all of the designs that they generated in the exploration phase and asked to choose their three favorites. After selecting three designs, they moved to the third phase of the study where they were given a second chance to design a garden using the Garden Design Interface. During this phase, their three favorite designs were displayed at the top of the screen for reference. After five minutes, the participants were asked to complete the Creativity Support Index based on their experience with the application and the study concluded.

5.1.5 Measures. The Creativity Support Index (CSI) is a standardized psychometric tool that evaluates the creativity support of a system [5]. The CSI provides quantitative assessments in six dimensions of creativity support: Enjoyment, Exploration, Expressiveness, Immersion, and Results Worth Effort. Each participant was asked to fill out the CSI survey after the second design activity. The CSI made it possible to evaluate how different design exploration functionalities supported the users' creative work.

We were also interested in understanding how using the different functionalities affected the participants' ability to produce more novel designs. We operationalized novelty by comparing each participant's initial design (created before using any of the three exploration interfaces) to the design they created after working with the interface. Through this comparison, we aimed to show quantitatively how much the design outcome was influenced by the different exploration methods. Again inspired by genetics, we used Levenshtein edit distance [25, 28] to quantify the difference between genetic representations of each participant's initial and final designs. We used the magnitude of the edit distance as a proxy

	No exploration		Random exploration		Mixing exploration	
	Factor counts *M (SD)*	Score *M (SD)*	Factor counts *M (SD)*	Score *M (SD)*	Factor counts *M (SD)*	Score *M (SD)*
Enjoyment	2.61 (1.31)	10.74 (5.91)	2.29 (1.23)	13.57 (3.50)	2.27 (1.67)	14.82 (4.00)
Exploration	3.57 (0.90)	10.83 (5.44)	4.05 (1.20)	13.14 (3.58)	3.50 (1.26)	15.27 (2.62)
Expressiveness	3.00 (1.35)	12.43 (5.53)	2.76 (1.22)	13.71 (4.08)	3.05 (0.95)	14.59 (3.61)
Collaboration	0.30 (0.47)	7.39 (4.82)	0.62 (1.16)	11.24 (4.41)	1.00 (1.23)	14.00 (3.45)
Immersion	1.91 (1.35)	11.57 (4.90)	1.95 (1.32)	14.38 (3.58)	1.95 (1.36)	13.41 (4.84)
Results worth effort	3.61 (1.41)	11.17 (5.48)	3.33 (1.28)	14.05 (3.73)	3.23 (1.31)	14.59 (4.04)
Overall CSI score		55.90 (26.24)		68.52 (17.57)		73.59 (15.01)

Table 1: CSI factor counts and scores of the three conditions

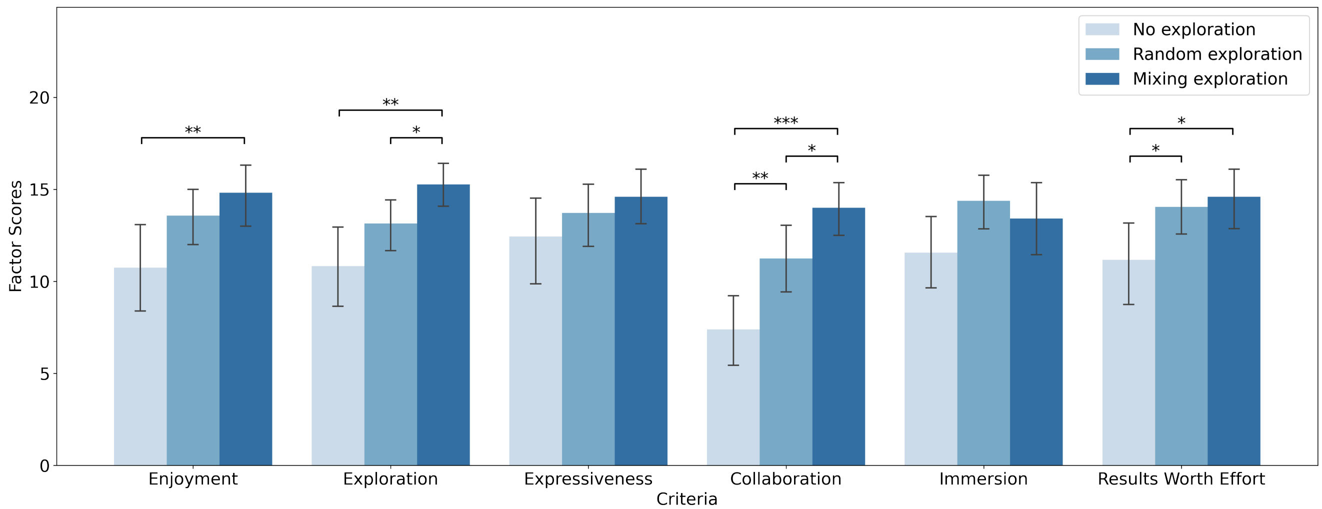

Figure 6: Comparison of CSI factor scores (*: $p < .05$, **: $p < .01$, ***: $p < .001$)

