Design material as a shared language: exploring human-AI co-creation to augment creativity

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Abstract

Recent advances in artificial intelligence (AI) have led to a growing interest in how AI can support and augment human creativity. With AI-powered tools increasingly transitioning from passive to active contributors in creative processes, a need arises for defining new interaction methods that support human-AI co-creation

The research conducted in this thesis views AI support in creative tasks as a reflective dialogue mediated by the design material. This perspective implies iterative creation, modification, and deriving inspiration from evolving problem and solution spaces in creative sessions. This closely aligns with theories of design practice and creativity theories that view the design process as an iterative and reflective process, extending these concepts to include a computational agent as a design partner.

We explore human-AI collaboration in two distinct creative domains, aiming to augment human creativity in problem-solving, through a computational system. First, we examine AI's potential to offer novel solutions in complex scenarios, such as profile designs for a sonic black hole. In this domain, we highlight the role of evolutionary algorithms in expanding the solution space. Second, we introduce Coevo, a 2D physics environment along with a design language to define proposals in this domain. Coevo facilitates real-time collaboration for creative problem-solving with an AI agent, allowing us to investigate various communication techniques and roles between humans and AI agents in the creative process. We show how AI suggestions augmented the human exploratory process by proposing novel solutions, improving human-generated ones, or providing new creative directions to explore. In addition, we show how humans could also influence the AI output, embodying the nature of collaboration.

Our work demonstrates how human-AI collaboration can augment human creativity through interacting with the design materials produced during a creative session. The notion of this creativity augmentation is supported through the experimental evidence presented in this work highlighting the importance of expressing intentions and evaluating AI's contributions. This research enhances understanding of the flexible role of AI as a collaborative partner in creative problem-solving scenarios, as it helps generate diverse solutions, enables the discovery of new ideas, and augments human creativity through the exploration of the problem space.

Keywords: human-computer interaction; computational creativity; co-creative systems; artificial intelligence; human-AI collaboration; human augmentation; human-AI co-creativity; mixed-initiative co-creation; evolutionary algorithms; shape grammars.

Resum

Els avenços recents en intel·ligència artificial (IA) han despertat un creixent interès en com l'IA pot augmentar la creativitat humana. Aquestes noves eines, potenciades per l'IA, cada cop més passen de tenir un rol passiu a ser col·laboradors actius en els processos creatius, fent sorgir la necessitat de definir nous models d'interacció que donin suport a la cocreació humà-IA.

La recerca realitzada en aquesta tesi considera el suport de l'IA en tasques creatives com un diàleg reflexiu mitjançat el material de disseny produït en aquesta sessió. Aquesta perspectiva implica una creació iterativa, on la modificació i l'obtenció d'inspiració sobre l'espai de solutions ens fa reflecciònar i entendre el problema original, que evoluciona durant la sessions creatives. Aquest fet, s'ajusta estretament a la pràctica del disseny i les teories de la creativitat que consideren el procés de disseny com un procés iteratiu i reflexiu, sobre les quals ampliem aquests conceptes per incloure un agent computacional com a co-creador en l'acte creatiu.

En aquesta tesi, examinem la col·laboració humà-IA en dos àmbits creatius diferents, amb l'objectiu d'augmentar la creativitat humana en la resolució de problemes mitjançant un sistema computacional. En primer lloc, analitzem el potencial de l'IA per oferir solucions noves en escenaris complexos, com ara el disseny de perfils per a un forat negre acústic. En aquest àmbit, destaquem el paper dels algoritmes evolutius en l'exploració de l'espai de solucions proporcionant noves propostes fins al moment inexplorades. En segon lloc, presentem Coevo, un entorn de físiques en 2D, juntament amb un llenguatge de disseny per definir propostes en aquest àmbit. Coevo facilita la col·laboració en temps real per a la resolució creativa de problemes amb un agent d'IA, permetent investigar diverses tècniques de comunicació i analitzar quins rols prenen humans i agents d'IA en el procés creatiu. En aquest àmbit, mostrem com l'intervenció de l'IA han millorat el procés exploratori humà, proposant solucions noves, millorant les generades per humans o proporcionant noves direccions creatives a explorar. A més, mostrem com els humans també poden influir en la sortida de l'IA, encarnant la naturalesa de la col·laboració.

El nostre treball demostra com la col·laboració humà-IA pot augmentar la creativitat humana mitjançant la interacció amb els materials de disseny produïts durant una sessió creativa. La noció d'aquest augment de la creativitat està recolzada per les evidències experimentals presentades en aquest treball, que posen de relleu la importància d'expressar intencions i avaluar les contribucions de l'IA. La recerca presentada en aquesta tesi, millora la comprensió del paper flexible de l'IA com a parella col·laborativa, ajudant a co-crear solucions creatives per diferents problemes, ja que ajuda a generar solucions diverses, permet descobrir noves idees i augmenta la creativitat humana mitjançant l'exploració d'aquest espai de problemes.

Paraules clau: interacció màquina-home; creativitat computacional; sistemes co-creatius; intel·ligència artificial; col·laboració màquina-home; augment de les capacitats humanes; co-creativitat home-màquina; interfícies co-creatives de iniciativa mixta; algorismes evolutius; gramàtica de formes.

Resumen

Los avances recientes en inteligencia artificial (IA) han generado un creciente interés en explorar cómo la IA puede apoyar y potenciar la creatividad humana. La llegada de nuevas herramientas impulsadas por IA, cada vez assumiendo un rol activo en los procesos creativos, genera la necesidad de definir nuevos métodos de interacción que fomenten la co-creación entre humanos y IA.

La investigación realizada en esta tesis considera el apoyo de la IA en tareas creativas como un diálogo reflexivo mediado por el material de diseño. Esta perspectiva implica la creación iterativa, la modificación y la obtención de inspiración a partir de la reflexión sobre las soluciones obtenidas durant la exploración, que nos permiten entender mejor el problema inicial y evolucionar durante la sesión creativa. Esta perspectiva se alinea con las teorías de la práctica del diseño y las teorías de la creatividad que ven el proceso de diseño como un proceso iterativo y reflexivo, por lo que en esta tesis, extendemos estos conceptos para incluir a un agente computacional como co-creador en un proceso creativo.

En esta tesis, exploramos la colaboración entre humanos e IA en dos dominios creativos distintos, con el objetivo de potenciar la creatividad humana en la resolución de problemas a través de un sistema computacional. En primer lugar, examinamos el potencial de la IA para ofrecer soluciones novedosas en escenarios complejos, como en el diseño de perfiles para un agujero negro acústico. En este dominio, destacamos el papel de los algoritmos evolutivos en la expansión del espacio de soluciones, proponiendo nuevas solucionas que no habían sido consideradas hasta el momento. En segundo lugar, presentamos Coevo, un entorno de física 2D junto con un lenguaje de diseño para definir propuestas en este dominio. Coevo facilita la colaboración en tiempo real para la resolución creativa de problemas con un agente de IA, lo que nos permite investigar diversas técnicas de comunicación y roles que asumen tanto humanos como agentes de IA en el proceso creativo. En nuestros experimentos, mostramos cómo las sugerencias de la IA mejoran el proceso exploratorio humano al proponer soluciones novedosas, mejorar las generadas por humanos o proporcionar nuevas direcciones creativas para explorar. Además, mostramos cómo los humanos también pueden influir y guiar las propuestas de la IA, encarnando la naturaleza de la colaboración en un proceso creativo

Nuestro trabajo demuestra cómo la colaboración entre humanos e IA puede potenciar la creatividad humana a través de la interacción con los materiales de diseño producidos durante una sesión creativa. La noción de este aumento de la creatividad se respalda a través de las pruebas experimentales presentadas en este trabajo, que resaltan la importancia de expresar intenciones y evaluar las contribuciones de la IA. Esta investigación mejora la comprensión del papel flexible de la IA como compañero colaborativo en escenarios de resolución de problemas de manera creativa, ya que ayuda a generar soluciones diversas, permite el descubrimiento de nuevas ideas y potencia la creatividad humana a través de la exploración de este espacio de problemas.

Palabras clave: interacción máquina-hombre; creatividad computacional; sistemes co-creativos; inteligencia artificial; colaboración máquina-hombre; augmentar las capacidades humanas; co-creatividad hombre-máquina; algoritmos evolutivos; gramática de formas.

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ACRONYMS

ABH: Acoustic Black Holes

AI: Artificial Intelligence

CMA-ES: Covariance matrix adaptation evolution strategy

CST / CSTs: Creativity Support Tool / Creativity Support Tools

CSI: Creativity Support Index

ES: Evolution Strategies

HCI: Human Computer Interaction

IEC: Interactive Evolutionary Computation

GA: Genetic Algorithm.

GE: Grammatical Evolution

MS: Mean Shift

MICIs: Mixed-Initiative Creative Interfaces

PCA: Principal component analysis

PCG: Procedural Content Generation

SBH: Sonic Black Holes

SG: Shape Grammars

Chapter One

Introduction

The idea that we could use machines to augment our capabilities or even that in the future machines would collaborate with us has been pursued for many decades across multiple fields. In the early 1960s, pioneers such as J.C.R. Licklider and Doug Engelbart envisioned how computers would be used to amplify thought and communications, as tools for intellectual work and social activity [1]. Licklider introduced the concept of man-computer symbiosis [2] describing how humans would share the initiative with a computer in decision-making processes. Engelbart expanded these original ideas on how to collaboratively solve problems with computers within his framework for augmenting human intellect [3]. He described the human problem-solving process as a series of multiple sub-processes addressing different parts of a global problem. Then, an augmentation could occur when one or multiple of these sub-processes were not performed by a human, but rather by a new system or interface augmenting original human capabilities.

In 1963, Ivan Sutherland first demonstrated the potential of human-computer interaction, creating the first system to offer computational support for designers, the Sketchpad. In Sketchpad, users were able to draw directly on computers using a light pen, making it possible for them to point to objects on the screen, interact with them and specify constraints and relationships between objects. This novel interaction mechanism revealed the potential of real-time computer interaction and later influenced the development of graphical user interfaces (GUIs) we use nowadays. Influenced by this work, Nicholas Negroponte introduced the concept of *design amplifiers*, referring to the use of computer-aided tools to amplify or enhance the design process [4]. Particularly in the context of architecture and design, Negroponte suggested a possible role of computers as partners in the design process, rather than being merely tools. He envisioned how designers could use artificial intelligence to augment their abilities, increase their productivity and stimulate their creativity based on their design intentions. These early pioneers' concepts and ideas influence how we think about the role of computers in design today.

For the purpose of this thesis, design is defined as a *goal-oriented, constrained, decision-making, exploration, and learning activity* [5]. In design theory, design is always a *situated* activity referring that is not an isolated process but one that is influenced by its specific context or environment. The goal of design activity is to propose a solution that achieves a certain objective within a constrained problem [6]. However, the assumption that this design activity starts with a well-defined problem has been challenged by the research community [6], [7]. Some authors [8], [9] describe the design as a process of co-evolution of both problem and solution spaces. As we engage with a design activity, we are learning about a certain problem through proposing and analyzing solutions, developing a better understanding of this problem [10]. According to Gero's situated framework [5] this design activity embodies our cognitive processes within a specific context allowing us to externalize our internal thought processes. Then, this activity is an iterative process where we reflect upon our understanding of problem and solutions spaces while exploring the design situation. This vision of design as a reflective activity is closer to Schön's concept of *Reflect-in-action* [11]. Schön views the design process as a reflective dialogue with the material being created. As designers reflect on these materials, they refine their understanding of the problem and develop potential solutions. Every time an action is performed, we can analyze the results and with this information decide our next actions. Then during this iterative search process, the discovery of new criteria and possible new constraints can redefine the original problem space producing new knowledge on both the problem and solution spaces. As stated by Gero [7], the interaction between a designer, the environment and previously acquired knowledge determines the design process. For that reason, the process itself plays an important role in the acquisition of human knowledge and design capabilities which could lead to the generation of new ideas and solutions.

This co-evolutionary process that we have described is where several authors claim that creative designs can emerge [10], [12], [13]. An idea for a solution can lead to a re-interpretation of the problem, which can help on expanding our current knowledge and even lead to discovering different approaches to a certain problem. Then a better understanding of the problem can spark new ideas for solutions. In this context, creativity or the *capability to generate creative designs*, can be related to how the introduction of *something new* which can lead to an unexpected result re-framing the problem and solution spaces [8], [14]. Therefore, human capabilities of being creative during a design process is relevant for exploring a certain problem space.

Regarding creativity, there are many multiple definitions of it since it has been considered a subjective term [15]. However, two main aspects recurrently appear in its definition: *originality* and *effectiveness*. Originality refers to how novel is a proposal compared to the rest of the previous proposals. This may lead to original proposals that may as well be useless. For that reason, effectiveness is also used as a parameter for evaluating creativity, considered a measure of proposal usefulness. Considering these two aspects, creativity will be referred using Boden's definition [13] as it follows:

> *Creativity is the ability to come up with ideas or artifacts that are new, surprising, and valuable.*

This definition considers evaluating the *product* of a creative process rather than other aspects such as the individuals who are responsible of the creative process, the creative process itself, or the environment on which they operate [16]. More specifically, Boden also distinguishes between different ways of evaluating creativity: *p-creativity* and *h-creativity*. *P-creativity* refers to personal creativity or how creative is a proposal considering a particular individual perspective. Instead, *h-creativity* refers to historical creativity or how novel a given proposal is compared to everything that came before. Note that both definitions consider the product of the creative process and its main difference is to which space of previous proposals we compare this product: a *personal* individual space or a *collective* space.

Creativity is also considered to not only be an internal thought process inside our own minds but in the interaction between a person's thoughts and a sociocultural context [17]. So, by extending thought processes externally, an individual is able to create different external representations or abstractions that can help them reflect and advance their thought processes [18]. According to Tversky [19], [20], when thoughts overwhelm the mind, people use whatever is available to them, their bodies or different tools, to create different visual representations of their thoughts. The author provides some external representations as historical examples, such as ancient paintings of animals on cave walls, to more recent representations such as the stories in Greek columns or vases or the explanations in the walls of Egyptian tombs. This relationship between thinking and physicality is deepened in the theory of Embodied Cognition which argues that cognitive processes are not only a product of mental processes, but also the motor behaviors and physical outcomes with and around our bodies [21]. Particularly, Clark and Chalmers [22] refer to how creative thinking can take place beyond the mind, in the objects and materials we use to solve a certain problem. Then, the usage of different materials or tools such as paper, pens or digital surfaces can be a way to expand and extend thinking processes beyond the mind [23], [24]. Furthermore, these representations could serve as key aspect to collaboration with another human or computational agent [18]. By externalizing our internal thought processes, others can visualize and later understand our mental model and help us to redefine our own perceptions.

Traditionally, the usage of different materials or tools such as paper, pens or digital surfaces has been used as a way to expand and extend creative thinking processes beyond the mind and communicate our thoughts with others. However, due to technological advances a new range of creativity support tools with more capabilities can now support current human thinking processes. In this context, Shneiderman described how computers had the potential to become tools for enhancing human creativity and proposed a framework to create digital-interactive tools for creative problem-solving [25]. Shneiderman defined creativity support tools (CSTs) as systems designed to help individuals or groups produce creative work in any creative field. This could include typical commonly used, general-purpose tools like text editors and spreadsheets as well as specialized software for graphic design, architecture, or engineering. According to some authors, these creativity support tools can take many forms [26] regarding their potential to either improve current human abilities or augment their capabilities by introducing new creative experiences they were not capable of. In this new context, there is a rise of a new paradigm of computational support tools: *mixed-initiative creative interfaces* or *co-creative* systems. These co-creative tools are a great example of introducing new creative capabilities since they can collaborate with humans to explore a certain creative domain. These types of tools put humans and computers in a tight interactive loop where given a specific problem both contribute in a certain domain [27]. In this sense, multiple computational tools have been explored in order to define interactive systems that can support human intervention during multiple steps of the whole design process [28]. This vision of augmenting human problem-solving by sharing an initiative with a computer is strongly related to Licklider's Human-computer Symbiosis [2] or Engelbart framework for augmenting human intellect [3].

This growing interest in how AI can improve human creativity implies that we must define new interaction methods that support human-AI co-creative collaboration. According to some authors, this is particularly challenging due to AI's algorithmic complexity and unpredictable system behaviors [29]. Traditional tools are often easier to master or use than AI-powered tools. As an example, a carpenter's hammer or an artist's paintbrush become invisible extensions of our bodies while we are using them, without any cognitive burden. Even nowadays mouse and cursor can be perceived as an extension of our body while interacting within digital domains. However, the capabilities of new AI-powered tools may allow them to go beyond traditional tools, emerging from being passive instruments to becoming active collaborators in the creative process.

For that reason, in this thesis, we explore how new AI-powered tools can support human creative processes. In the following section, we describe our research goals and our main research questions for this dissertation.

1.1 Research goals

This thesis focuses on supporting creative problem-solving by computational means, as well as exploring possible interaction models, communication techniques, and emerging roles during human-AI collaboration in co-creative systems.

By *creative problem-solving* we refer to Boden's definition of creativity [13] on which creativity is evaluated based on the value and novelty of the solutions proposed for a given problem space. For this thesis, value is defined as a measure of utility, that is related to how well a solution solves a problem given an evaluation method. In contrast, novelty is a measure obtained by comparing either the other solutions created for a given problem or the knowledge about that domain.

By *computational means* we refer to AI-powered tools and co-creative systems that can help humans to explore a given problem space by proposing the best solutions given evaluation criteria. This approach consists in helping humans in two main ways: by autonomously generating human-level creative solutions for a given domain and co-creating with humans in real time. For the latter, we investigate the possible roles and define new interaction models for these systems to support real-time collaborative creative problem-solving.

Our hypothesis is that the product that emerged during the collaboration with an AI-powered tool or co-creative system is more creative in terms of value and novelty [13] than the product an individual could achieve alone. However, in order to support this collaboration, new methods for exploring solution space need to be defined together with efficient ways to communicate and share knowledge between humans and artificial agents. As introduced before, externalizing our internal cognitive processes in a shared material can influence others' exploration leading to new potential solutions and a fresh perspective on the problem space.

For that reason, the core contribution of this thesis is to demonstrate that co-creative systems can augment human creativity by communicating with humans through the materials generated during the creative session. In this thesis, computer-assisted support in creative tasks is considered a reflective conversation mediated by the design material. This implies iterative creation, modification, and deriving inspiration from the co-evolving problem and solution spaces in the design situation. This work draws inspiration from design and creativity theories on human collaboration and applies them considering a computational agent as a design partner. [5], [8], [11].

The main research question of this thesis can be summarized as follows:

> *"How can a computational system augment human creativity by interacting with shared design material and lead to more novel and useful solutions than those generated by individuals working independently?"*

More specifically, this question can be narrowed down and answered by the following research questions:

1. "What impact does the design and use of the design language have on the emergence of creative proposals, and how do these tools support exploration?"

2. What types of computational means can be integrated into different creative processes? How do they impact the exploratory process?

3. How does the communication mediated by the creative product influence the human-AI collaboration? What other techniques can be used?

4. What is the main role of AI in the creative process? How do AI-generated proposals contribute to the exploration and discovery of new ideas and perspectives?

1.2 Research contributions

This dissertation moves at the intersection of design and creativity theories, human-computer interaction, and tools to support creativity in combination with AI research, and focuses on how computational approaches can foster human-AI co-creativity (Figure 1.1).

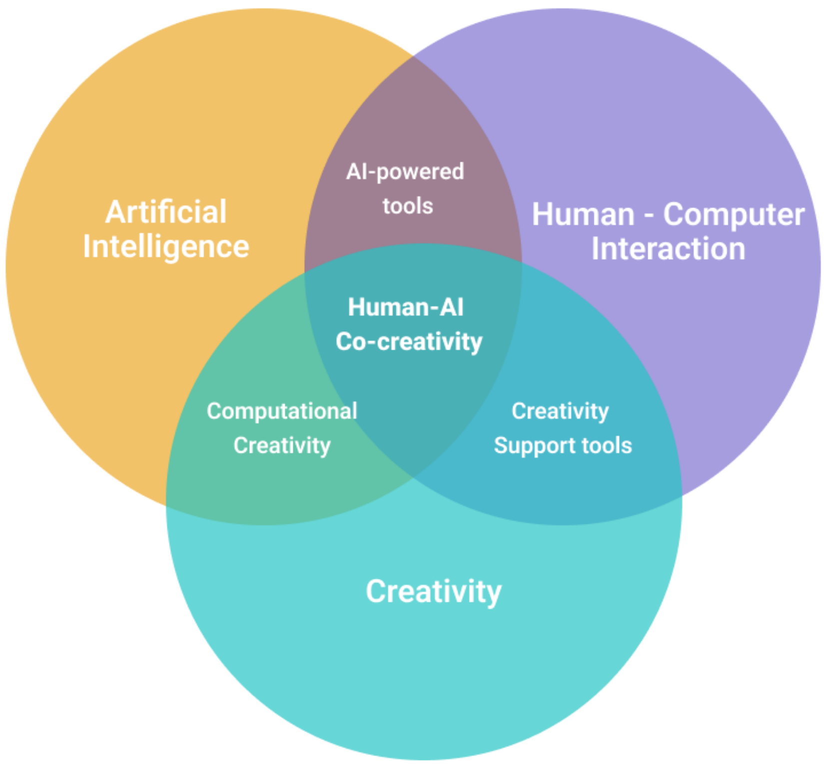

Figure 1.1 Positioning of the research. This thesis sits at the intersection of Human-Computer Interaction, creativity and artificial intelligence. More specifically we explore possible interaction methods and roles during the collaboration between human and AI-powered systems in co-creative scenarios.