for novelty, where large edit distances indicated that the second design was more novel, and smaller edit distances indicated that the second design was less novel.

5.2 Results

5.2.1 Creativity Support Index. We found a significant difference among the three conditions on the overall CSI score ($F(2, 63) = 4.53$, $p < .05$). Post-hoc comparisons showed that the CSI score of the mixing-exploration condition ($M = 73.59$, $SD = 15.01$) was significantly higher than the no-exploration condition ($M = 55.90$, $SD = 26.24$), $t(41) = 2.79$, $p < .01$. The score of random exploration ($M = 68.52$, $SD = 17.57$) was not significantly different from either no exploration, $t(41) = 1.89$, $p = .066$, or mixing exploration, $t(41) = 1.01$, $p = .32$ (See Table 1).

We performed a statistical comparison between the three conditions on the six scales of CSI and found statistically significant differences in four criteria: Enjoyment, $F(2, 63) = 4.60$, $p < .05$, Exploration, $F(2, 63) = 6.66$, $p < .01$, Collaboration, $F(2, 63) = 13.6$, $p < .001$, and Results Worth Effort, $F(2, 63) = 3.73$, $p < .05$. We did not find a significant difference for Expressiveness, $F(2, 63) = 1.31$, $p = .28$, and Immersion, $F(2, 63) = 2.24$, $p = .11$. The comparisons of the six factor scores across the three conditions are shown in Figure 6.

We performed post-hoc comparisons on each of the four factors to better understand the differences between conditions. On the Exploration scale, the mixing-exploration group ($M = 15.3$, $SD = 2.62$) scored significantly higher than both no-exploration ($M = 10.8$, $SD = 5.44$), $t(41) = 3.52$, $p < .01$, and random-exploration ($M = 13.1$, $SD = 3.58$), $t(41) = 2.22$, $p < .05$. The difference between the random-exploration and no-exploration groups was not significant, $t(41) = 1.68$, $p = .10$.

On the Collaboration scale, the mixing-exploration group ($M = 14.0$, $SD = 3.45$) was significantly higher than both no-exploration ($M = 7.39$, $SD = 4.82$), $t(41) = 5.30$, $p < .001$, and the random-exploration ($M = 11.2$, $SD = 4.41$), $t(41) = 2.28$, $p < .05$. The random-exploration group also scored significantly higher than no-exploration, $t(41) = 2.76$, $p < .01$.

On the Enjoyment scale, the mixing-exploration group scored significantly higher than the no-exploration group $t(41) = 2.72$, $p < .01$, but did not score higher than the random-exploration group $t(41) = 1.09$, $p = .28$. Finally, on the Results-Worth-Effort scale both the mixing-exploration group scored significantly higher

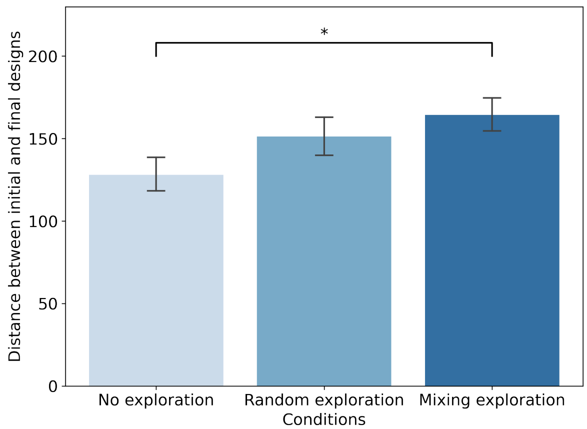

Figure 7: Comparison of the edit distance between initial and final designs. The error bars show standard errors (*: $p < .05$)

than the no-exploration group $t(41) = 2.39$, $p < .05$, but did not score higher than the random-exploration group, $t(41) = 0.458$, $p = .65$.