To answer the research question stated before, this thesis provides different scenarios where computational means have supported the human creative process, including providing novel communication and interaction techniques together with algorithms to explore given solution spaces. Furthermore, this work contributes to the body of knowledge on creativity and design research, creativity support tools, and human-AI co-creativity by providing evidence of creativity enhancement in different domains and describing new interactive methods and emerging roles for human-AI collaboration in creative domains. More specifically, we detail the specific contributions below:

- **Empirical results on AI-powered creativity**: A study to investigate how AI can support creativity in a real-case complex scenario: designing a sonic black hole profile (SBH). This work yields experimental results on how evolutionary computation can be used to explore and advance knowledge in a given specific domain. It also shows how solution exploration can be enhanced by computational means to new creative designs for SBH profiles through the collaboration between humans and AI systems.

- **Coevo, a new design language and environment to explore real-time human-AI collaboration in creative-problem solving**: This environment, Coevo, plays a central role in this project, which demonstrates the importance of defining a flexible design language to support human-AI collaboration through the creative product. In addition, this environment served as a shared platform for human-AI collaboration, where we investigated new interaction models with AI-powered agents and preferred roles for both humans and AI agents in cooperative scenarios.

- **New evolutionary-based techniques** : We present, evaluate and compare different evolutionary methods and their capabilities to produce creative designs. Our findings indicated how defining flexible tools to support the exploration of the given problem space can lead to better results in terms of value and novelty. This means that it is not only the definition of the algorithm that influences the creative output but also the way the problem space is explored.

- **Supporting personal creativity with AI**: We demonstrate via two studies how creativity can be augmented using AI. In the first study, we show how an AI agent can design solutions for Coevo scenarios at human level in terms of novelty and value. Then, in a second study, we present a co-creative system that supports human-AI collaboration in Coevo environments. This study evidences how the product of the collaboration between human-AI is more creative than the one generated by only humans.

- **AI Role in creative-problem solving**: This thesis provides pieces of evidence of how AI can assume multiple roles during creative sessions, responding to different creative needs that may emerge. This indicates how AI's role in the creative process should be dynamic and flexible depending on the scenario context and the creator's needs.

- **Human-AI collaborative guidelines**: This thesis proposes design guidelines for human-AI collaboration co-creative systems based on empirical experiments implemented in Coevo platform.

1.3 List of publications

In this section, we list our research publications, which are the outcomes of the investigations conducted on augmenting creativity through computational means, presented in this thesis. Each publication corresponds to the various contributions outlined in the previous section, and it forms the foundation for the corresponding chapters in this thesis.

I. G. Serra and D. Miralles. "Coevo: a collaborative design platform with artificial agents." *in Workshop Designing Crowd-powered Creativity Support Systems - Extended Abstracts of the 2019 CHI Conference on Human Factors in Computing Systems.* 2019. [30]

II. G. Serra, D. Miralles, M. Casals, and M. Lopez. "Exploring the flexibility of a design tool through different artificial agents." *in Proceedings of the Eleventh International Conference on Computational Creativity, (ICCC)* 2020. (pp. 90-97). [31]

III. G. Serra and D. Miralles, "Human-level design proposals by an artificial agent in multiple scenarios." *in Design Studies 76* (2021): 101029. [32]

IV. O. Guasch, M. Arnela, G. Serra, and D. Miralles, "Evolutionary strategy to optimize sonic black hole profiles in duct terminations", *in Noise and Vibration: Emerging Methods (NOVEM2023)*, 2023 [33]

V. G. Serra, O. Guasch, M. Arnela, and D. Miralles, "Optimization of the profile and absorption of sonic black holes in duct terminations", *(in preparation)* [34]

In Table 1.1, we provide an overview of how these publications contributed to each of this thesis' chapters.

Publication	**Chapter**
I	4
II	5
III	6,7
IV	3
V	3

Table 1.1 Publications influence in each chapter

Apart from the publications listed before, during my thesis, I also contributed to and investigated on exploring multimodal learning in artificial cognitive systems (ACS). These explorations consist of incorporating haptic knowledge in an ACS in order to augment their sensory perception, initially consisting only of vision. We show how this approach can improve ACS resilience to changes in the environment allowing a better self-adaptation via crossmodal knowledge transfer. This exploration includes the following articles:

I. G. Garrofé, C. Parés, A. Gutiérrez, C. Ruiz, **G. Serra**, & D. Miralles, "Virtual haptic system for shape recognition based on local curvatures," In Advances in Computer Graphics: 38th Computer Graphics International Conference, CGI 2021, Virtual Event, September 6–10, 2021, Proceedings 38 (pp. 41-53). Springer International Publishing.[35]

II. D. Miralles, G. Garrofé, C. Parés, A. González, **G. Serra**, A. Soto, X. Sevillano, H. O. de Beeck, and H. L. Masson. "Multi-modal self-adaptation during object recognition in an artificial cognitive system," Scientific Reports, 12(1), 3772.[36]

1.3.1 Thesis overview

Chapter 2 provides a review of the literature and studies that have been conducted in the field of creativity support tools, computational creativity, and co-creative systems focusing on exploring human-AI collaboration across various creative domains.

Following the literature review, Chapter 3 focuses on how AI systems can create valid solutions in real-world scenarios, specifically in the context of finding new profile designs for an acoustic black hole. This chapter presents the first empirical evidence results on how creativity can be enhanced through computational means, with the challenge being the improvement of current existing profile performance. The chapter discusses how the proposition of innovative solutions can contribute to historical creativity and advance scientific knowledge in this field. The research findings demonstrate how evolutionary algorithms can broaden existing domain knowledge and inspire humans to expand the current solution space. However, the complexity of the computations and simulations required in this experiment increases the time to obtain valid solutions, which can be higher than multiple hours, which makes real-time collaboration with the AI-powered system impossible. For that reason, Chapter 4 introduces the second stage of the work, exploring another scenario to augment creativity in a real-time setting. In this chapter, we discuss the importance of defining a common language to explore a solution space. Then, we present a set of shared design tools and a 2D physically based prototype, Coevo, to explore real-time human-AI collaboration for creative problem-solving. Our initial findings from this chapter give insight into how an AI system can exhibit creative behaviors using a set of shared design tools. Chapter 5 further explores different computational techniques to generate solutions for Coevo scenarios space using the defined design tools. This exploration allows us to better understand the implications of algorithm design in the context of creativity support and helps us to define a more generalistic AI agent to support creative exploration in multiple scenarios. This AI agent is then utilized in subsequent chapters as a creative partner for Coevo scenarios. In Chapter 6 we compare agent's proposals to those designed by humans, demonstrating agent's capability to provide human-level solutions in multiple scenarios. The ability of this AI to explore a certain design space and find novel solutions can inspire human creators, enabling them to broaden their original solution spaces. These promising results drive us to continue exploring this space and to study potential relationships between human and AI agents in the creative process. For this reason, Chapter 7 introduces a new version of Coevo that is interactive and facilitates collaboration between humans and AI agents. Our research indicates that humans generally want to take the initiative to collaborate by first stating their design intentions or providing examples of potential solutions. So they expect to ask an AI-powered tool for help or inspiration primarily when they are stuck or want to explore new solutions. The communication facilitated by the design material improves the user's control and the predictability of the system while fostering a sense of co-creation where both humans and AI contribute to the evolution of the design proposal. Therefore, it is crucial to provide tools and interfaces for humans to express their intentions and select, evaluate, or refine the AI's responses, thus fostering collaboration between humans and AI.

Finally, in Chapter 8 we conclude by detailing our findings from this dissertation discussing future directions and possibilities of the work presented in this thesis and their implications for the human-AI co-creativity field. In addition, we provide some design guidelines for creating future AI-powered creativity-support tools or co-creative systems, taking into account the diverse needs during a creative session and the emerging roles during the collaborative process.

Chapter Two

Related work

The main focus of this thesis is exploring how AI can support creative problem-solving in different creative domains. In this Chapter, I summarize previous related work from design and creativity theories, creativity-support tools, computational creativity, co-creative systems for human-AI collaboration in creative domains and evolutionary algorithms as a computational mean to support exploration. The following chapters will also present further relevant related work to contextualize the research.

2.1 Design & creativity

Design has been described as a process of co-evolution of both problem and solution spaces [9], [10]. This iterative process seeks possible ideas that can solve a given problem [37]. However, during this search, a discovery of new criteria and possible constraints can redefine the original problem space. This has been widely explored by various authors [10], [12], [13] who state that creative design can emerge during this process of co-evolution. This emergence can help on expand our current knowledge and even discover different approaches to a certain problem. Therefore original problem or solution spaces are extended based on that. This can be done through different actions that allow us to explore solution space [12]. Every time an action is performed we can analyze the results and with this information decide our next actions. Thus, as a consequence of designing, knowledge is produced [12] and original capabilities of generating creative designs can be increased. As stated by Gero [7], the interaction between a designer, environment, and previously acquired knowledge determines the course of designing. Then, designers' capabilities to generate creative designs are directly related to their previous learning and experiences. For that reason, the process itself plays an important role in human knowledge acquisition and capabilities in designing leading to the generation of new ideas and solutions. As mentioned by Donald Schön's, the design process can be defined as a reflective dialogue with the material being created. In his theory of *Reflect-in action*, he highlights the importance of externalizing our internal processes in order to reflect on our own actions. Particularly in ill-defined scenarios, humans can refine their understanding of the problem and develop potential solutions by exploring both the solution and problem spaces. Then, an idea can lead to a reinterpretation of the problem, and a better understanding of the problem can spark new ideas for solutions. As mentioned in Chapter 1, creativity is closely related to how the introduction of *something new* which can lead to an unexpected result re-framing the problem and solution spaces [8], [14]. For the purpose of this thesis, we refer to Boden's definition of creativity that considers *creativity as the ability to come up with ideas or artifacts that are new, surprising, and valuable* [13]. More specifically during the work of this thesis, we support two types of creativity also introduced by Boden: personal creativity *(p-creativity)* and historical creativity *(h-creativity)*. Following Boden's approach, we will evaluate creativity based on the product of the creative process and explore how different methods can support the emergence of more creative outputs.

In order to support and augment our creative capabilities [10], many computational tools have been defined [28]. These tools range from early design stages such as inspiration, exploration and generation [38]–[42] to more advanced design phases that require an already defined proposal that must be redefined or optimized [43]–[45]. These tools demonstrate the potential of creativity support through different phases of the design process. In the following section, we describe different computational approaches to support creativity.

2.2 Creativity support tools

Creativity support tools (CSTs) have seen a growing interest in the study of creativity in Human-Computer Interaction (HCI) [46]. As mentioned by some authors, this research field has been identified as a grand challenge for HCI [47]. Particularly, Shneiderman describes a *creativity support tool* (CST) as one that helps a human achieve their creative potential, by empowering a user to be more productive and more innovative [25]. We refer to different techniques and tools to support early design exploration outlined in [48]. The authors argue that current computer-aided design (CAD) tools primarily focus on the manipulation and generation of optimized designs based on pre-determined parameters. Therefore, to obtain meaningful results, designers must articulate these parameters, representing their design intent. However, this approach often falls short in the initial phases of the design process, particularly when dealing with ill-defined problems. The main goal during these stages is to generate a hypothesis and establish novel directions. Therefore, the authors recommend using computational mechanisms that can explore a diverse range of solutions and concepts to facilitate establishing new connections and providing inspiration for designers [49].

Dreamsketch [41] is an exemplar of this approach. It consist on a 3D design interface that combines free-form sketching for defining the problem and design intent with generative design as a method to explore solution space. This allows for creative exploration while also visualizing possible solutions, enabling better-informed decisions early on.

Note that within these tools, searching and visualizing solution space play a significant role in creative exploration. In that line, Wiggins [50] proposes a formalization of Boden's previous creativity concepts [13] to consider exploring possible proposals, named artifacts, mainly as a search in a conceptual space. This approach, with its focus on exploration and generation of creative artifacts, emerges as a new research field termed Computational Creativity [51]. This sub-field of Artificial Intelligence (AI) investigates computer systems and algorithms capable of exhibiting behaviors commonly associated with human creativity. It involves applying various computational techniques, such as AI, to understand and simulate different aspects of the creative process. In this context, the automation of an intelligent task is seen as an opportunity to generate something of cultural value [51]. With that approach, many computational systems have been defined in multiple creative areas such as drawing [52]–[54], poetry and storytelling [55], [56], music generation [57][58] amongst others.

Our approach to supporting creativity via autonomous solution space exploration using a computational agent is influenced by this previous work. As mentioned by Deterding, computational creativity support, has been broadly explored in the field of procedural content generation (PCG) for games [27]. Subsequently, we outline several examples of computational creativity, focusing on this domain.

2.3 Computational Creativity in Games

Particularly in the field of Procedural Content Generation (PCG), there has been a wide definition of tools that create content automatically, through algorithmic means [59]. One primary motivation for PCG is to reduce the cost and resources needed for the manual creation of game content and assets. In these tools, artificial systems should accommodate human design intentions and adjust accordingly to improve collaboration between them. Some examples in this domain are Ropossum which aids the game designer in designing and optimizing a physics-based video game [60] or Tanagra [61] which uses procedural content generation to assist game designers in 2D-level design. Both systems explore the relationships between a human and a computer in PCG, inspiring us to explore how humans can define their intention, and artificial agents can explore the solution space. Specifically, we are interested in investigating how communication between humans and these artificial agents can be articulated in terms of creation. This question is also examined in Sentient Sketchbook [62] where authors explore how can humans can be assisted by artificial agents in the context of game-level design. Their system provides real-time feedback while the human is creating the map. In later research [63], they discuss fostering human creativity through co-creation with Sentient Sketchbook, as opposed to merely using the tool as an assistant. They refer to this approach to Mixed-Initiative Co-Creativity (MI-CC), situating it within the literature of human and computational creativity, with connections to lateral thinking [64] and exploratory creativity [13]. This concept builds upon the extended mind theory [65] introduced in Chapter 1 which suggests that an external object (e.g. the Sentinel Sketchbook) that consistently aids and is relied upon by a human to perform cognitive or reasoning functions can be seen as an integral part of that subject's cognitive process. Their results suggest that co-creative tools such as Sentient Sketchbook allow exploring the possibility space guided by human decisions during the creative process promoting human-AI creativity.

These approaches inspire us to investigate which computational tools best support creative exploration in various domains. Several authors have discussed three different categories for creative systems based on their capabilities [66]: standalone generative systems, creative support tools, and co-creative systems. This categorization aligns with other work [27] which describes the spectrum of these creative systems based on who leads the initiative of the creative session. On one end, there are the previously mentioned creativity support tools where the human is the main controller of the actions. On the other end is computational creativity, outlined in this section, where an artificial agent generates autonomously creative proposals. In the middle of this spectrum sits human-AI co-creativity approaches where both AI agents collaborate to perform a certain creative task. This approach is gaining traction due in part to the democratization of AI. It has the potential to generalize to multiple fields apart from the already mentioned game design such as sketching, music creation, interface design, or text generation.

This thesis aims to provide new interaction techniques for communication together with exploring different roles for AI systems in creative sessions. For that reason, in the next section, we highlight co-creative systems and the potential role of AI in other creative domains.

2.4 Co-creative systems and AI roles

Mixed initiative interfaces aim to facilitate efficient collaboration between humans and intelligent agents to accomplish tasks [67]. In order to do that, these agents must be able to understand human goals and respond appropriately. This concept firstly introduced by [67], [68] has influenced the design of interfaces for human-computer interaction across various fields such as user modeling [69], adaptive systems [70], [71] or even human-robot interaction [72].

Co-creative systems [66] or mixed-initiative creative systems [27] evolved from the idea of merging autonomous generative systems with creativity support tools. In such systems, computers and humans both take an active role in the creative process, functioning as co-creators

A key aspect of these tools is that they transition from passive roles to becoming active collaborators in the creative process[73]. Lubart outlines four distinct ways computers can assist human designers: acting as a management tool to set deadlines, timers, and performance measurements, aiding in idea representation and projection; serving as communication enhancers between individuals through technology; evolving into expert systems providing diverse information to stimulate creativity; and finally, the most ambitious one acting as a collaborator during the creative act.

However, the role computers play in specific scenarios is not fixed, as individual human perceptions and expectations of computers can vary. Research conducted by [74], investigates how different AI agents can interact with humans on a turn-by-turn basis to design a Super Mario Bros level. This research further explores diverse roles for AI in interaction with humans, describing four potential behaviors: *Friend*, where users find the interaction enjoyable and actively explore the system's offerings; *Collaborator*, where users expect the AI to act as an equal design partner, affecting their experience based on the AI's responsiveness and the consistency of its contributions; *Student*, where users expect to instruct the

AI to mimic their actions; and *Manager*, where users perceive the AI as giving instructions or assessing their design process. As Lubart points out [73], these roles are not mutually exclusive and can change during the creative session. In our approach, we provide examples of how these roles can shift to meet varying creative needs and human expectations of the creative act.

Another instance of AI-human collaboration is DuetDraw [54] where an AI agent collaboratively draws with a human. Their studies suggest how participants preferred role is to lead the initiative and the agent acting when they asked them to do so. They emphasize the importance of explanations to understand AI intentions, which aids collaboration. Similarly, in Creative Sketching Partner [75], an intelligent interface offers visual analogies to inspire designers during sketching. The suggestions are influenced by the current state of the user's sketch. The authors introduce a control for the system's exploration/exploitation strategy, which guides the AI's exploration, better adapting the co-creative system to expectations during the creative session.

Morever, in May AI [76] and ImageSense [77], authors examine how AI can support mood board ideation sessions, particularly when inspiration is lacking by providing suggestions based on the material they share on the board. Their findings underline the importance of user perception control during interaction to integrate intelligent tools within their creative session. They suggest how it depends on the users' situation and their expectations of system responses highlighting the importance of having ways to steer and influence system responses.

These co-creative tools illustrate the importance of understanding humans' perceptions of AI roles when collaborating with AI, an aspect that needs to be considered when designing AI-powered tools for creative work. To support collaboration between humans and AI, these systems must include different communication strategies and interactive methods that allow humans to influence system responses based on their creative needs

In our approach, we consider that co-creative systems can augment human creativity by communicating with humans through the materials generated during the creative session. Consequently, in our work, we stress the significance of a shared design language for generating solutions for a given design space. Using this language, both humans and AI agents will be able to create, modify, and draw inspiration from the proposals they generate during the creative session. We hypothesize that by combining this shared language with AI-powered tools or co-creative systems that can help humans to explore a given problem space, proposing optimal solutions given evaluation criteria, we can augment their creativity within that space. Specifically, we adopt evolutionary algorithms as our computational method to navigate the various domains presented in this thesis.

2.5 Evolutionary algorithms for problem exploration

Natural evolution has progressively adapted organisms to diverse environments, effectively overcoming complex [78]. Countless solutions present in nature in the form of living organisms are proof of this process. This evolutionary principle has sparked the development of Evolutionary Computation [79] an artificial intelligence subfield that focuses on problem-solving optimization. As highlighted in [80], authors collect multiple examples of evolutionary-inspired algorithms that demonstrate how digital evolution experiments can also produce a wide diversity of surprising and creative results in digital worlds. The broad application of these techniques [81] spans the optimization of specific design solutions [82] to evolving complete morphologies from scratch [83]. These techniques [81] have been widely applied in Evolutionary Robotics [84]. Through simulating environments and behaviors in a digital world, learning can later be transferred to create real robots in the physical world [85]. For instance, simulations can propose innovative solutions to design problems in specific environments [86] or anticipate failure scenarios in the real world [87]. A remarkable breakthrough in this domain involved constructing robots from frog cells that could self-repair when damaged [88]. Another example of possible applications of evolutionary algorithms is to optimize robot hardware design and control in order to minimize energy consumption and ensure robust performance [89].

These algorithms' capacity for generating and exploring diverse solutions also extends to supporting human roles in design and creation. As shown in [39], an evolutionary algorithm can create novel designs from scratch given a set of pre-determined design conditions. However, human interaction with this system was based on providing some inputs and receiving system-generated output solutions that can later inspire designers. A more interactive approach is offered by Interactive Evolution [90], which is based on allowing humans to select appealing proposals within the evolutionary process. This approach is more similar to the human design process in which knowledge acquisition is related to the exploration of possible designs and the relationships with their environment throughout the design process [7].