5.2.2 Novelty of Design Outcomes. The difference between each of the participant's initial and final designs was computed using Levenshtein edit distance. We used this difference as a proxy for novelty, where a large difference between the two designs was considered more novel than a smaller difference. We found that the mixing-exploration group ($M = 164.4$, $SD = 47.6$) produced significantly more-novel designs than the no-exploration group ($M = 128.0$, $SD = 47.0$), $t(41) = 2.55$, $p < .05$. However, the mixing-exploration group's designs were not significantly more novel than the random-exploration group ($M = 151.3$, $SD = 54.4$), $t(41) = 0.84$, $p = .41$, and the random-exploration group's designs were not significantly more novel than the no-exploration group's designs, $t(41) = 1.50$, $p = .14$. The results are shown in Figure 7.

5.2.3 Mediation Analysis Connecting Support for Exploration with Novelty of Outcome. We performed a simple mediation analysis where the outcome variable was novelty of design outcome, the mediator variable was the support for exploration from the CSI measure, and the independent variable was the experimental condition. The indirect effect of experimental condition on the novelty of the design outcome was statistically significant ($effect = 6.67$, 95% $C.I.(1.34, 14)$, $p < 0.01$). More details can be found in Figure 8.

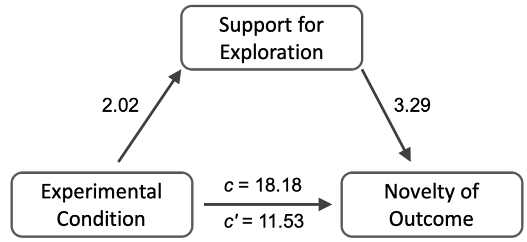

Figure 8: Support for Exploration (CSI) fully mediated the relationship between the experimental condition and the novelty of the outcome. The total effect (c) of Experimental Condition on Novelty of Outcome was 18.18, $SE = 7.45$, $t(63) = 2.44$, $p = 0.017$. The direct effect (c') of Experimental Condition on Novelty of Outcome after removing Support for Exploration was 11.53, $SE = 7.89$, $t(62) = 1.46$, $p = 0.15$. The mean bootstrapped indirect effect (ab) of Experimental Condition on Novelty of Outcome through Support for Exploration was 6.67 with $SE = 3.27$, $C.I.(1.34, 14)$, $R = 0.39$, $R2 = 0.15$, $F(2, 62) = 5.43$, $p = 0.0022$.

5.3 Discussion

Study 2 was designed to investigate the creativity support of the design-mixing functionality for novice designers and its impact on the novelty of the design outcome. Our results showed that design mixing provided significantly better support for novices' creative activities, particularly for the Exploration and Collaboration factors. Additionally, we found that the participants were able to produce designs that were more different from their initial designs after using the design-mixing functionality. Finally, a mediation analysis allowed us to connect these findings and show that making it easier for novices to explore and keep track of different ideas directly affects the novelty of the designs they produce.

5.3.1 Design Mixing with Mixplorer Supports Novices' Creative Practices. Recall that two of the instructors in Study 1 raised doubts about whether the full functionality of the Garden Exploration Interface was necessary to support students' creative practices. This was the main inspiration for Study 2, which was designed to determine whether the full design-mixing functionality of Mixplorer provided added value over (a) nothing and (b) simply showing novices examples. By using the CSI we were able to break up the construct of "support for creative practices" into six sub-scales. We found that Mixplorer was better than the baseline condition on four of the six sub-scales: Enjoyment, Exploration, Collaboration, and Results Worth Effort. These results showed that the full design-mixing functionality of Mixplorer provided robust support for novices' creative practices (i.e., that it was better than nothing).

However, these results could not answer the question about whether this was due to engaging in the design-mixing activity, or if it was due to simply seeing the new examples generated by design-mixing. This question could only be answered by comparing the mixing-exploration and random-exploration groups. We found that the full design-mixing functionality of Mixplorer provided significantly better support than the random-exploration condition on two of the scales: Exploration and Collaboration. This meant that (a) the full Garden Exploration Interface made it easier to explore and keep track of many different ideas or designs than an example-only interface, and (b) the full Garden Exploration Interface was felt to be better for sharing ideas with others and for working together with others. This second result is likely to be related to the comments from the instructors in Study 1 regarding the potential use of Mixplorer as a collaboration tool among multiple designers. Together, these findings tell us that design mixing *does* provide added value over simply showing students examples. Furthermore, this additional support happens to be along the two most-relevant dimensions of the scale, since Mixplorer was specifically designed for *social* design space *exploration.*