Despite its generative capabilities, much of the preceding research focuses on problem-solving rather than exploring a collaboration between humans and AI agents [43], [91]. For that reason, our approach seeks to explore how both humans and artificial agents can generate valid proposals in multiple design problems using a common set of tools and compare the artifacts produced in their creation process.

In the remaining chapters, we discuss in more detail the specific algorithms used in our experiments. In our approach, we primarily apply evolutionary algorithms in two domains highlighting the importance of defining a design language and expressive tools that facilitate exploring a particular problem space. Chapter 3, discusses how these algorithms can promote *h-creativity* in a complex scenario: defining profiles for a sonic black hole. There, we discuss how human-AI collaboration can emerge when interacting with a (semi)-autonomous computational system where the human role mainly consists of defining experiment conditions. In Chapter 4 we introduce a new environment, Coevo together with a design language that will allow real-time collaboration with AI agents through interacting with the materials produced during the creative session. Chapter 5 analyzes various evolutionary techniques to understand their exploration potential. Chapter 6 showcases our approach's effectiveness, combining an evolutionary algorithm with a shared design language, allowing an AI agent to produce designs at a human level across various problems. Finally, in Chapter 7, we introduce a novel co-creative system that explores human-AI collaboration, offering specific examples of how a reflective dialogue through design material can enhance human creativity, while offering AI flexibility in its roles.

Chapter Three

Computational creativity for complex problem solving

This chapter addresses the problem of supporting human creativity by computational means in complex scenarios. Particularly, we want to focus on solving complex real-world scenarios from a different perspective than before. This corresponds to historical creativity or *h-creativity* [13]. As introduced in the previous Chapter 2, *h-creativity* refers to the ability to create new ideas, products, or solutions by combining existing knowledge in a new and original way. This type of creativity assumes that the product of the creative process advances to current human knowledge of a given problem space and is often found in fields such as science, engineering, and technology, where progress builds on the work of previous generations.

To address *h-creativity* we decided to choose the optimization of acoustic black holes (ABHs) as a problem space. In general terms, an acoustic black hole in mechanics refers to the phenomenon in which a bending wave (in plates or beams) or a sound wave (in ducts) is trapped in a region from which it cannot be reflected. The phenomenon is somewhat reminiscent of black holes in astrophysics and hence its name. The black hole effect can be achieved by power-law indentations in beams and plates or by placing sets of rings and cavities of decaying inner radii at a duct termination. An incident wave will progressively slow down, its wavelength will decrease and its amplitude will increase. In an ideal scenario, the wave will never reach the end of the ABH and no reflection could occur, but in practice, this is not possible and reflection does take place. However, this can be minimized by placing some damping mechanism at the end of the ABH.

In this chapter we focus on the optimization of acoustic black holes in ducts, often referred to as sonic black holes (SBHs).

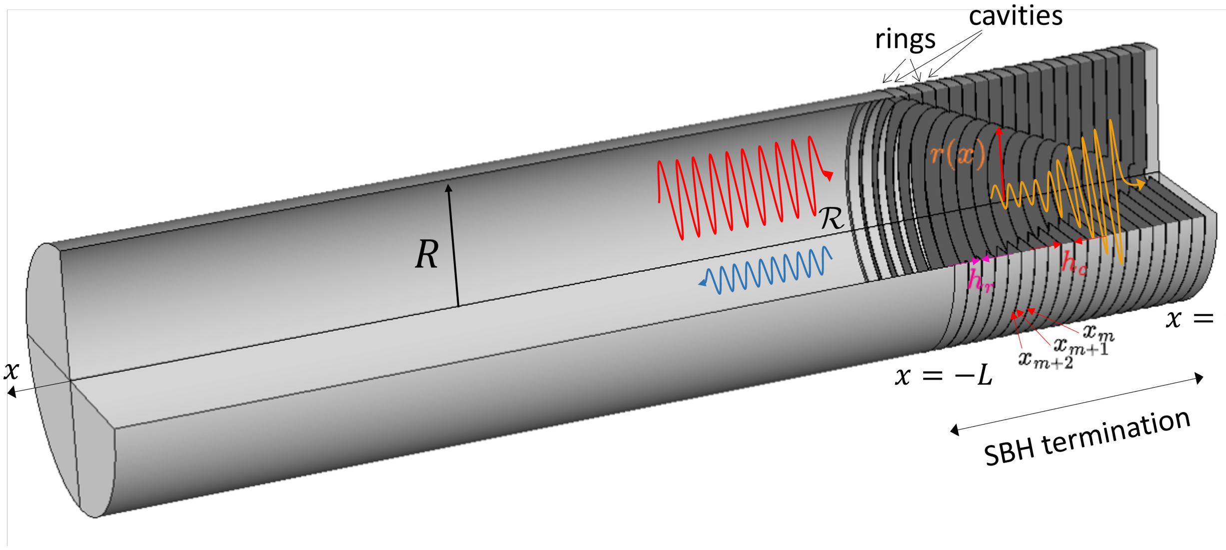

Figure 3.1 Schematic of the SBH. A wave impinges on the SBH and as it propagates its amplitude grows while its wavelength and sound speed decrease. The small reflection coefficient $\mathcal{R}$ characterizes the performance of the SBH. The unit cell for the TMM is made of a ring of thickness h_r and a cavity of width h_c. The inner radius of the SBH, $r(x)$ decreases according to a power-law.

The idea of building sonic black holes (SBH) at the end of duct terminations was first proposed in [92]. The original design consisted of a set of rings separated by cavities, whose inner radii decay from the duct entrance to its termination following a power law profile. Such design slows down incoming waves, whose energy gets dissipated by viscothermal losses and/or additional absorption material, resulting in very small reflection. In [93], a transfer matrix method (TMM) was proposed to characterize the performance of the SBH, which was experimentally tested in [94]. The TMM has also been used in the design of fractional order models to emulate the absorbing behavior of SBH terminations [95], or in periodic arrangements to also benefit from Bragg scattering and get broadband frequency absorption [96]. In [97], a meta fluid analogy was used to show that the TMM was consistent and tend to the solution of the continuous problem in [92]. A similar idea was employed in [98] to build an SBH where the effective density of the medium increases due to increasing mass layer concentration towards the end of the duct. On the other hand, a first analysis on the role of cavity resonances in the SBH behavior was studied by means of the finite element method (FEM) in [99]. With independence to developments in SBHs, in [100] a cascade of resonators was proposed to achieve broadband noise reduction in ducts. Very recently, the damping mechanisms of SBHs have been explored in detail by means of FEM simulations [101], [102].

The design of SBHs involves complex mathematical modeling, and it can be challenging to identify the optimal design parameters that produce the desired acoustic properties through traditional trial-and-error methods. This makes the problem of designing a SBH an interesting domain for augmenting human *h-creativity* by computational means such as *evolutionary algorithms* (EA). EAs can handle complex, non-linear, and multi-objective optimization problems, making them suitable for optimizing the acoustic properties of complex structures. In addition, using EAs to optimize SBHs requires creativity on the part of the human designer in defining the problem, setting the objectives and constraints, and interpreting the results. The designer must have a deep understanding of the design problem and the desired outcomes to effectively use EAs to generate creative and innovative solutions. For example, in the case of optimizing a SBH, the design variables can include the geometry, material properties, and other parameters that affect the acoustic properties of the structure.

In this particular domain, we will focus on evolutionary strategies to optimize sonic black hole profiles in duct terminations. Our design goal is to improve the performance of the standard power-law designs such as linear and quadratic profile designs, which are widely used in this field. To do that, we address two optimization problems related to SBHs. The first one concerns finding the SBH order that provides a minimum reflection coefficient for existent power law profiles. The second one involves an optimization problem in which the SBH inner radii are varied to obtain an alternative profile that can reduce the reflection coefficient of power-law profiles in a broadband frequency range. A derandomized ES with covariance matrix adaptation algorithm (ES-CMA) has been used to solve these problems [103], [104]. It is to be mentioned that despite several works that can be found in the literature to improve the performance of acoustic black holes on beams and plates, the latter has not been yet applied to SBHs, as far as the authors know. This second experiment allows us to obtain novel optimized profiles that perform better than traditional profiles in most frequencies. Building upon this work, we also explored how to use evolutionary algorithms for defining new configurations for absorbent material distributed across the SBH cavities which can further enhance the efficiency of the designs. The new design goal is to find a distribution of absorbent material filling the minimal number of SBH cavities that improve the performance of already known SBH profiles and novel ones.

The results presented in this Chapter show our approach to designing SBH profiles by combining the exploratory process of evolutionary algorithms with human expertise in the field. They rely on our work in optimizing profiles in duct terminations from our previous publications [33], [34]. In this work, novel SBH designs have been found supporting *h-creativity* in this field and expanding our knowledge on the physics of SBHs.

3.1 SBH modeling and optimization strategies

In this section, we describe the methods used for the simulation of SBH behavior together with the general cost functions and optimization algorithms used to generate solutions in this design space.

3.1.1 Transfer matrix model and reflection coefficient for the SBH

The TMM model used to simulate wave propagation inside the SBH is the one discussed in [93] (the reader is referred to that work for details). It is briefly summarised below. The SBH has length L and is placed at the end of a uniform duct of radius R. The origin of coordinates, $x = 0$, is located at the right end of the SBH, while its entrance is at $x = -L$. We consider a SBH made of a total of M rings, which are labelled by an index m ranging from $m = 0$ at the SBH termination to $m = M$ at the entrance of the SBH. The inner radius of the SBH follows the power-law profile,

$$r(x) = \frac{R - r_0}{L^m} |x|^m + r_0, \tag{3.1}$$

where r_0 is the radius of the first ring at the SBH termination and m in Eq. (3.1) designates the SBH order (not to be confused with the index labelling the rings). Acoustic plane waves impinge on the SBH from the left, see Fig. 3.1.

To start with, let us take an arbitrary m-th unit cell consisting of an inner ring and its back cavity. Let x_{m+2} be the position of the beginning of the edge of the inner ring and x_{m+1} be the position of its end, so that $h_r = |x_{m+2} - x_{m+1}|$ is the ring thickness, which is taken constant for all the rings of the SBH. The end of the back cavity is at x_m and its width is therefore $h_c = |x_{m+1} - x_m|$, which is also assumed to be constant throughout the SBH (see Fig. 3.1). The TMM provides a simple way to relate the state vector for the acoustic pressure and acoustic volume velocity, $(p_{m+2}, u_{m+2})^\top$, at x_{m+2} with the state vector, $(p_m, u_m)^\top$, at x_m. This is done by means of the product of three transfer matrices, $\boldsymbol{T}^{\mathrm{ring}}_{m+1}$, $\boldsymbol{T}^{\mathrm{p}}_m$ and $\boldsymbol{T}^{\mathrm{V}}_m$, which respectively account for wave propagation through the small cylinder defined by the ring thickness, the wave propagation across the width of the m-th cavity and the influence of its volume. We obtain,

$$\begin{pmatrix} p_{m+2} \\ u_{m+2} \end{pmatrix} = \begin{pmatrix} \cos[k_0(h_r+h_c)] + \mathrm{i}\frac{Z_0 Y_m^{\text{cav}}}{S_{m+1}} \sin[k_0(h_r+h_c)] & \mathrm{i}\frac{Z_0}{S_{m+1}} \sin[k_0(h_r+h_c)] \\ \mathrm{i}\frac{S_{m+1}}{Z_0} \sin[k_0(h_r+h_c)] + Y_m^{\text{cav}} \cos[k_0(h_r+h_c)] & Y_m^{\text{cav}} \cos[k_0(h_r+h_c)] \end{pmatrix} \begin{pmatrix} p_m \\ u_m \end{pmatrix}$$

$$\equiv \boldsymbol{T}_{m+1}^{\text{rc}} \begin{pmatrix} p_m \\ u_m \end{pmatrix}, \tag{3.2}$$

where $\boldsymbol{T}_{m+1}^{\text{rc}} = \boldsymbol{T}_{m+1}^{\text{ring}} \boldsymbol{T}_m^{\text{cav}} \boldsymbol{T}_m^{\text{V}}$. In Eq. (3.2), $\mathrm{i} = \sqrt{-1}$, $k_0 = \omega/c_0$ is the wavenumber (with ω and c_0 respectively denoting the angular frequency and the speed of sound) and $Z_0 = \rho_0 c_0$ is the air characteristic impedance, with ρ_0 being the density. On the other hand, $Y_m^{\text{cav}} = \mathrm{i}k_0 V_m / Z_0$ is the admittance of the cavity, with V_m being its volume, and S_{m+1} is the cross section at x_{m+1}.

Regarding the damping of the system, we will contemplate two options in this TMM model. On the one hand, a rough model for the visco-thermal losses will be used, which consists of taking a complex speed of sound $c = c_0(1 + \mu\mathrm{i})$, with $\mu \in \mathbb{R}^+$, as in [92] (see e.g., [101], [102], [105] for the limitations of this option). On the other hand, we will also consider the possibility of filling some of the cavities with sound-absorbing material. The cavities will be taken as fully filled or empty, partial filling not being an option for simplicity. The absorbent material is assumed to be locally reacting and wave propagation in it is characterized by an impedance $\tilde{Z}$ and a wavenumber $\tilde{k}$. Empirical expressions can be found for $\tilde{Z}$ and $\tilde{k}$, see [106]–[108], namely,

$$\frac{\tilde{Z}}{Z_0} = \begin{cases} 1 + 0.0485E^{-0.754} - j0.087E^{-0.73} & E < 1/60 \\ [0.5/(\pi E) + j1.4]/(-1.466 + j0.212/E)^{1/2} & E > 1/60, \end{cases} \tag{3.3}$$

and

$$\frac{\tilde{k}}{k_0} = \begin{cases} 1 - j0.189E^{-0.6185} + 0.0978E^{-0.6929} & E < 1/60, \\ (1.466 - j0.212/E)^{1/2} & E > 1/60, \end{cases} \tag{3.4}$$

where $E := Z_0 k_0 / (2\pi\sigma)$ with σ being the air flow resistivity. When a filled cavity is considered, we replace Z_0 and k_0 in $\boldsymbol{T}_m^{\text{V}}$ of Eq. (3.2) by $\tilde{Z}$ and $\tilde{k}$. Therefore, plane acoustic waves traveling within the SBH will experience the following wall impedance at point x_m (see e.g., [109]),

$$Z_m^w \sim -\mathrm{i}\tilde{Z}\cot[\tilde{k}(R-r_m)]. \tag{3.5}$$

Moreover, the wavenumber k_0 in $\boldsymbol{T}_m^{\mathrm{p}}$ of Eq. (3.2) should be also substituted by the complex expression

$$k_m^x \simeq k_0\sqrt{1-\mathrm{i}\frac{Z_0}{Z_m^w}\frac{2}{k_0 r_m}}, \tag{3.6}$$

and the admittance Z_0 with

$$Z_m^x \simeq Z_0\frac{k_0}{k_m^w}, \tag{3.7}$$

to take into account also the effects of the absorbing material in the m-th cavity (see [93] for further explanations).

The above expressions are valid for a single SBH cell. To relate the state vector of any section x_{k+2} to that of x_n, $(k \geq n)$, we make successive products of $\boldsymbol{T}_{m+1}^{\mathrm{rc}}$. The matrix $\boldsymbol{A}(k+2,n) \equiv \prod_{m=n}^{k}\boldsymbol{T}_{m+1}^{\mathrm{rc}}$ is such that $(p_{k+2},u_{k+2})^\top = \boldsymbol{A}(k+2,n)(p_n,u_n)^\top$ and if we regard the whole SBH, the state vector at the entrance $x_M = -L$ is connected to the one at the termination, $x_0 = 0$, by $(p_M,u_M)^\top = \boldsymbol{A}(M,0)(p_0,u_0)^\top$. This allows us to obtain the admittance of the SBH at the inlet, $Y_L = u_M/p_M$, and the reflection coefficient, $\mathcal{R}_L(f) \in [0\ 1]$, as follows,

$$\mathcal{R}_L = \frac{\pi R^2 - Z_0 Y_L}{\pi R^2 + Z_0 Y_L}. \tag{3.8}$$

3.1.2 General cost function and optimization algorithms

In this work, we will be interested in solving several optimization problems to minimize the weighted L^1-norm of the SBH reflection coefficient $\mathcal{R}_L$. In general, these problems can be posed as that of finding $\{p_n\}$, such that

$$\min_{\{p_n\}}\int_{f_1}^{f_2} w(f)\,|\mathcal{R}_L(f,\{p_n\})|\,\mathrm{d}f, \quad | \quad g_k(\{p_n\}) \lesseqgtr c_k,\ k=1\ldots N_c, \tag{3.9}$$

where $\{p_n\}$ is the set of parameters to be modified and g_k, with $k = 1 \ldots N_c$, represents a set of equality and/or inequality constraints to be imposed on $\{p_n\}$, with $c_k \in \mathbb{R}$, $\forall k$. The lower limit of integration in the cost function of Eq. (3.9), $f_1 \geq 0$, represents the first frequency of interest, while the upper one, $f_2 \leq f_c$, is the highest frequency of interest. f_c is the duct cutoff frequency, beyond which non-planar wave propagation can occur. The coefficient $|\mathcal{R}_L|$ is weighted by the function $w(f)$. Three different options for $w(f)$ are considered, namely

$$w_1(f) = 1, \qquad \forall\ f \in [f_1, f_2] \text{ Hz}, \tag{3.10a}$$

$$w_2(f) = -\frac{f}{f_2} + 1, \qquad \forall\ f \in [f_1, f_2] \text{ Hz}, \tag{3.10b}$$

$$w_3(f) = \begin{cases} 1, & \forall\ f \in [f_1, 500] \text{ Hz}, \\ -1.4 \times 10^{-3} f + 1.7, & \forall\ f \in [500, 1000] \text{ Hz}, \\ 0.3, & \forall\ f \in [1000, f_2] \text{ Hz}, \end{cases} \tag{3.10c}$$

which are depicted in Fig. 3.2. As can be observed, $w_1(f)$ does not affect at all $|\mathcal{R}_L|$; equal importance is given to all frequencies. As for $w_2(f)$, it decays linearly with frequency, while $w_3(f)$ is a compromise between $w_1(f)$ and $w_2(f)$.

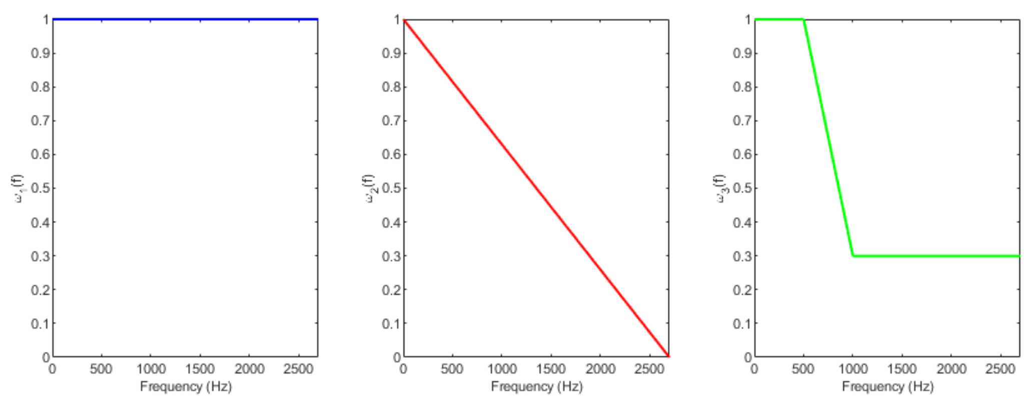

Figure 3.2 Weight functions defined in Eq. (3.10) to be used in the cost function of Eq. (3.9).

It should be noted that instead of minimizing the weighted L^1-norm of $\mathcal{R}_L$ with constraints in Eq. (3.9), one could also have chosen other norms such as $L^{3/2}$ or L^2, among others. Obviously, this will lead to different solutions. Some preliminary, albeit limited, tests to minimize the SBH order (not shown here), have revealed that using $L^{3/2}$ or L^2 did not lead to large differences in the solution, so we have focused on L^1 to avoid dealing with an excessive number of cases and situations.

In this Chapter we will address three types of optimization problems. In the first one our aim will be to find the optimal SBH profile to minimize a particular case of the cost function in Eq.(3.9). In the second case, we will try to get the best distribution of absorbent material within a limited set of cavities in order to minimize again another specific example of the cost function in Eq.(3.9).

The optimization problems involving the SBH profile will be solved using a derandomized ES with covariance matrix adaptation (CMA) strategy [103], [104]. The latter consists of a non-gradient algorithm particularly suitable for hard non-linear problems. The essential idea of the CMA is to construct a multivariate Gaussian distribution of sample solutions by varying the set of parameters $\{p_n\}$. A subset with the best solutions is then selected and a new mean value is calculated from it. For the next iteration, the covariance matrix is not calculated with respect to the new mean value of the current iteration, but with respect to the old mean value of the previous iteration. This is the key to the method. New solutions are generated with this mixed covariance, which allows for a much wider exploration of the solution space, drastically accelerating convergence with respect to conventional ES methods (see e.g., [31]).

As far as the optimization of the absorption distribution inside the SBH is concerned, ES-CMA is not the best choice because it is not well suited to problems with binary solution due to the use of the normal distribution in the generation of populations. Remember from section 3.1.1 that the SBH cavities are either empty or completely filled with absorbent. Therefore, the set of parameters $\{p_n\}$ in Eq. (3.9) will be a binary set $\{b_n\}$ of zeroes and ones that can be represented by a vector of length M. The use of a genetic algorithm is a more appropriate option to solve this type of problem. In this experiment we will use a standard one [110], [111], which proved to be very efficient in previous works by some of the authors [32]. In a nutshell, a genetic algorithm works as follows. It starts by initializing a set of vectors $\{b_n\}_i$ randomly and then evaluates their performance according to the cost function. This set constitutes the first generation, which evolves according to the well-known process of crossover with mutations included, if deemed necessary. From each generation, the best solutions are selected and used as the starting point for the next one. The process continues until a predetermined maximum number of generations is reached or if the results do not improve for a certain number of generations. For the SBH problem at hand, we will need to perform some additional operation that will be described in section 3.3. On the other hand, a note on terminology is in order. In genetic algorithms, it is customary to call the set of initial conditions iterations, while the sets obtained at each evolutionary step are referred to as generations. By contrast, in most numerical methods, iterations refer to the solutions obtained in each step of computation (i.e. the generations in genetics). Throughout this Chapter we will try to respect the notation of each research field and provide clarifications where necessary.

3.2 Optimization of the SBH profile

In this section, we describe the experiments and the design variables used by the different evolutionary algorithms presented in this chapter.

Unless otherwise specified, for the simulations in this and the following sections we will consider an SBH of radius $R = 0.05$ m, length $L = 0.5$ m and having $M = 40$ rings. The cutoff frequency of the duct is $f_c = 1.84c_0/2\pi R = 1991$ Hz with $c_0 = 340$ m/s being the speed of sound. For the visco-thermal losses, we take $\mu = 0.05$ in the complex speed of sound. It should be noted that a similar SBH configuration with a slightly smaller radius of $R = 0.03$ m and a length of $L = 1$ m, with a total of 40 rings, was tested in [94]. Experiments were compared with TMM predictions showing fairly good agreement. Therefore, the TMM of the section 3.1.1 is expected to approximate the analyzed SBH behavior well.

3.2.1 Optimization of the SBH power law order

As an initial case, we consider an SBH whose inner radii follow the power-law profile in Eq. (3.1) with $r_0 = 0$. Our goal is to find the optimum value $m \in \mathbb{R}$ of the SBH-order. The general optimization problem in Eq. (3.9) then reduces to that of finding m such that,

$$\min_m \int_{f_1}^{f_2} w(f) \left|\mathcal{R}_L(f,m)\right| \mathrm{d}f \;\; \Big| \;\; r(x) = \frac{R}{L^m} \left|x\right|^m . \tag{3.11}$$

This problem has been solved using the ES-CMA algorithm in [103], [104] described in section 3.1.2. We started from 10 different initial conditions and ran 200 generations for each, leading to rapid convergence to a unique solution for each of the weight functions in Eq. (3.10).

In Fig. 3.3, we present the absolute value of the SBH reflection coefficients $|\mathcal{R}_L(f)|$ obtained from solving the problem in Eq. (3.11) using the weighting functions $w_1(f)$ (top-left subfigure), $w_2(f)$ (top-right subfigure) and $w_3(f)$ (bottom-left subfigure). In all cases, we compare the resulting $|\mathcal{R}_L(f)|$ with those of the usual $m = 1$ (linear) and $m = 2$ (quadratic) profiles. Regarding the latter, it is worth noting that the quadratic SBH (black line in the subfigures) performs better than the linear SBH for frequencies below 600 Hz, but the situation is reversed for higher frequencies, with the reflection coefficient of the linear SBH being smaller. Focusing on the optimized solutions, it can be seen that the envelope of $|\mathcal{R}_L(f)|$ for $w_1(f)$ in the top-left subfigure (blue line) outperforms the quadratic one for all frequencies. It is however slightly larger than the linear SBH envelope for the higher frequencies, but somewhat smaller in the low frequency range. If the linear weight $w_2(f)$ is used (top-right subfigure, red line), the performance deteriorates slightly at higher frequencies as $w_2(f)$ tends to zero, while the response at low frequencies closely resembles that of $w_1(f)$, with more prominent peaks and dips. The envelope of $|\mathcal{R}_L(f)|$ using $w_3(f)$ (bottom-left subfigure, green line) is lower than those of $w_1(f)$ and $w_2(f)$ for the entire frequency range. This can be seen in the comparison of the bottom-right subfigure. Although the differences are not very significant, weighting the cost function with $w_3(f)$ seems to be the better option

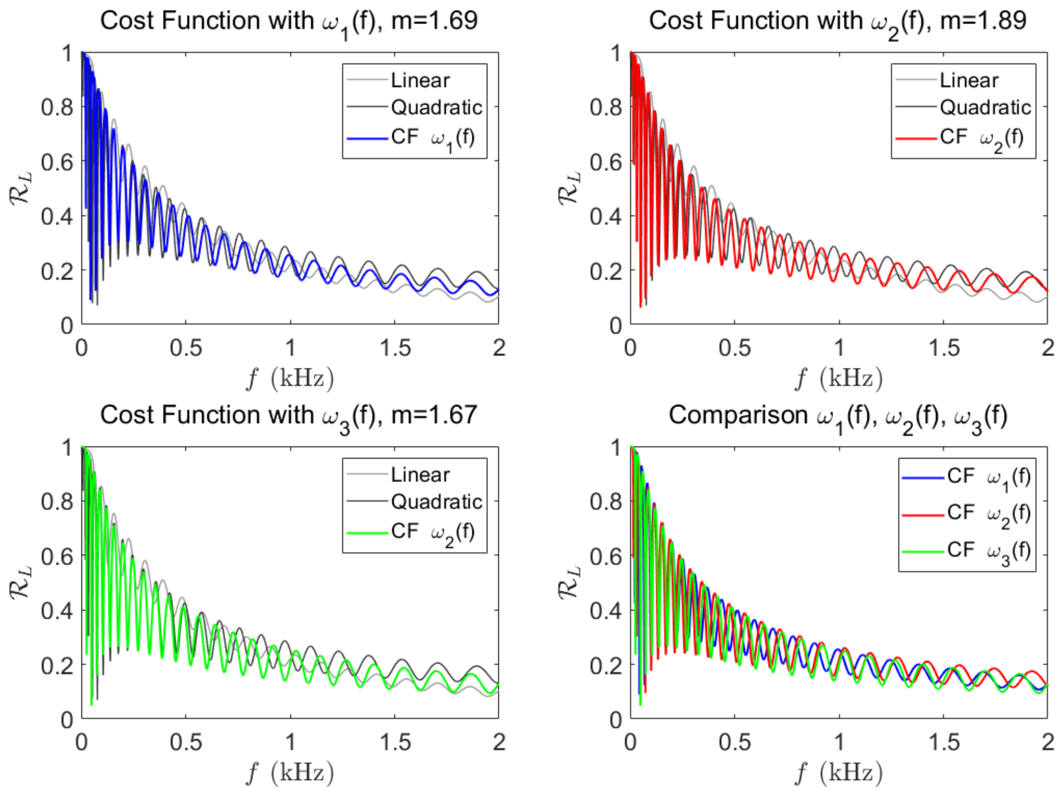

Figure 3.3 SBH reflection coefficients $|\mathcal{R}_L(f)|$ found from the optimization of the SBH order, m, by solving Eq. (3.11) for the weight functions $\omega_1(f)$ (top-left), $\omega_2(f)$ (top-right) and $\omega_3(f)$ (bottom-left). The optimum values of m are given in the titles of the subfigures. The reflection coefficients of the linear, $m = 1$, and quadratic, $m = 2$ cases have been included in the subfigures for comparison. The plots of $|\mathcal{R}_L(f)|$ for the three weight functions are depicted in the bottom-right subfigure.

for this problem.

In Fig. 3.4, we display the profiles that led to the reflection coefficients in Fig. 3.5 using the same color coding as in that figure. Both the linear and quadratic cases are plotted again for comparison. The optimized orders for the SBH power-law profiles are $m = 1.69$ for $\omega_1(f)$, $m = 1.89$ for $\omega_2(f)$ and $m = 1.67$ for $\omega_3(f)$. Although there was no restriction on the values that the order m could take, they all lie between $m = 1$ and $m = 2$. This provides an adequate impedance matching for the incident waves entering the SBH. If m were too large, reflections would be excessive and ruin the SBH effect.

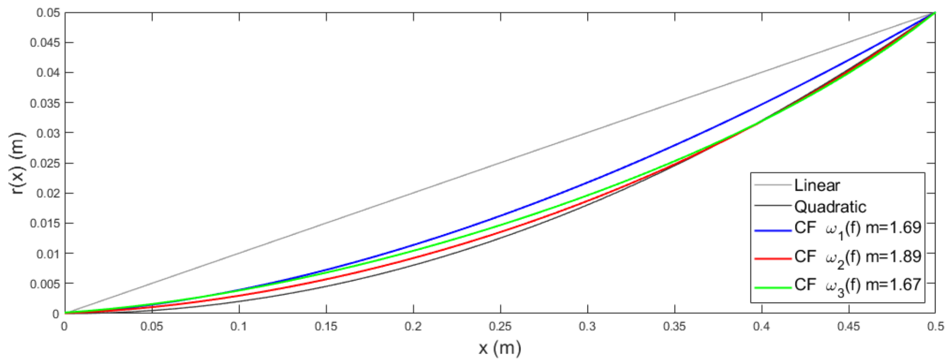

Figure 3.4 Optimum power-law profiles of the SBH obtained by solving Eq. (3.11) with the three weight functions in Eq. (3.10).

3.2.2 Optimization of the SBH profile

In this section, we explore to provide more freedom on defining solutions by our algorithms. We abandon the restriction of having a power-law profile as in Eq. (3.1), and look for alternative SBH profiles that could result in lower reflection coefficients than those found in the previous section. Therefore, the parameters to be optimized are the inner radii of the SBH, i.e., $\{p_n\} \equiv \{r_m\},\ m = 0 \dots M$ subject to a monotonic constraint. The general optimization problem of Eq. (3.9) can be posed as that of finding $\{r_m\}$ such that,

$$\min_{\{r_m\}} \int_{f_1}^{f_2} w(f)\, |\mathcal{R}_L(f, \{r_m\})|\, \mathrm{d}f, \quad | \quad r_{m+1} > \alpha r_m,\ \alpha \in (1, 1.25],\ m = 0 \dots M, \tag{3.12}$$

where the admissible values of α in the constraint $r_{m+1} > \alpha r_m$ have been determined after some heuristic experiments. This requirement compels the inner radii to be monotonically decreasing from the SBH entrance to its termination. The α parameter specifies the freedom to pick a new radius in the optimization process.

Eq. (3.12) has been solved again with the ES-CMA algorithm, starting from 10 different initial conditions and performing 300 generations for each of them. This case is more demanding than the previous one in section 3.2.1 and the results did not always converge to a unique solution, although these were quite similar on the mean, with a very small variance. Therefore, the mean solution values for $|\mathcal{R}_L(f)|$ and their corresponding SBH profiles will be presented below.

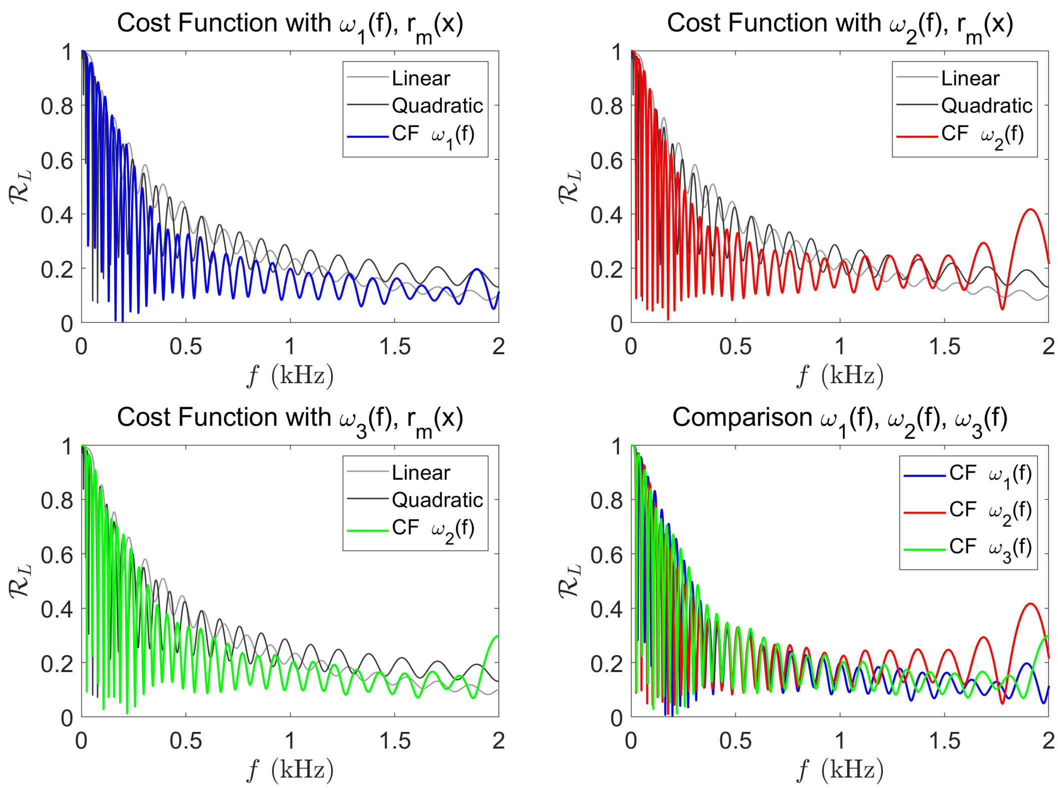

Figure 3.5 SBH reflection coefficients $|\mathcal{R}_L(f)|$ corresponding to the radii optimizing the cost function in Eq. (3.12) for the weight functions $\omega_1(f)$ (top-left), $\omega_2(f)$ (top-right) and $\omega_3(f)$ (bottom-left) in Eq. (3.10). The reflection coefficients of the linear, $m = 1$, and quadratic, $m = 2$ SBHs have been included in the subfigures for comparison. The plots of $|\mathcal{R}_L(f)|$ for the three weight functions are depicted in the bottom-right subfigure.

Fig. 3.5 is analogous to Fig. 3.3, but for the newly calculated reflection coefficients, $|\mathcal{R}_L(f)|$, obtained with the optimized profiles. Again, $|\mathcal{R}_L(f)|$ for the weight function $\omega_1(f)$ is plotted in the top-left subfigure (blue line), $|\mathcal{R}_L(f)|$ for $\omega_2(f)$ in the top-right subfigure (red line) and $|\mathcal{R}_L(f)|$ for $\omega_3(f)$ in the bottom-left subfigure (green line). All subfigures include the reflection coefficients for the linear and quadratic cases for comparison, and in the bottom-right subfigure we show $|\mathcal{R}_L(f)|$ for all three weight functions together.

As observed in the top-left subfigure of Fig. 3.5 for $w_1(f)$, the reflection coefficient is close to the quadratic one for frequencies below 0.4 kHz, but from that frequency to 2 kHz the improvement is remarkable except for the peak near 1.8 kHz. In fact, $|\mathcal{R}_L(f)|$ is not only better than that of the linear and quadratic cases, but also better than those of the optimum power-law profiles in Fig. 3.4 (see their reflection coefficients in Fig. 3.3). Looking at the top-right subfigure for the linear weight $w_2(f)$, we get a substantial improvement from 200 Hz, but this deteriorates completely beyond 1 kHz because the weight is too small for the higher frequencies. The results for $w_3(f)$ in the bottom-left subfigure are very are similar to those of $w_1(f)$ over the whole frequency range, yet slightly worse in the range $[0.4, 1.8]$ kHz and clearly poorer at the higher frequencies. All the reflection coefficients $|\mathcal{R}_L(f)|$ are compared in the bottom-right subfigure, which shows that the best solution is obtained when using the weight function $w_1(f)$.

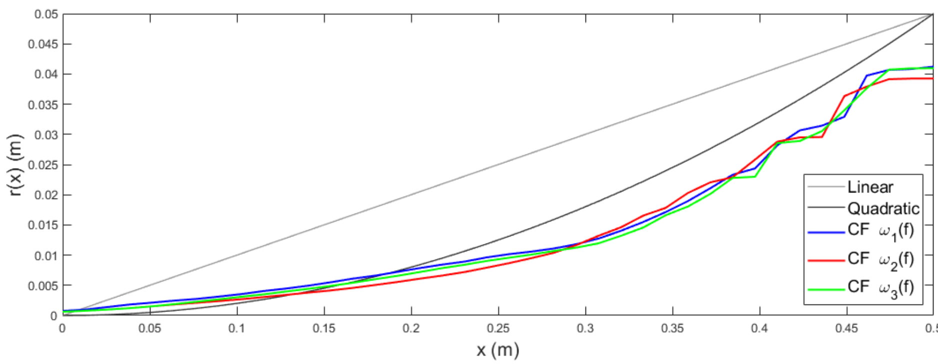

Figure 3.6 Optimized profiles solving Eq. (3.12) using the three different weights in Eq. (3.10) with no predetermined law but satisfying the increasing monotonic constraint.

The SBH profiles corresponding to the results shown in Fig. 3.5, are depicted in Fig. 3.6. They all have a similar appearance consisting of two intervals with different slopes. The first interval has a lower slope than the linear and quadratic profiles and runs from the SBH termination to ~ 0.35 m. From ~ 0.35 m to the SBH entrance at 0.5 m, the local slope of the new profiles is steeper than the linear and quadratic ones and present some small steps as they approach the exit. These new designs, which are very different from the optimum power-law ones in Fig. 3.4, are not new to acousticians. They can be recognized as belonging to the horn family, typical of some wind musical instruments. Surprisingly, they were very recently tested as potential profiles for SBHs in [105], showing that the average speed of sound inside horn SBHs is lower than for power-law SBHs. Our optimization approach has found the horn solution automatically. However, from Fig. 3.5 we have seen that the performance of the horn SBH can deteriorate at higher frequencies (a point also reported in [105]). This is clearly the case when using $w_2(f)$ in the cost function although the problem is not as marked for $w_1(f)$. By modifying the cost function in Eq. (3.9) one could try to improve the performance of the new horn design. Following our line of reasoning, however, one should also view the cost function as a tool that could help improve the design of new solutions. In other words, by taking a look at $|\mathcal{R}_L(f)|$ for $w_1(f)$ in the top-left subfigure of Fig. 3.5 and its corresponding profile in Fig. 3.6, it is clear than one could reduce the peak at high frequencies by smoothing the profile to have smaller cavities at the entrance of the SBH.

This has been done in Fig. 3.7 where we show the old horn profile (blue line) and the redesigned one (orange line) together with their reflection coefficients. As can be seen, the peaks of the new horn profile slightly surpass the old ones between 1 kHz and 1.2 kHz (as is logical since the new design does not optimise the cost function), but performs better at higher frequencies, as intended.