5.3.2 Novices Create More Novel Designs After Using Mixplorer. In the first set of results, we found that novices reported that Mixplorer provided extra support for creative practices. We were also interested in seeing whether this additional support would have an effect on the design outcome. As discussed previously, one of our hypotheses was that the support provided by Mixplorer would translate into more novel designs, where novelty was evaluated by comparing each participant's second design to their initial design. We found that the final designs created by the participants in the mixing-exploration condition were significantly more different from their initial designs than those created by participants in the no-exploration condition. And as shown in Figure 7, the novelty of the random-exploration condition was between the other two conditions, although the difference was not significant. These findings indicated that the design-mixing interface of Mixplorer provided support that resulted in the creation of more novel designs.

5.3.3 Exploration Support Fully Mediates the Relationship Between Interface Used and Novelty of Final Designs. In order to better understand why the mixing-exploration group produced more novel designs than the other two groups, we conducted a simple mediation analysis (Figure 8) where the experimental condition was the independent variable, the novelty of the outcome was the dependent variable, and the Exploration score of CSI was the mediating variable. We found that Support for Exploration fully mediated the relationship between experimental condition and novelty of outcome. In other words, making it easier for novices to explore and keep track of different ideas directly affects the novelty of the designs that they produce. This result confirmed that participants in the mixing-exploration group produced more novel designs than participants in the other groups because Mixplorer provided better support for creative exploration.

6 LIMITATIONS AND NEXT STEPS

Taken together, the results of the two studies showed the benefits of design mixing in Mixplorer for design space exploration and the potential usefulness for novice designers. The results from our interviews with instructors showed the feasibility and potential benefits of using Mixplorer in an educational setting, however, it also raised some questions about the value of design mixing for novices. The results of the second study helped answer these questions. In this study, we found that design mixing supports exploration and collaboration, and supports designers in making more novel designs.

Mixplorer has been designed to be used with novice designers in an educational setting. However, it remains to be seen whether the positive results reported here will translate to students in a classroom setting. A logical next step would be to conduct a follow-up study with garden-design apprentices in a VET institution. In addition to replicating results reported here, this follow-up study could also investigate the effect of using one's peers' designs as the initial set of designs in the Garden Exploration Interface. Additionally, this study could evaluate whether the usability and expressiveness of the Mixplorer interface were appropriate for the novice garden designers (i.e., that it had high-enough ceilings, wide-enough walls, and low-enough thresholds to support their creativity [32, 37]). Moreover, it would be interesting to investigate how Mixplorer could function as a collaboration tool to help multiple designers converge on a common solution to a design problem.

Another open question has to do with the effects of design mixing on subsequent designs. Although our work shows that the design-mixing process supported the participants in generating new designs that were more different from their initial designs, it has nothing to say about the quality of these designs. For an ill-defined problem such as garden design, it is difficult to define an objective measure that can evaluate a solution. Answering this question would require an expert evaluation of the designs. In a classroom scenario, this would be feasible as it would be natural for the instructors to give feedback on the apprentices' designs and evaluate their quality.

In the current study we focused on garden design as the target domain, but we can anticipate the extendability of Mixplorer to other design domains. If the designs in the domain contain different types of objects that are arranged in two-dimensional spaces and some degree of symmetry is considered pleasing (e.g., interior designs or texture pattern designs), then the method used by Mixplorer should work without modification. For other domains, what is required in order to use the Mixplorer methods is to come up with new ways of genetically representing the designs tailored to the domains [6, 30, 33], but the general idea of social design-space exploration certainly applies across a wide range of design domains.

7 CONCLUSION

In this paper we present Mixplorer, a system designed to support novices' creative practices by scaffolding the process of design space exploration. Mixplorer uses a genetic algorithm approach we call "social design space exploration" where the designs created by a group of people serve as the starting set of populations in the genetic operations and a novel interface makes it possible to replace the fitness function with a human-in-the-loop. In Study 1, we conducted interviews with garden-design instructors and validated the feasibility of using Mixplorer in an educational setting and the potential benefits for novices' divergent thinking. In Study 2, we conducted a controlled experiment to more closely investigate whether design mixing provided any particular support for novices' creative practices. We found that design mixing provided significantly better support for novices' creativity when compared to no exploration or random exploration, and that those who used the design-mixing interface produced more novel designs than participants in the other groups. Our work shows the importance of scaffolding creative exploration for novice designers and demonstrates the feasibility of using social design mixing for this purpose.

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