3.3 Optimization of the distribution of absorption material in the SBH

Let us next try to improve the performance of the SBH by filling some of its M cavities with absorbent material. We would like to fill no more than a certain number of cavities, say M_A, to save material. On the other hand, we assume a fixed profile of the SBH. In particular, three cases will be addressed: a linear profile, a quadratic profile and the redesigned profile introduced at the end of section 3.2. The general optimization problem of Eq. (3.9) is now

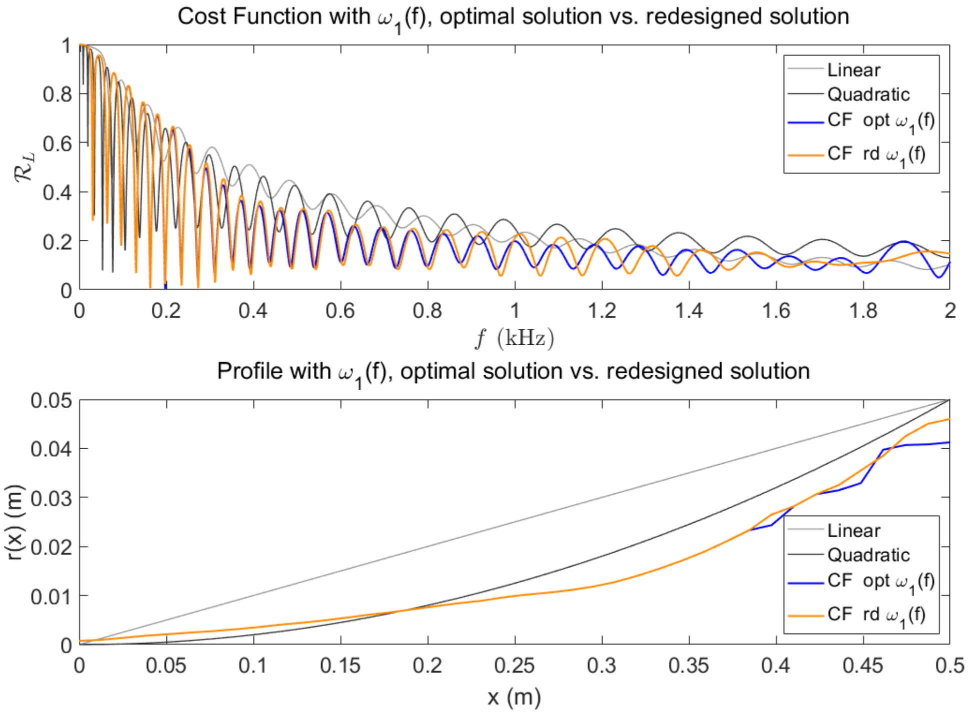

Figure 3.7 Redesigned profile (orange line) to smooth the peaks of the reflection coefficient at higher frequencies.

posed as the one of finding $\{b_m\}$ that satisfies,

$$\min_{\{b_m\}} \left\{ (1-\alpha) \int_{f_1}^{f_2} w_1(f) \, |\mathcal{R}_L(f, \{p_n\})| \, \mathrm{d}f + \alpha \frac{M_c}{M_A} \right\} \quad \text{such that}$$
$$M_c \lessapprox M_A \ \wedge \ \left(r(x) = \frac{R}{L^m} \, |x|^m \, , \ m = 1, 2 \ \vee \ r(x) = r_{\mathrm{rd}}(x) \right) , \tag{3.13}$$

where $\{b_m\}$ is a binary set of zeroes and ones. $b_m = 1$ indicates that the m-th cavity is full of absorbent, while $b_m = 0$ means that it is empty. M_c is the number of cavities filled with absorbent that we would like to be no greater than $M_A = 20$. Note that this constraint is not strict, but is imposed by the penalty term $\alpha M_c/M_A$ in the cost function. The second constraint in the second line of Eq. (3.13) indicates, as mentioned above, that we consider a linear profile, $r(x) = (R/L)\,|x|$, a quadratic one, $r(x) = (R/L^2)x^2$, or the redesigned one, $r(x) = r_{\mathrm{rd}}(x)$, for the radius of the SBH. For the calculations we take $\alpha = 0.05$.

As explained in section 3.1.2, a genetic algorithm has been used to solve the optimization problem in Eq. (3.13). We start with an initial population of ten binary random vectors

$\{b_m\}_i,\ m = 1 \ldots 40,\ i = 1 \ldots 10$ (i.e., ten iterations) and evaluate each proposal according to Eq. (3.13). We then evolve to the next generation using tournament-based selection and single-point crossover with a probability of 0.9. A mutation probability of $1/40$ is also introduced to provide diversity. When a mutation occurs, an entry of $\{b_m\}$ flips from 0 to 1, or vice versa. The offspring generated replaces the least fit individuals in the population. The algorithm evolves through selection, crossover and mutation processes until a total of 100 generations is reached, or if the results do not improve for more than 15 generations.

In Fig. 3.8 we show the procedure we have followed to distribute the absorption in the cavities. The first row of the figure contains the results for the linear profile, the second row for the quadratic profile and the third row for the redesigned one. As explained, we have started from ten iterations which have provided ten solutions for each profile, shown in the first column of Fig. 3.8.

Black denotes filled cells and white denotes empty cells. As can be seen, the different solutions share several cells, as expected, but not others. Also the distribution of filled cells is very different in the three profiles. This will be discussed further below. Since the genetic algorithm has not provided us with a unique solution, but with ten that present some variations, we have to choose a criterion to decide which cells to fill. Several options could be valid. For instance, we could simply choose the solution that gives the smallest value of the cost function in Eq. (3.13). However, we have decided to go for a more conservative option. As shown in the histograms in the second column of the figure, we have counted the number of occurrences of each cavity in the solutions. If a cavity appears in more than 30% of the solutions, it is selected for filling with absorbent material. Obviously, this is a rather arbitrary criterion and we could have decided to be more restrictive by increasing the percentage to, say, 50%.

As a result of the above procedure, 14 cavities are filled in the linear SBH, 25 in the quadratic one and 19 in the redesigned SBH. Let us look at them in more detail. As mentioned above, the first thing to observe is that the optimal distribution of absorption

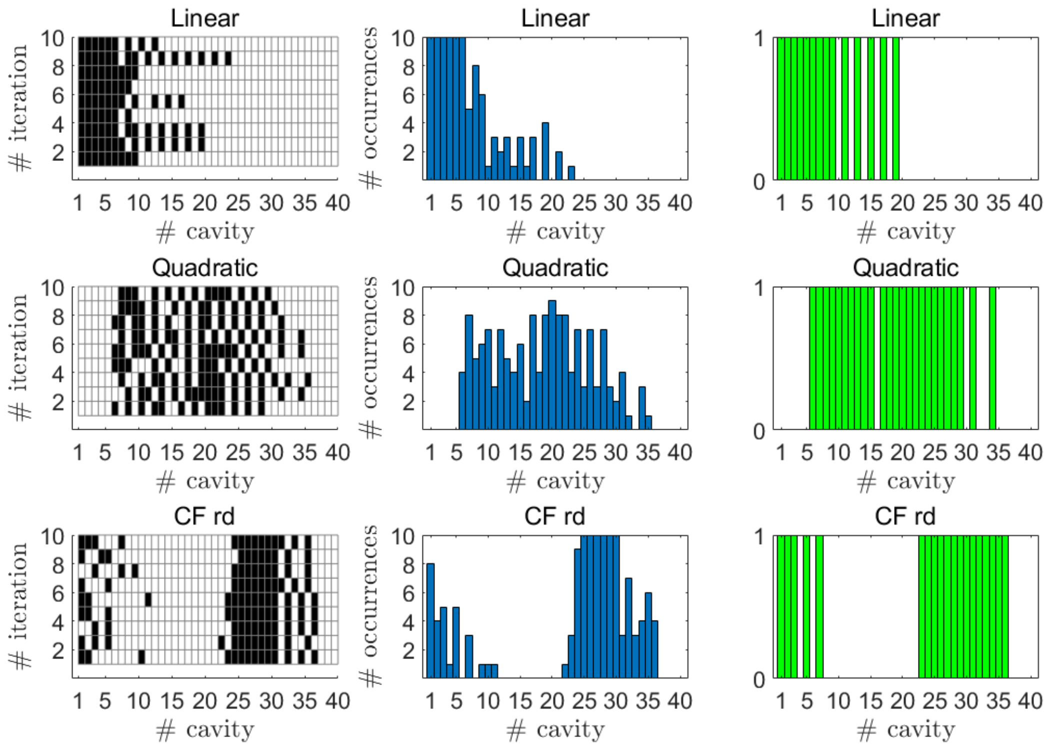

Figure 3.8 Procedure for filling the SBH cavities with absorbent using genetic algorithms for the linear (first row), quadratic (second row) and redesigned (third row) profiles. Starting from ten iterations (initial conditions) we arrive at ten solutions in each case (first column). Black indicates filled cells and white indicates empty cells. We then calculate the histogram of the number of occurrences of each cavity in the solutions (second column). If the occurrence of a cavity is greater than 30%, we fill it with absorbent material. The green bars in the third column in the figure indicate the cavities that containing absorbent.

in the cavities is very different from one profile to another. In the linear case, the cavities closest to the termination of the SBH and some more in the left half of the SBH need to be filled (see the top-right subfigure in Fig. 3.8). Note that only $14 < M_A = 20$ cavities are filled as required by the first constraint of Eq. (3.13). In contrast, the distribution of absorbing material in the quadratic SBH is large and concentrated in its central region, filling cavities from the fifth to the 35th. A total of $25 > M_A = 20$ cavities are filled, thus exceeding the target value of $M_A = 20$. There is a reason for this. If one takes a look at the ten solutions in the left subfigure of the second row of Fig. 3.8, it can be seen that some of the solutions are very similar to each other but have alternate cavities. This is because in the central part of the quadratic SBH the cavities have very similar volumes and depending on the initial condition selecting one or its neighbor will not produce significant changes in the value of the cost function. Therefore, a clustering algorithm could be used to separate these two solution sets and select one as the final solution for the qudratic SBH. This would likely result in a smaller number of filled cavities than M_A and will be tested in future work. Finally, looking at the results for the redesigned profile in the third row of Fig. 3.8, it can be seen that the cavities are filled at the beginning of the two profile slope changes, especially in the second one (see the bottom subigure of Fig. 3.7). For the redesigned profile only 19 cavities have been filled, satisfying the criterion of $M_A \leq 20$. The very different distribution of absorption material within the three SBHs is curious and must be related to the distribution of the acoustic velocity and pressure within the SBH, a question that would be worth exploring in future work.

In Fig. 3.9, we present the absolute value of the SBH reflection coefficients $|\mathcal{R}_L(f)|$ when filling the SBH cavities with absorbent material according to the distributions found in the third column of Fig. 3.8. The top-left subfigure shows $|\mathcal{R}_L(f)|$ for the linear SBH with and without absorbing material, while the top-right subfigure does the same for the quadratic SBH. The bottom-left subfigure depicts the result for the redesigned SBH and, finally, the bottom right subfigure compares the absolute value of the reflection coefficients of the three profiles.

As can be seen in all the figures, filling some cavities with absorbent produces a substantial improvement, since the reflection coefficient decreases significantly at all frequencies (see [93] for the influence of damping without optimization processes). It is observed that this is the case except for the highest frequencies in the linear and redesigned cases, a problem already noticed in experimental work in the literature [98], [112], [113], for which a plausible explanation has recently been proposed [101], [102], [105].

It should be noted that this high-frequency problem is small in our case but more pronounced for large radius SBHs, where the SBH effect is not the main sound dissipation

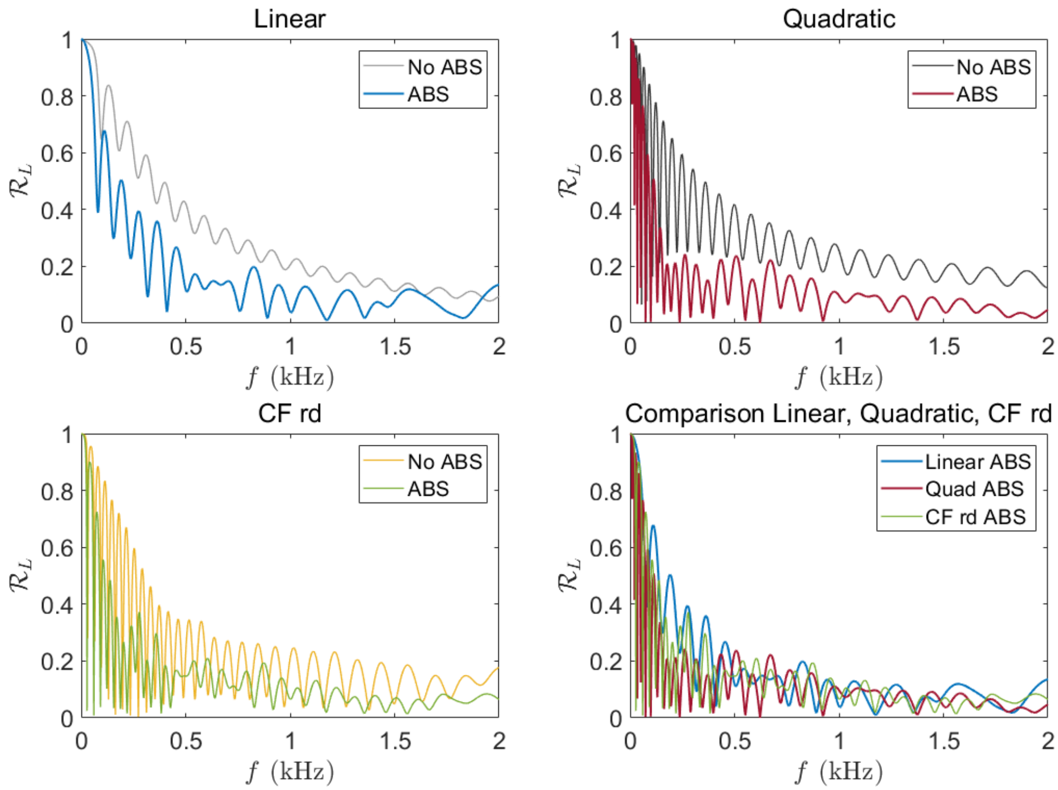

Figure 3.9 SBH reflection coefficients $|\mathcal{R}_L(f)|$ found from the optimization of the absorption by solving Eq. (3.13) for the linear (top-left), quadratic (top-right) and CF rd (bottom-left) profiles. Results with and without absorption. The plots of $|\mathcal{R}_L(f)|$ for the three profiles with absorption are compared in the bottom-right subfigure.

mechanism, but cavity resonances play a major role. Comparing $|\mathcal{R}_L(f)|$ for the three profiles in the right-bottom subfigure of Fig. 3.9 makes it clear that the quadratic and redesigned profiles with absorbent perform better than the linear one, especially between 200 Hz and 500 Hz and also beyond 1.5 kHz. However, as explained before, the comparison is not entirely fair, since we are filling 25 cavities for the quadratic SBH, while only 14 are used for the linear SBH and 19 for the redesigned profile. In any case the results are remarkable since $|\mathcal{R}_L(f)|$ barely exceeds 0.2 beyond 200 Hz in the quadratic case and 400 Hz in the redesigned one.

3.4 Conclusions

In this Chapter, we explored how human *h-creativity* could be supported by computational means. Particularly, we focus on defining three different experiments where different evolutionary algorithms try to improve the design of conventional SBHs at duct terminations. To that goal, we defined a cost function with three different possible weights and addressed three different cases which different design parameters. In the first one, we fixed the SBH radius profile to follow a power law and set its order as the free parameter. The obtained optimum profiles have orders between the standard linear (order one) and quadratic (order two) which show new knowledge on optimal SBH profiles beyond standard ones. In the second case, another optimization approach was followed in which the free parameters were the radii of the SBH submitted to a monotonic constraint. The solutions showed that the reflection coefficient was clearly smaller than those of linear and quadratic SBHs beyond 300 Hz, although in some cases worsened at very high frequencies. The three newly obtained profiles have the common feature of presenting a clear double slope profile. These new designs, which are very different from the optimum power-law ones in Fig. 3.4, are not new to acousticians. They can be recognized as belonging to the horn family, typical of some wind musical instruments. However, they had not been previously considered as profiles for SBHs, which makes them a novel contribution to the given domain.

In addition, in this Chapter's experiments, we show possible roles for humans and AI in this (semi)-autonomous scenario. After the initial human role of setting up the design conditions, the optimization algorithm, and the cost functions, the system was responsible for exploring the solution space, and proposing a promising set of new designs. Then, the human again intervened modifying part of the proposal based on the knowledge of how that could behave in a real scenario, obtaining a better profile. This illustrates how interaction with the final outputs of a generative system can also lead to the definition of novel solutions, obtaining one of the highest performances across multiple frequency ranges, in this particularly complex problem space.

Our results show how by combining evolutionary algorithms we can widely explore the solution space of possible SBH, finding original proposals that provide additional knowledge in the field and inspire humans to explore further directions. Moreover, we have developed new combined techniques utilizing evolutionary algorithms for optimizing profiles together with optimizing the absorbent distribution across the end section of the duct, further enhancing the effectiveness of the designs.

While these experiments illustrated how a *h-creativity* problem could be supported by computational means and how AI can contribute to advancing knowledge of the field [114], in this thesis we aim to explore systems that can collaborate with the user on a shared creative product within a creative session. However, due to the nature of the computations and simulation needed for modeling SBH behavior, we were not able to study human-AI collaborative dynamics in real time. Each optimization process ranged from a few hours, in the first power-law experiments, to half a day in the latest experiments with absorbent material. Therefore, this sense of collaboration could not be fully explored in this first domain. For that reason in the next Chapter 4, we introduce a new environment for exploring creative problem-solving in real-time. This environment will focus on simplifying the computation and simulation requirements in order to ensure a rapid feedback loop, helping the user to maintain their engagement and support their creative flow [17] through continuous interaction with the material generated by computational means, and their own creations.

Chapter Four

Towards a collaborative language for creative problem-solving

In this Chapter, we define a shared design language to support creative problem-solving. This language definition supports usage for both humans and AI agents, enabling future collaboration and shared understanding. We also introduce a new problem space, Coevo, which supports the creative definition of tools for problem-solving within 2D physically-based scenarios. In order to validate this environment, we conduct an initial experiment with an evolutionary agent to evaluate its generative capabilities in an initial set of scenarios.

As noted in Chapter 1, human capabilities to creatively use tools to interact with the world, accomplish goals, and resolve problems have been instrumental for our history and cognitive evolution [115]. Despite the fact that tool usage [116], [117] has been observed in other animals it is a rare trait and it has been essential to the cognitive evolution of humans. Drawing parallels with our ancestors, who crafted tools to fulfill their needs, participants in our subsequent studies explore defining different 2D shapes to solve different problems. This process of generating, testing, evaluating, and refining these proposed shapes through simulation in this environment highlights the iterative nature of problem-solving, involving continuous learning and adaptation to each design situation.

This is not only about creative problem-solving but also about generating original, efficient solutions that provide a rich field for the study of the creative process. The simplicity and accessibility of the 2D environment encourage broad participation and remove the barriers to specialized knowledge required by the problems in Chapter 3. This allows for the exploration of *personal creativity* within the realm of creative problem-solving [114].

Even though the environment is simplified, it can encapsulate complex problems with constraints that mimic real-world challenges. The 2D environment also promotes visual thinking and the visual representation of ideas in the form of shapes that offer a wide range of possibilities for potential solutions - a key element in creative exploration. It also allows us to compare and evaluate the creative output in terms of novelty and value, providing valuable insights into the creative process, and helping us to evaluate creative based on the creative output [118].

Furthermore, we simplify the computation and simulation of scenarios, enabling our AI agent to provide more immediate feedback. The concept of low latency in system responses has significant implications for the iterative solution-defining process. For instance, when a user proposes a shape to solve a particular problem, our environment can quickly evaluate it and provide feedback while the AI system can propose a suggestion to improve this proposal. This quick response allows the user to promptly react to the evaluation, either by revising the idea based on the AI's feedback or by proposing a new approach. As a result, this can lead to more iterations within the same time frame, enabling a more exhaustive exploration of potential solutions. In line with Csikszentmihalyi's concept of flow [17], this is crucial as it maintains the user's full engagement and immerses them in the task, which can lead to more innovative and effective solutions. By providing instant feedback, we support creative flow while allowing a more fluid and continuous interaction between humans and AI systems.

In order to support this creative flow and enable future human-AI collaboration, a language to define proposals for a given problem space must be defined. To better define our design language, we reflect on human capabilities for creative problem-solving and the process of designing creative solutions within a certain problem space.

Design is described by some authors [8], [9] as a co-evolutionary process involving both problem and solution spaces. As we engage with a problem through design, we not only generate potential solutions but also develop our understanding of the problem [10]. In this sense, Gero's situated framework [5] proposes that design is not merely an externalization of our internal thought processes. Instead, it embodies our cognitive processes within a specific context. This aligns with Donald Schön's concept of *Reflect-in-action*, which he introduced after observing architectural designers engaged in sketching concepts [11]. Schön views the design process as a reflective dialogue with the material being created.

By externalizing internal processes through the design material, we can reflect on our own actions and adjust them on the basis of that reflection. For instance, in a situated activity such as design, we can reflect on whether the current design proposal supports the intended function, and then make modifications or explore different solution spaces based on this reflection. This is particularly useful in scenarios where both the problem and solution space may be ill-defined. As designers iterate through the process, they concurrently refine their understanding of the problem and develop potential solutions. An idea for a solution can lead to a reinterpretation of the problem, and a better understanding of the problem can spark new ideas for solutions.

This externalization of thought is not only beneficial for our individual processes but also for collaboration. According to some authors, externalizing our internal cognitive processes and making them visible to other collaborators can influence others' perception of the design situation providing new shared knowledge that can inspire a new creative perspective on the problem-solution space [18], [119].

Figure 4.1 illustrates how externalizing our internal cognitive processes in shared material can influence each collaborator's internal mental processes. This reflection can lead to new potential solutions and a fresh perspective on the problem space.

In the same vein, Clark and Chalmers [22] argue that our mental processes extend beyond the boundaries of our minds to include external tools, artifacts, and environments. In the

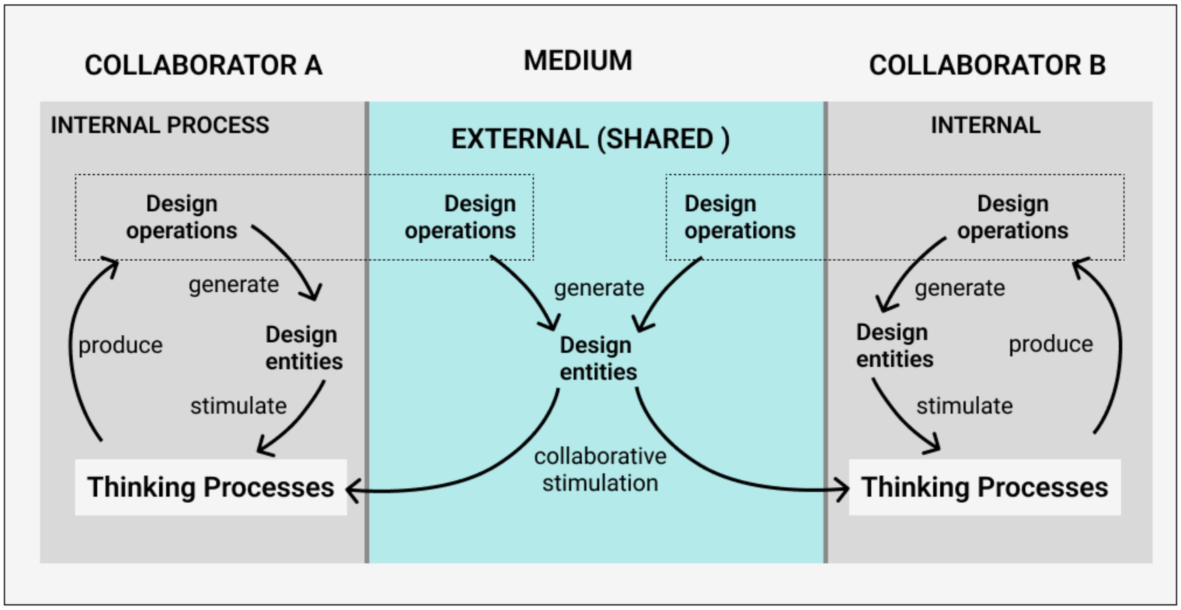

Figure 4.1 Collaborative thought stimulation. By externalizing our mental processes into a shared space, we can reflect through the material we generate and stimulate others' mental processes. Others can also contribute equally by externalizing their thoughts, influencing our own perspective of a problem space. Schema adapted from [18], [119]

.

field of design, expressive tools are critical for transforming creative ideas into tangible material. This transformation involves defining a specific language to materialize these ideas and mental processes, serving as a conduit for individual reflection or sharing with others.

A shared language in the design process is an important aspect of any creative collaboration. It enables effective communication among team members, allowing them to understand each other's ideas, feedback, and suggestions. In addition, a shared language provides a common understanding of the current design situation. It reflects current thinking processes which can be visualized and accessed by other participants of the design situation. Then if a shared language is expressive enough to represent human thinking processes, other individuals can understand these representations and contribute to exploring together a possible solution space.

To facilitate this, we use Shape Grammars (SG), introduced by George Stiny and James Gips as a generative system to analyze and explore designs. They were originally used in architecture [120] and later expanded to design and computer graphics. Shape grammars consist of a set of shape rules that apply in a step-by-step way to generate a set, or language, of designs in both 2D or 3D spaces [121].

In shape grammar, a design is understood as a composition of shapes, and the design process is guided by a set of rules on how these shapes are manipulated to generate more complex designs. These rules form the 'grammar' of the design language to explore a certain space of designs. In this exploration, a phenomenon, called emergence plays an important role in finding novel structures. These emergent structures are not defined a priori in the initial set but emerge as a result of interactions between shapes and transformations.

This set of simple rules can become an expressive tool for representing complex shapes. As shown in Figure 4.2, a shape grammar based on a Greek cross is used to design a Renaissance church by decomposing into two 2x1 rectangles [122].

This example illustrates the flexibility and creativity inherent in shape grammars as a design language. In addition, this process can be closely associated with the iterative and reflective process, an important aspect to be considered in a creative-problem solving activity. The use of shape grammar involves an iterative process of design, where each step of the process can be evaluated and reflected upon. Each new shape can be seen as a rule applied to a previous shape. This immediate feedback allows for reflection-in-action [11], as the designer can modify their approach based on the outcomes of each iteration. From this perspective, shape grammar can also be seen as an extension of the designer's mind. By creating, manipulating, and transforming shapes, designers can externalize their cognitive processes into cognitive artifacts that reflect their mental processes and ideas. Furthermore, in a collaborative setting, these generated shapes can distribute cognitive processes among several collaborators. Each collaborator can understand and apply the grammar rules, contributing to creating different creative directions inspired by each other artifacts. As introduced by

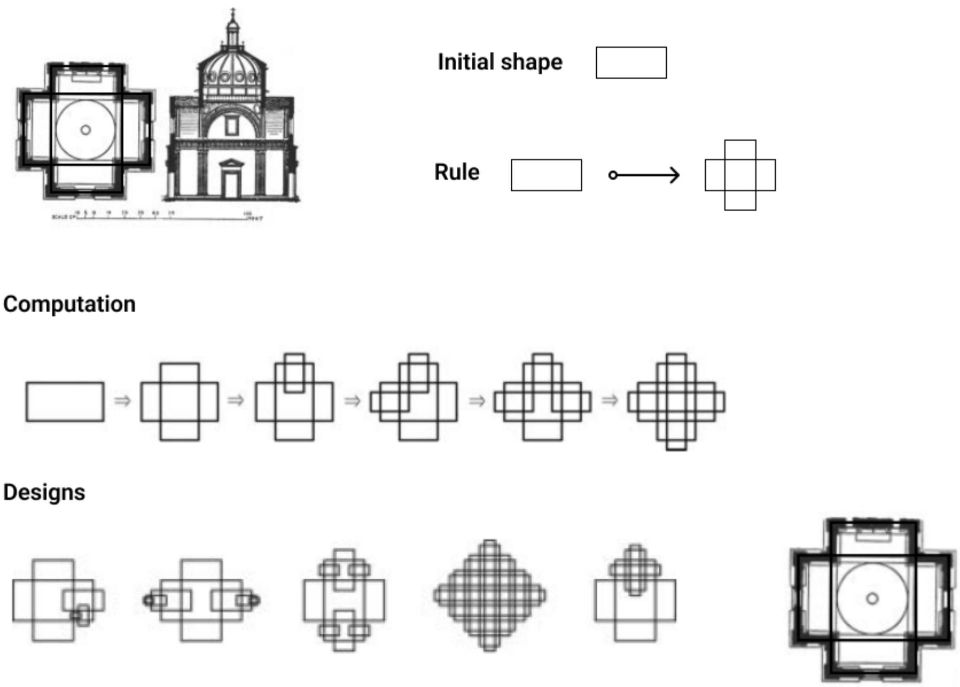

Figure 4.2 Simple shape grammar for Greek cross church plans (adapted from [122]). Note that, from a basic rule of dividing squares into four smaller squares, complex structures emerge by applying this rule to the newly created squares.

[18], materializing our internal cognitive processes allows others to contribute with different perspectives. In addition, since we share the same language of creation, we can communicate directly through the design material and generate new variations. The rule-based nature of shape grammar makes the design process explicit and transparent, which can facilitate reflection-in-action. By comparing and evaluating these variations, designers can reflect on the design space and their design decisions, and adjust their approach as necessary. The interaction between the designer and the shape grammar can be seen as a form of cognitive coupling [22]. The designer's thoughts and the grammar rules become so intertwined that they form a single, integrated system.

As pointed out by shape grammars' original authors, SG can be very useful for AI systems, particularly those involved in generative design [122]. Shape grammars serve as a language for defining design space possibilities, allowing AI to generate a wide range of variations based on set rules. By reflecting in action, designers can interact with the system during the design process, offering real-time feedback and adjustments. This interaction can spark new ideas and creative possibilities that might not be realized otherwise. Then if an artificial system is given a set of explicit rules for generating designs, this system can be programmed to generate a wide range of design variations. These variations can be helpful for designers to explore design directions they might not have considered inspiring them to push beyond their usual boundaries, potentially leading to more innovative designs supporting human exploration and potentially leading to more innovative and effective designs. Due to the exploration of possible solutions and the relationships with their context [14] our perception and knowledge acquisition of both problem and solution space is augmented. Then, in the context of AI-human collaboration, this knowledge is lost if the AI system's reasoning is not well-communicated and understood by humans. We are especially interested in how AI-powered systems can support humans during the whole creative-problem solving process. It is crucial to explore techniques that support reflection-in-action and better knowledge transfer between humans and artificial agents during the whole process of designing rather than only receiving final outputs given by AI systems.

For that reason, we consider that using shape grammar as a design language combined with an AI agent using this language to explore solutions in a given problem space presents an opportunity for collaboration and creativity support within the context of creative problem-solving. This collaboration supports reflection in action through interacting with the design material produced either by the human or the AI which can lead to a more dynamic, interactive, and creative design process. Through the language and the produced output, designers can reflect and directly manipulate these outputs based on their needs. In addition, the AI can learn from the feedback and iteratively refine its understanding of the designer's design space and preferences, improving the quality of the generated designs over time.

In this Chapter, we introduce a new shape grammar as a design language for exploring 2D physically based scenarios. Together with this design language, we present a new environment for creative problem-solving, Coevo. This new environment allows us to study creativity through multiple problem spaces that can lead to a wide range of novel solutions. In addition, it allows us to investigate real-time human-AI collaboration supporting iterative exploration and reflection-in action through the design material thanks to the immediate feedback of the system. Using this language and the Coevo environment we show how both humans and an artificial agent can provide solutions to this initial set of problems.

4.1 Language design

4.1.1 Shape grammars as a design language

In order to generate proposals, we decided to create a language inspired by the formalization of a simple shape grammar [120] to generate 2D shapes. As shown in Figure (4.3) our SG has the following elements:

- **Initial Shape**. Single block with a fixed width and length. This is the minimal element of our language.
- **Shape**. Shapes are constituted by a single block (initial shape) or by concatenating blocks, one after another, until the desired shape is reached.
- **Rule**. Finite transformation rules are applied to shapes. Four specific rules have been defined regarding block size, construction (add or remove blocks) and rotation, see Figure 4.3

In our shape grammar, no restrictions have been defined on overlapping shapes to allow more freedom in design. These 2D shapes are internally represented by an array of floats. This array is described by an initial numeric value which corresponds to the length of the block followed by an open-ended stream of angles in radians which represent all the shapes,

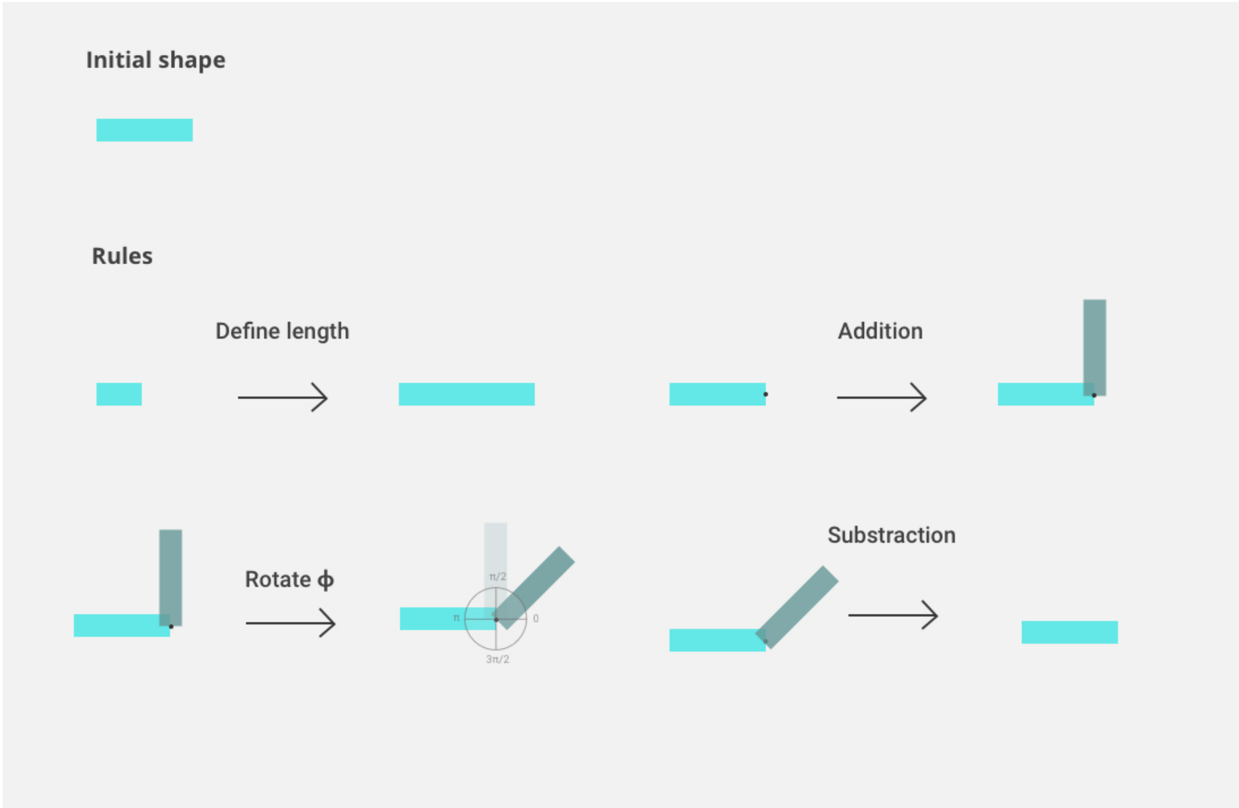

Figure 4.3 Shape grammar definition shared by humans and our artificial agent. Four rules can be applied to a shape. From top left to bottom right: Define global block length, add a block at the end of the last block, rotate a single block from the previous block endpoint (midpoint of the end), remove the last block of the shape. As shown, the free end of each block is the anchor point for the next block.

as is shown in the equation (4.1). Some possible examples of these representations are shown in Figure 4.4.

$$\text{design proposal} = [\,\text{length},\ \phi_1,\ \phi_2,\ \ldots,\ \phi_N\,] \tag{4.1}$$

where N is the number of blocks of the proposed shape.

These representations will be shared both in humans and our artificial agent proposals. As described in the following section this language will be used within an interactive interface for humans and for our artificial agent algorithm.

As seen in many studies [10], [12], [13], [118], the design process itself can allow us to create novel proposals given a certain problem by being continually inspired by previous proposals.

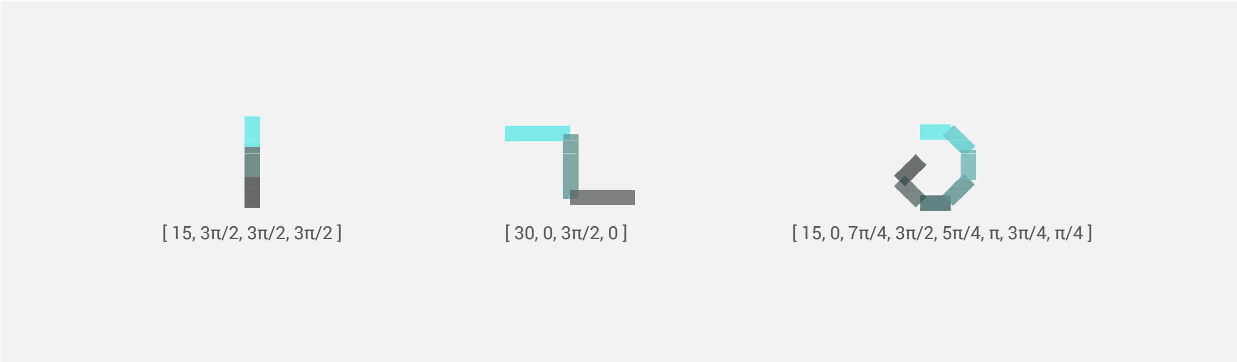

Figure 4.4 Some design representations with their corresponding inner values. By concatenating multiple 2D blocks complex shapes can emerge. Block colors indicate the order of the shape, the darker the newer.

These shared languages can help creators to explore the solution space and evaluate their proposals in our environment.

Then once a proposal is defined, it is placed and evaluated on this specific scenario and a specific score is awarded based on its performance and its completion of the given goal. Since this score is provided, a learning process can emerge based on obtaining higher scores on the design proposal given. Note that, our approach allows us to directly compare human and artificial agents' capabilities to design in this environment since common processes and tools are used.

4.1.2 Environment and initial scenarios

As shown in Figure 4.5, an initial set of four design challenges have been defined: collect, move, cut, and protect. In Appendix A, a more detailed visualization is provided in order to illustrate the dynamics of the elements of these scenarios

For each challenge, a scenario with initial design conditions is generated, involving positioning of the elements and design proposal and their physical behavior. In addition, an objective definition is set in order to measure design performance.

When a human or artificial agent proposes a solution, the system will place it on the environment and evaluate it regarding each objective definition. Then it returns a score from

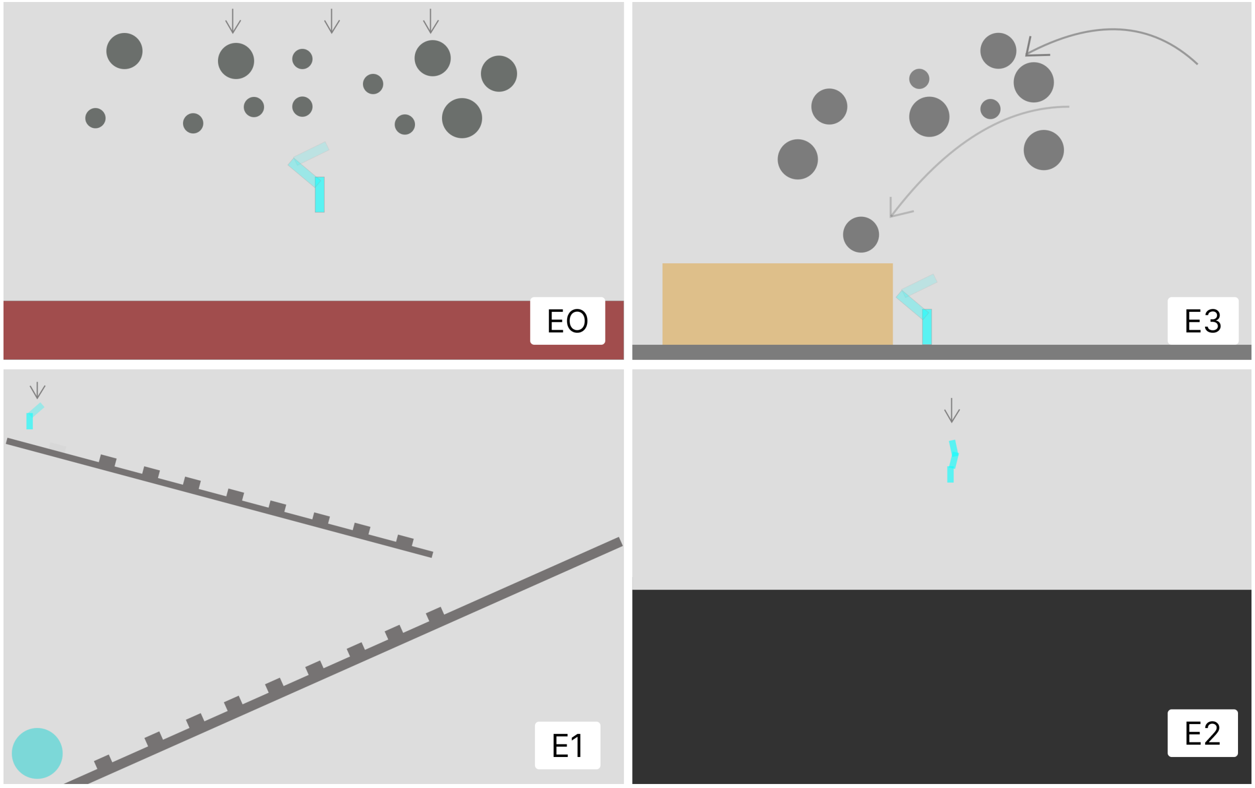

Figure 4.5 Design challenges. E0. Collect falling balls; E1. Move to a certain point; E2. Cut through a dense medium (dark area); E3. Protect orange area;

0 to 1 to quantify the overall performance within that experiment based on each specific goal definition.

Similar to other research projects and benchmarks [123]–[125], by evaluating the behavior of an AI agent and a human under the same conditions, we can directly compare their performances. Since our environment provides a quantitative score based on design performance, an incremental learning process can be defined. Designers will be encouraged to obtain output solutions with their higher score associated. The same goes for our algorithm that by receiving the scores of the generated proposals it will seek to maximize its final score.

Scenario evaluation

In this section, an evaluation criterion for each scenario is described.

E0: Collect balls. Define a proposal to maximize the number of balls collected. Balls start falling from the top of the scenario and the proposal score is defined by the number of collected balls (Equation 4.2)

$$\text{score} = \left(\frac{n}{t}\right)^2 \tag{4.2}$$

where n refers to the balls that are collected and t refers to the total number of balls

E1: Move along an inclined plane. Define a proposal that moves along an inclined plane until reaching a certain position as fast as possible. This proposal starts on a free-fall position and no further forces are applied within the experiment. Proposals are evaluated based on both the checkpoints reached (squared obstacles) and the distance moved within the 30 seconds the experiment takes to complete. In addition, a bonus is awarded if the proposal reaches this position in less time (Equation 4.3)

$$\text{score} = 0.6\left(\frac{c_n}{c_t}\right)^2 + 0.4\left(\frac{x_n}{x_t}\right)^2 + 0.2\,T \tag{4.3}$$

where c_n and c_t refer to the number of checkpoints reached and the total respectively and x_n and x_t refer to the horizontal distance moved and the total respectively. Finally, T corresponds to the time remaining in the experiment and it is a bonus to finish the experiment faster than expected.

E2: Move through a different medium. Define a proposal that reaches the bottom of the scenario. Similar to the previous scenario, the proposal is initialized on a free fall position but in this case, it must move from one medium to another until reaching this bottom area. As in the previous case, proposals are evaluated based on the distance moved within the duration of the experiment. Here the remaining time is considered within the fitness function instead of being considered a bonus (Equation 4.4)

$$\text{score} = 0.85\left(\frac{y_n}{y_t}\right)^2 + 0.15\left(\frac{t_n}{t_t}\right)^2 \tag{4.4}$$

where y_n and y_t refer to the vertical distance moved and total respectively and t_n and t_t refer to the elapsed time and total time.

We decided to simplify this experiment by computing a drag force applied to the proposal when entering the different mediums. The greater the area, the greater the drag force and it will be more difficult to reach the bottom within the given time.

Regarding the weights, we decided to prioritize the total moved distance and later on benefit the proposals that reached the bottom fastest.

E3: Protect area. In this scenario, creators must define a proposal that minimizes the number of balls that hit a specific area. This area is highlighted in orange in Figure 4.5. In contrast to E0, these balls now move following a random parabolic shoot that ends in the target area. As we show in equation 4.5, the score is inversely proportional to the number of balls that hit the area. (Equation 4.5).

$$\text{score} = \left(\frac{t-n}{t}\right)^2 \tag{4.5}$$

where n refers to the balls that hit the area, t refers to the total number of balls.

Once the language, scenarios, and evaluation function are defined, we conduct an initial study where AI agents generate solutions to proposed design problems. To conduct this study we build an environment consisting of an interactive website with proposed challenges to be solved in multiple physically based scenarios with capabilities to simulate 2D rigid body physics. It has been built on Javascript [126] libraries p5.js and matter.js [127] combined together to generate an interactive web interface with a common set of tools to create design proposals for a given goal and scenario.

4.1.3 Artificial agent study.

In this section, we describe the initial experiments performed by our artificial agent. As stated before, we are interested in evaluating agent capabilities to generate creative design proposals from scratch in multiple scenarios. Then, its training will not incorporate any previously labeled data with possible solutions.

Our artificial agent is based on a genetic algorithm (GA) that generates design proposals in our solution spaces. Population-based search techniques make it possible to explore many areas in these spaces at once [128]. Particularly, these algorithms can be used to explore wider solution spaces and potentially propose novel designs through the exploration and recombination of their proposals.

The genotype is composed of the array of characters described before (see equation (4.1)), that will be evolved during the learning process similar to other Grammatical Evolution (GE) [91], [129]. Then to generate the phenotype we decoded this array drawing the shape of a design proposal. Initially, these 2D pieces have a predefined width and length for each scenario. However, in order to define a unique and single agent for all the scenarios, we decided to incorporate the length as a parameter as well to be evolved.

Regarding fitness, it is obtained based on the objectives of each scenario where proposals are evaluated. In order to optimize them, basic GA operators such as selection, crossover, and mutation have also been implemented.

Selection is based on Roulette-wheel selection via stochastic acceptance [111] in order to reduce computational resources during the simulation.

Crossover: we divide the genes by randomly assigning a middle value, M, creating two groups of genes (0-M and the resting ones) from each parent respectively. Since we have not limited the number of genes on proposals, we also have considered how to perform combinations between genotypes with different sizes. To do that, we created a growth parameter with two possible behaviors: get the maximum size of parents or randomly select which parent length to use. These two behaviors directly effect on genotype growth which is beneficial in some experiments but negative in others. For that reason, we decided to evolve also this parameter in the optimization process.

Mutation: two mutations have been defined: alter mutation rate (AMR) defining the probability of each gene changing to another one; multiplier mutation rate (MMR) which defines the probability to add or delete one gene in the last position of genotype.

The aim of this initial study is not focused on optimizing these parameters. For that reason, we decided to randomly assign a discrete number of values that converge to valid design solutions. These study conditions can be found in Table 4.1.

Initialization parameters for artificial agent					
Single proposal genotype			Generation of proposals		
Size	Growth Alele	N pieces rotation	Population	AMR	MMR
8-60	0 or 1	[0-2π , ... , N]	50,100,150	0.01, 0.02, 0.05	0.02, 0.05, 0.12

Table 4.1 Once a simulation is started, each parameter is randomly initialized. Note that genotype parameters are evolved and change within a generation. In contrast, generation parameters are fixed during the whole simulation.

All design proposals are placed on the same corresponding initial position and evaluated using each scenario-specific fitness function.

4.1.4 Results

In this initial experiment, optimization is an open-ended process that constantly generates proposals for a given scenario. This process is stopped when there is no indication of progress between multiple generations. To measure this we use the variation of mean fitness value.

Once a simulation is stopped we save all the design proposals generated until that moment in order to perform our future analysis presented in the following chapter. These initial experiment has allowed us to generate solutions for each proposed scenario. Particularly in some scenarios, such as Movers one, a wide range of solutions were proposed by the algorithm. As described in other studies [80], [128], population-based algorithms can explore wider solution spaces and potentially propose novel designs. As shown in Figure 4.6, we expose valid solutions generated by our algorithm when given the task to create an object that moves through an inclined plane.

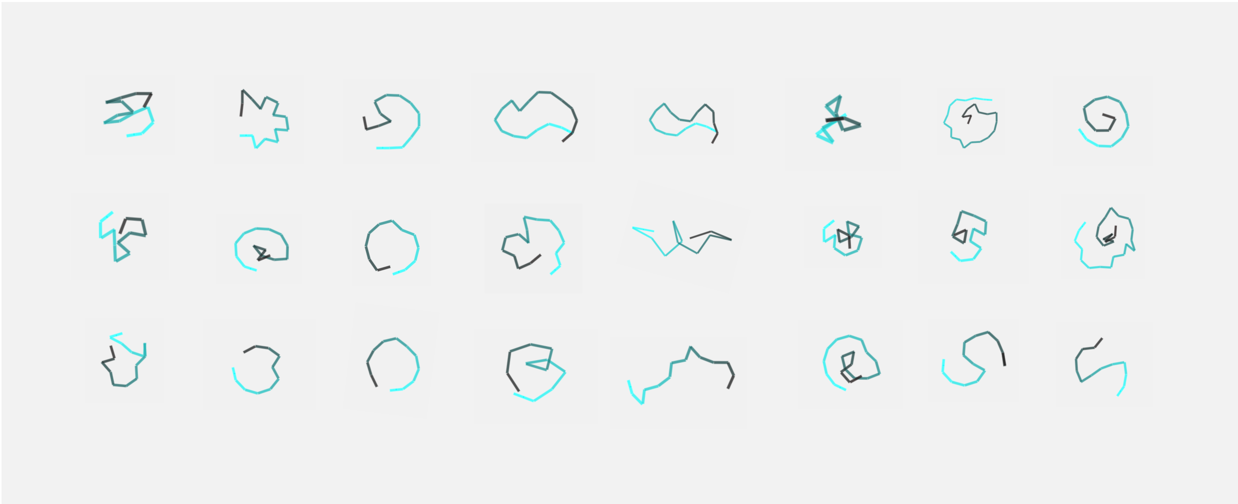

Figure 4.6 Gallery of agent-generated designs. In a design problem such as "Create an object that moves on an inclined plane" we can observe multiple solutions that differ from the common solution in that context: the wheel.

Our algorithm has converged into solutions in all the presented scenarios. Particularly in Movers scenario, our system produced innovative shapes such as spirals or sleeves that perform better than originally intended shapes for this simple scenario, a wheel. These unexpected proposals can inspire creators with new approaches for solving a defined problem and augment their capabilities in designing by expanding their vision on a possible solution space

4.2 Conclusion

In this Chapter, we introduced our design language and presented Coevo, an environment to investigate creative problem-solving for both humans and AI agents in multiple physically simulated scenarios.

Regarding our design language, it has been defined to explore solutions given a problem space that can allow a wide range of creative possibilities by building complex structures with minimal elements and a set of simple rules. Together with the language, we present a new environment where creators can define solutions to given 2D physically-based scenarios.

As part of this Chapter, we conducted a first study to validate how an evolutionary algorithm can generate valid and novel solutions to multiple given 2D physically-based problems using the presented language. Population-based optimization algorithms also help on maximizing the exploration of the solution space. This exploration provides not only variants of similar designs but also sometimes radically novel proposals. This new knowledge can help to augment human creative problem-solving capabilities offering a broader view of the problem and the solution space.

In contrast to Chapter 3, generating solutions and testing design proposals in this environment can be done in a few seconds. This will allow real-time creation and testing of design proposals while allowing an exploration that can benefit future collaboration between human and AI agents while maintaining creative flow [17].

Based on this first study on how evolutionary-based algorithms can propose solutions to multiple physically-based problems using a flexible design language, in the next chapter we discuss further how the definition of the language and the algorithms used can benefit creative exploration and lead to more valuable and novel solutions given a certain problem space.

Chapter Five

Exploring the flexibility of design tools through different artificial agents

In this Chapter, we explore how the definition of more general design language can allow artificial agents to better explore the solution space and generalize through multiple problems in the Coevo environment.

Many machine learning approaches are focused on defining artificial agents able to find solutions to a certain problem given fixed design tools or parameters to optimize. In order to do that, creators must have a certain knowledge of the solution space to define design parameters that ensure enough exploration allowing agent to find its best configuration. However, this approach may limit artificial agents since they are restricted by their initial conditions of a certain problem (e.g: block size, position where they are placed, total number of blocks...). In addition, specific initial conditions also limit them to scale across multiple challenges.

When defining a language, we are setting rules and actions to generate proposals for a given problem. This definition plays a crucial role in exploring the solution space since it can limit the creator's capabilities to design a solution. For that reason, we consider that flexibility is one of the key aspects to allow computational systems to explore problem space and re-adapting from possible non-favorable initial conditions while generalizing better across different scenarios. Particularly, we demonstrate how this flexibility in using language can allow artificial agents to better explore the solution space and generalize through multiple design problems. To do that, we compare different population-based search algorithms that use the defined language in two different ways. The first one is based on learning to optimize a shape with an already defined number of pieces. This approach can benefit the algorithm to find solutions, but it requires that creators know the problem space since a possible number of pieces must be proposed for the solution. In contrast, the second method consists in allowing the agent to freely modify its shape by adding or removing pieces. We evaluated each method's capabilities to generate creative designs by comparing their artifacts produced considering both their performance and novelty [118], [130]. Although the first constructive method is more efficient in finding possible solutions since an optimal number of blocks is already defined, the second method can even provide more novel and valuable proposals in multiple scenarios. By defining a flexible language, our system is able to generate design proposals from scratch that resembles human proposals within multiple environments and without any previous knowledge.

Our results show the importance of defining tools that can perform more actions to explore the solution space rather than focusing solely on the complexity of the algorithm.

5.1 Evolutionary agent study

We have performed our experiments in Coevo environment presented in the previous Chapter 4. As mentioned, this environment allows us to test a collection of physically based scenarios with specific design problems. A total of five of the previously presented scenarios have been proposed as a benchmark for our comparative study (Figure 5.1).

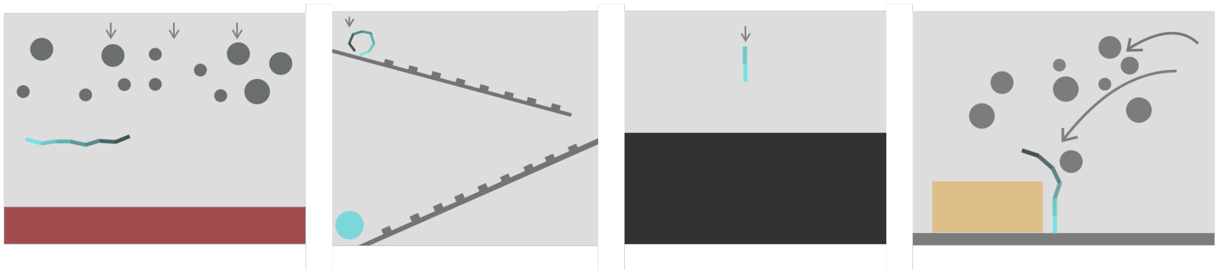

Figure 5.1 Scenarios. From left to right: collect falling balls, move along an inclined plane, move through a different medium, and protect a target area.

- **E0 - Collect balls.** Each proposal is evaluated by the number of falling balls collected. We have two variants based on the design proposal position: the left side (E0.1) or at the middle of the scenario (E0.2).

- **E1 - Move along an inclined plane.** Each proposal is evaluated based on the total distance moved within the simulation steps that the experiment lasts.

- **E2 - Move through a different medium**. Each proposal is evaluated on the total distance moved from an initial free fall position and experimenting with a drag force $\vec{F}_s$ when entering the different medium

- **E3 - Protect area.** Each proposal is evaluated by counting the number of randomly generated balls that hit the highlighted orange area (Figure 5.1).

We have chosen these scenarios from Coevo environment since they allow us to evaluate our evolutionary agents' capabilities to produce creative solutions in different scenarios, each one with its specific set of unique solutions. While E0 and E3, require a larger number of blocks to be solved, E1 and E2 perform better with less number of blocks. Based on this knowledge, we can define constructive rules and initial configurations that allow the system optimally solving the scenario. However, this definition may not be optimal for other scenarios or even limit system capabilities to solve another specific scenario. So, we want to explore how to define a system that can perform better globally while allowing a proper exploration of the problem space. This aspect will be discussed in the following sections.

5.1.1 Artificial agent definition

For this study, we created three different artificial agents that learn to generate design proposals using the previously described tools. All these AI agents are based on evolutionary techniques that learn to optimize their shape to fit the problem of each scenario. Here, we summarize each agent used:

- **Fixed Genetic algorithm**: this agent is based on a simple genetic algorithm [131] that selects best candidates using roulette-wheel selection via stochastic acceptance [111]. Crossover is performed by combining selected candidates' representation and we also add a mutation value that randomly changes angles $(0, 2\pi)$ to add noise when defining a new population

- **Fixed CMA-ES** : this agent is based on Covariance-Matrix Adaptation Evolution Strategy [104] adapted to optimize a shape with a certain number of blocks. The initial population is randomly generated. Then, each new population is generated within time from multiple distributions of mean and co-variances (one for each block) based on previous generation performance. Note that the number of distributions depends on the initial number of blocks defined for that certain experiment. For that reason, the number of blocks cannot be modified through the experiment.

- **Variable Genetic algorithm**: similar to the first agent, this approach is also based on a genetic algorithm. Its main difference is that a mutation value for adding and removing pieces has been also added. This allows the agent to optimize also the number of pieces required and explore possible valid morphologies for each scenario.

We have chosen to define our agents based on these evolutionary techniques as some of the simplest and most popular among researchers in the field [132], [133]. In addition, population-based search techniques make it possible to explore many areas in these spaces at once [128] so we have considered appropriate for our experiments. All experiments are initialized with a fixed number of blocks and only the third one is able to add and remove blocks. This decision allows us to evaluate how an agent with more design capabilities performs in comparison with the other ones.

5.1.2 Experiment conditions

Here we enumerate all the experiments performed with each artificial agent and scenarios described in the previous section.

As seen in Figure 5.2, each scenario and algorithm has been initialized with three different number of blocks (6,12 and 24, respectively). Each combination (scenario, agent, number of blocks) has been simulated for 200 generations with a population of 100 members each one initialized randomly at the beginning of the experiment. A condition to stop if no improvement is detected after 10 generations has also been included. We decided to propose these diverse conditions to compare how the different agents behave in possible optimal or bad initial configurations. As an example, a larger number of blocks may not be an optimal initial configuration for problems that require shape precision such as the Movers and Cutters scenario. In contrast, a larger number of blocks is beneficial for scenarios such as Collectors and Protectors since it's easier to propose a shape that can collide with the fallen balls. Since we are especially interested in the global performance and novelty of each agent, we consider that initializing the agent with three different number of blocks gives us a general idea of how the agent is able to adapt and provide different solutions within a limited number of iterations (200 generations). Finally, we repeated each experiment 10 times to have enough data to extract design patterns. This makes a total of 450 experiments to be analyzed

All design proposals are placed in the same corresponding initial position and evaluated individually using each scenario-specific fitness function.

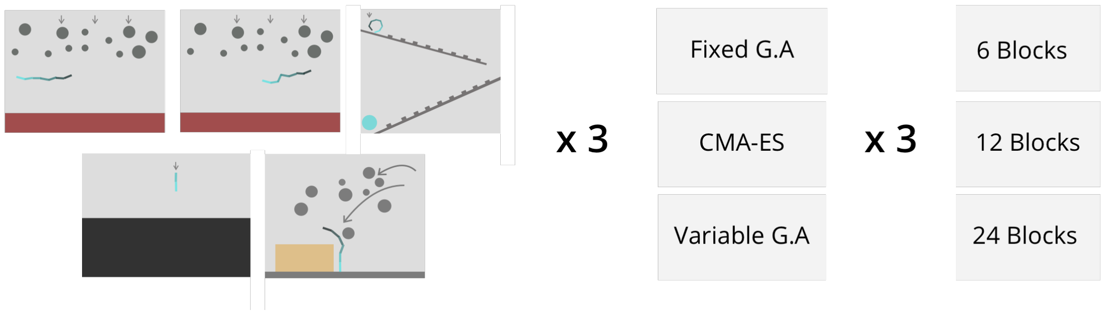

Figure 5.2 A total of 45 combinations can be performed considering given variables: scenario, agents, and number of blocks

5.2 Results

In this section, we present the results based on the design proposals generated by each agent. Our goal is to evaluate agents' capabilities to produce creative designs. We considered Ritchie's approach [130] for evaluating individual creativity by its produced artifacts rather than from the process used. To do that, we evaluate each individual artifact based on Maher's proposal [118] that considers three parts for evaluation:

- **Value**: performance measure of the design.
- **Novelty**: similarity from the rest of the proposals.
- **Surprise**: how an artifact can exceed the value and novelty expectations of the already defined patterns found in the solution space.

5.2.1 Value evaluation

Since we have captured and analyzed all the designs produced, we measure the value by computing the fitness obtained by the best member of each generation from each experiment.

As we can see in Figure 5.3, there is a common behavior between configurations with a fixed number of initial blocks reaching high fitness in most scenarios when their number of blocks is optimal for that scenario. In contrast, they perform worse when this initial number is not optimal. For example, in Scenarios 0.1 and 0.2, only the configurations that start with 24 blocks are able to reach higher fitness. This behavior is also seen in Scenario 3, in which configurations with higher amount of blocks perform better. Opposite to that, in Scenario 2, the configuration with a lesser number of blocks performs better reaching maximum fitness faster. In this Scenario 2, the agent based on GA-24-fixed is the only place where this agent does not find a solution. We also observe that both fixed agents are also able to reach higher fitness within generations with the exception of the fixed ones that started with only 6 blocks.

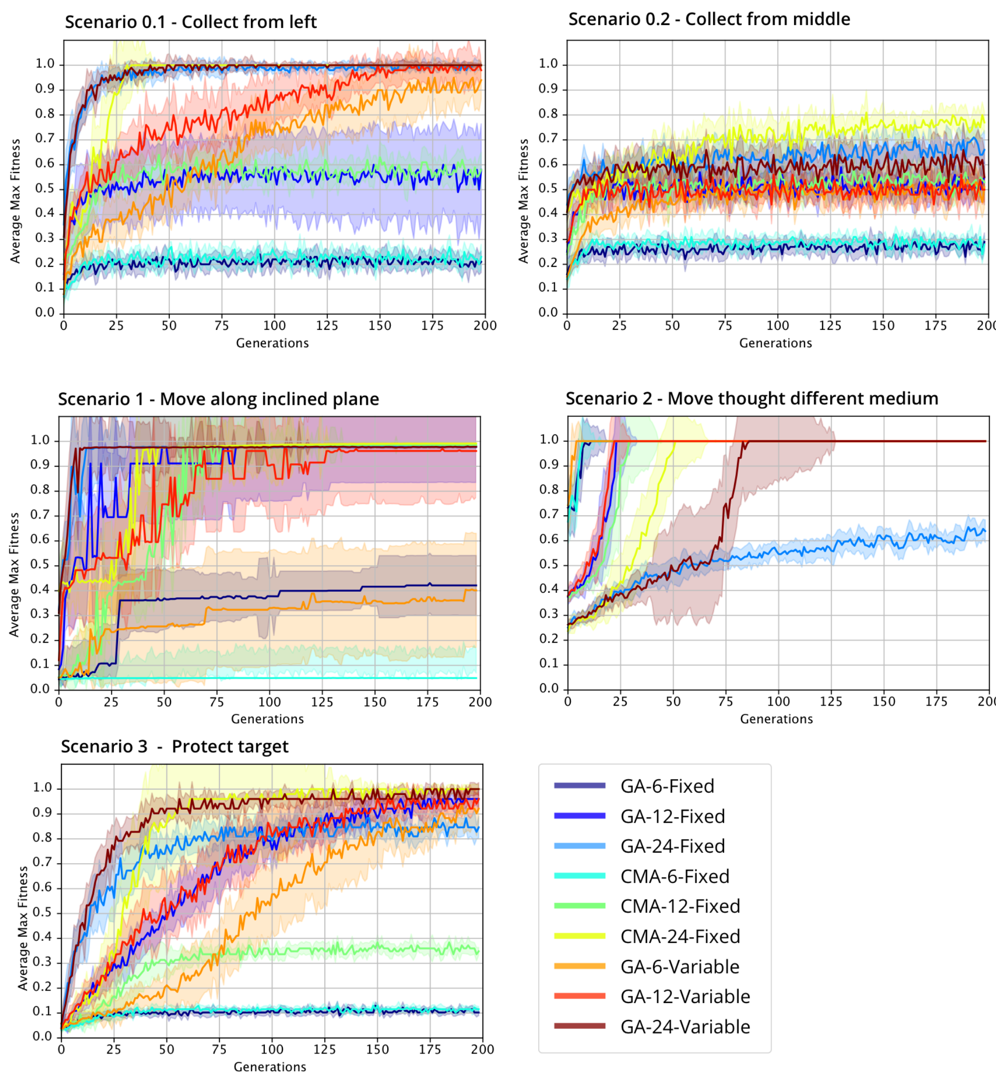

Figure 5.3 Learning process from each scenario and agent configuration considering 10 random rollouts

Fitness performance comparison						
	Fixed G.A		**CMA-ES**		**Variable G.A**	
	Min	Max	Min	Max	Min	Max
E0.1	0.24	1	0.27	1	0.95	1
E0.2	0.3	0.71	0.32	0.81	0.54	0.66
E1	0.43	0.97	0.05	0.99	0.4	0.98
E2	0.65	1	1	1	1	1
E3	0.12	0.88	0.13	1	0.94	1

Table 5.1 Comparison between worst fitness and best fitness obtained by each agent configuration. As shown, Variable G.A agent performances are more similar.

In contrast to that, as also shown in Table 5.1, the agent with a variable number of blocks can perform better, no matter the number of blocks it is initialized. Similar to previous agents, proposals generated by this third agent can reach higher fitness in all scenarios except from Scenario 0.2, also the worst scenario for the other agents. Using its constructive capabilities is able to optimize the number of blocks needed to solve the scenario. One exception to this behavior is in Scenario 1 with the agent starting from the lowest number of blocks (6), and the third agent has not been able to reach higher fitness.

5.2.2 Novelty and surprise evaluation

In terms of agent novelty, we have decided to evaluate each group of generated design proposals based on how similar are to each other, following Maher's approach [118]. She proposes evaluating similarity using the distance of potentially creative designs and later on clustering them based on that. Since each agent proposes a large number of designs, we only considered those with a threshold performance greater than 0.9. In addition, to further reduce the number of proposals, we randomly pick only 15 proposals for each roll-out for each agent.

This ensures having enough representatives of each agent while maintaining a small data set for our similarity comparison. Then we have multiple data sets of valuable design proposals generated by each artificial agent. These two decisions ensure that selected design proposals are valuable to the given problem, while we can also evaluate how different they are across agents.

Then, we must define an efficient comparison method for determining which data set contains more novel designs. To do that, we decided to generate an image containing each proposal. To ensure enough resolution, we centrally place each proposal in a 300x300 image and then we reduce their dimensionality into two components using Principal Component Analysis (PCA). This reduction helps us to visualize similar proposals closer in a 2D space allowing us to navigate between them and understand better similarity relations. We decided to use this approach to standardize all the design proposals within a single measurement since each agent may provide solutions with a different number of pieces. Then, for each scenario, we have placed each proposal in 2D dimensional space based on these two PCA components and clustered them.

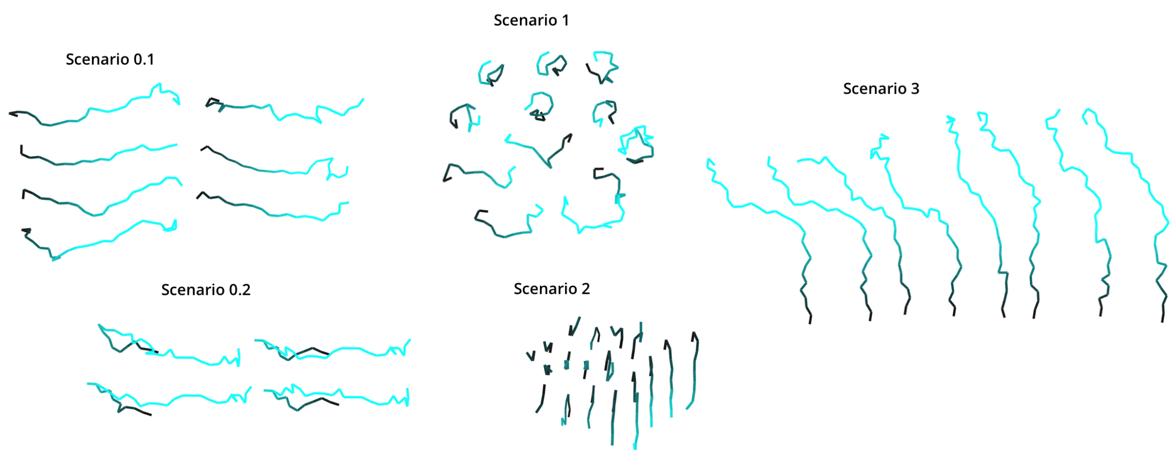

Figure 5.4 Artifacts randomly selected from third agent (G.A Variable) proposals. As shown different proposals can emerge from simple parts in each scenario.

For clustering, we propose the Mean Shift algorithm (MS) [134]. We decided to use the MS algorithm because it does not predetermine the number of clusters. We are interested in the emergent clusters from our current distribution of proposals. Then from each cluster, we randomly selected multiple representative proposals to compare them visually. As an example of this selection Figure 5.4 provides a visual overview of the divergence of solutions present in each scenario.

Regarding novelty between agents, in general, there is not a significant differentiation between the novelty produced by agents with a fixed initial number of blocks and the others. All three agents can produce similar design proposals considering their number of blocks. However, as observed in Figure 5.5, the number of blocks strongly conditions the shape of generated proposals. As an example, proposals from agents that use CMA-ES with 24 blocks resemble a lot each other. In contrast, the agent with a variable number of blocks can converge to a wide range of solutions with multiple numbers of blocks. This flexibility in design results in a greater dispersion of the generated artifacts.

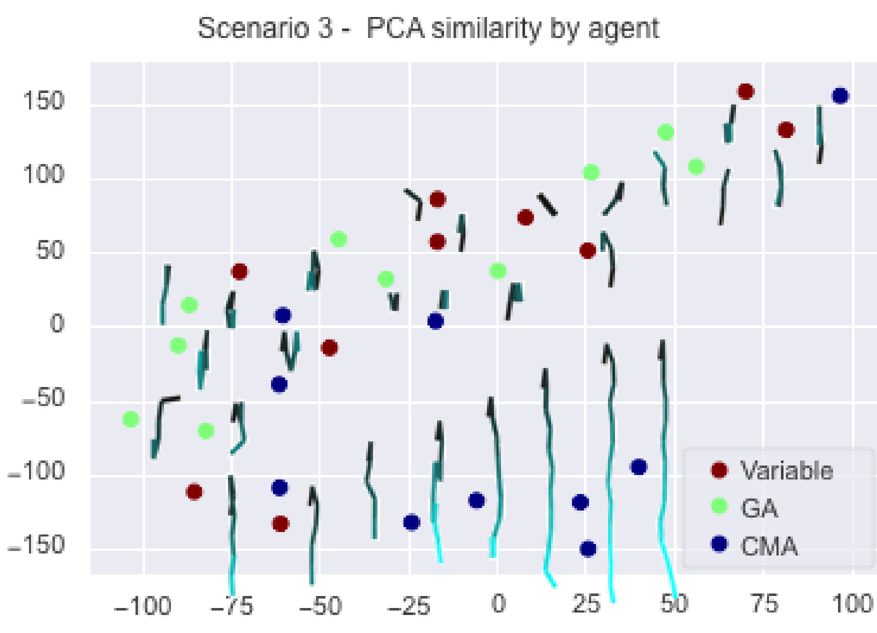

Figure 5.5 A total of 30 selected proposals (10 from each artificial agent) from Scenario 3 distributed on a 2D space. We can observe how a rich number of proposals are being generated by each artificial agent.

5.3 Discussion

In this section, we discuss the results presented before and the findings based on the proposals generated by our artificial agents. We also include the current limitations of our approach and plans for future work.

To perform our analysis, we have compared all the designs produced by our three different artificial agents in a total of 5 different scenarios. In general, all three agents have been able to produce valuable artifacts for each scenario. In terms of performance, Scenario 0.2 has been proved to be the most difficult one, directly lowering the performance obtained by the agents. In this particular scenario, only the proposals generated by the CMA-ES agent with 24 blocks have been able to surpass the value of 0.8 in fitness. In other scenarios, the Variable G.A agent has been the unique one that has generated proposals even when the initial design conditions are not favorable, compared to other agents. This result evidences how an approach that allows more freedom in designing influences positively the exploration of the design space ending up in a richer number of highly valuable generated artifacts. In contrast, both Fixed G.A and CMA-ES agents highly depend on initial parameters having fewer capabilities to adapt to each scenario. Then, only when initial parameters are beneficial, their performance is better reaching higher fitness faster than the others. One limitation of the current work is related to the initial conditions given to the system in terms of the number of blocks and allowed iterations (200). As shown in our results, some of these configurations may limit the agent's capabilities of finding optimal solutions. However, this has not happened in the flexible agent which, despite being affected by the iterations necessary to find optimal solutions, its exploratory capabilities allowed it to find solutions regardless of its initial conditions. This supports our approach that defining flexible constructive methods allows our computational tools to generalize better since we are not embedding scenario-specific knowledge that may affect negatively other situations.

Since the number of valuable proposals has been large in all the scenarios, the definition of metrics and tools to evaluate, compare and cluster them based on similarity has become crucial in our work. We have defined a comparison method inspired by [118] work on evaluating novelty as a distance between individual proposals. Regarding novelty, our results show how by using these simple design tools a wide diversity of proposals emerge in all the scenarios and agents. This behavior is also stronger in Variable G.A agent since is not influenced by its initial conditions, its solution space exploration is higher. Our results also suggest how population-based algorithms combined with simple design tools inspired by shape grammars can be a powerful combination for iteratively exploring multiple solution spaces

As we see in Figure 5.4, the same tools can generate a rich diversity of proposals for each scenario. Then, the designer's role in this creative environment can be focused on defining the problem space and collaborating with artificial agents to propose proper solutions to that problem. Our current environment is limited to only five different scenarios. However, new evaluation techniques can be applied to each of them or even new scenarios can be created and tested using our artificial agents.

An interesting future work would be to explore how problem space definition by designers can influence the novelty of designs generated by artificial agents. It has been shown that the most complex scenario (E1: Move along a plane) is the one that produced a greater emergence of novel design proposals. In natural evolution, the environment plays an important role in diversity, however, more research should be done to determine if this also happens in digital environments. This topic will be discussed in Chapter 7.

5.4 Conclusions

In this Chapter we explored how by providing an artificial agent with more degrees of freedom on using the design language, it can better adapt to multiple design challenges by offering proposals of greater value and novelty. To do that, we conduct new experiments on Coevo, the environment presented in the previous Chapter 4, together with the design language proposed. Our results suggest that the degrees of freedom given to the tool allowed the system to generate more novel designs with higher performance providing also solutions that are not influenced by initial design considerations based on the expected solution of a given problem.

In our studies, we have defined three population-based different evolutionary agents that have generated design proposals for a total of five different scenarios. Two agents are initialized with a fixed number of blocks that can be used for building, a third agent is allowed to modify this number of blocks during its learning process. By defining the initial number of blocks we are providing some knowledge on the solution space since some environments can be solved optimally depending on this number. However, this knowledge is related to a certain set of solutions that the creator may have in mind limiting the system to explore other solution spaces. In addition to that, it cannot be generalized in different scenarios, since this knowledge that can be beneficial in some scenarios is a limitation in others. As an example, E0 and E3 involve that the solution includes a larger number of blocks than scenarios E1 and E2. Then, agents initialized with the optimal number of blocks learn faster than others that may not even reach higher fitness due to their initial definition 5.3. Then when defining these systems, creators must consider initial configuration as a key aspect in their design. This requires an initial human effort to understand the problem and also an initial limitation since the creators are already embedding their knowledge in the tool they are creating. However, our results suggest that flexible agent does not show this limitation in the given scenarios. In contrast to fixed ones, the Variable agent is able to reach optimal solution spaces despite the fact of being initialized in a less beneficial solution space or even with a configuration that has no possible solutions to the given problem. As a result of this, our artificial agent can construct valid design proposals across multiple scenarios surpassing the other two agents in terms of performance and novelty. It is also especially relevant that this agent is also able to find novel solutions with high performance compared to fixed agents initialized on optimal spaces. Our results suggest that allowing more degrees of freedom influences the ability to innovate by reconfiguring its morphology, augmenting the space of possibilities, and exploring new paths within this space in each scenario. Especially in E1, by continually adding pieces, different new shapes emerge to the wheels, such as spirals or S-shaped morphologies similar to sleds. This phenomenon may be related to the evolutionary path followed by the solutions provided by the Variable agent since all the possibilities found by the fixed agent end up in the wheel as an optimal shape.

With the work presented in this Chapter 5, we show how an artificial agent using a more flexible language can generate more valuable and novel solutions to multiple design challenges. Despite the fact that we have compared the proposals generated by multiple agents, these solutions have not been compared to ones produced by humans. Thus, in the following Chapter 6, we compare proposals generated by an artificial agent to human-generated ones. This evaluation will help us to show how an artificial agent can generate novel proposals that later on inspire human designers in their creative process. These results will be the basis of human-AI collaboration in creative problem-solving, which is addressed in Chapter 7.

Chapter Six

Human-level design proposals by an artificial agent

In the prior two chapters, we introduced a new design language and an environment, Coevo, that allows us to explore real-time creative problem-solving in 2D physically based scenarios. We discussed the importance of defining a design language to explore the problem space. In addition, we demonstrated how an artificial agent can generate both valid and novel solutions to given multiple 2D scenarios. The approach we presented, assumes no previous knowledge of both the solution and problem spaces which means that solutions generated by AI agents are not influenced by human knowledge. Through the exploratory process, these agents have been able to generate new knowledge, as solutions, to the given design problem. However, we can not argue that the knowledge produced by artificial agents is beneficial nor the solutions are more creative than the ones that can be produced by humans. In the context of AI's role and tasks in a creative session, the term *beneficial* refers to the potential benefits that AI-generated solutions can provide to human designers. These benefits can include providing new perspectives and inspiration to human designers, as well as assisting with tasks that designers may not want to perform themselves.

Chapter 7 will delve further into the expected role and tasks of AI in creative sessions, and how AI-generated solutions can be leveraged to enhance the creative process for human designers.

Then, to support human-AI collaboration, we need to validate how these agents can generate valuable knowledge for humans. Then, it can be used to inspire humans and augment their understanding of both the problem and solution space.

For that reason, in this Chapter, we compare the artifacts produced by our agent to the ones produced by human designers in terms of performance and novelty. Our novelty analysis is based on a perceptive test performed by multiple human evaluators who are asked to directly compare artifacts in terms of similarity.

Our results show how our artificial agent proposals are at human-level in terms of performance and novelty, even surpassing human proposals in some scenarios. These primary results indicate how artificial agents can enhance human design capabilities by providing them with inspiration from novel designs. In addition, since proposals are generated using the same language, a future human-AI collaboration can be defined by allowing both creators to interactively modify, adapt or reuse proposals generated during the creative act. This will be discussed in depth in Chapter 7.

6.1 Experimental design

In this experiment, using the language given above (see Chapter 4), the creator (human or artificial agent) must design a 2D shape that solves a given goal in a 2D scenario.

In contrast to previous experiments (see Chapter 5), here, only two limitations have been defined. On the one hand, all blocks must have the same dimension. No limitations in growth have been defined while using this language. This means that addition and subtraction operators can be continually applied until at least one block is composing a shape. In addition, one particularity of these operators is that both are applied to the end edge. Finally, as in previous experiments (Chapter 5), no restrictions on overlapping shapes have been defined to allow more freedom in designing.

Once defined, the shape proposed as a solution is placed and evaluated on a specific scenario of our 2D simulated environment (Figure 6.1). Then it returns a specific score of this proposal based on its performance in completing the given goal (as described in Chapter 4). Since a score is provided for each proposal, a learning process can emerge based on obtaining higher scores on the design proposal given. Note that we also provide the same language, environment, and tools both for humans and artificial agents. This approach allows us to directly compare humans' and artificial agents' capabilities to design in this environment since similar design processes and tools are used to propose solutions.

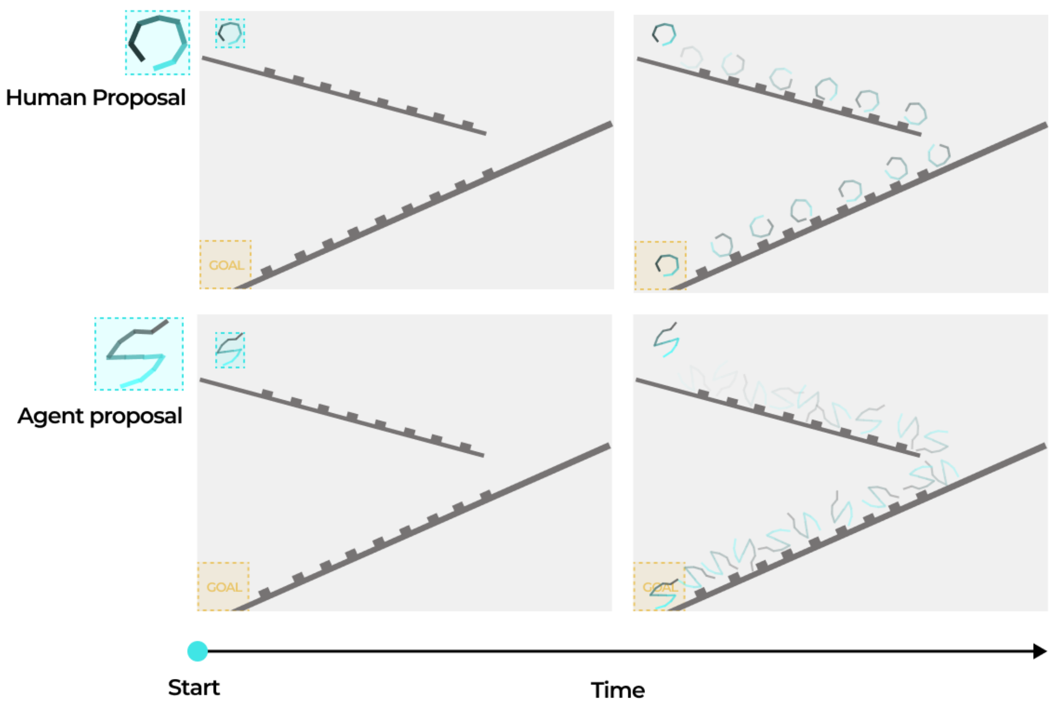

Figure 6.1 Human and agent comparison experiments. Given a certain proposal, this proposal is placed on the initial position and the experiment. The experiment will continue until it completes the objective or it runs out of time.

Then, our study will consist of evaluating solutions in terms of the value and novelty of a set of given proposals by a certain creator [13]. Note that then we are evaluating creativity based on the artifacts produced in the creative process rather than the process itself. This means we are evaluating creators' (humans and AI agents) design capabilities based on the proposals generated for a given goal and scenario. Moreover, we aim to evaluate not only their capabilities in a single scenario but given multiple problems to be solved in independent scenarios. The scenarios used for this experiment are the same ones described in Chapter 4. The main difference with the previous tests is that we are now evaluating human creators as well (Figure 6.2)

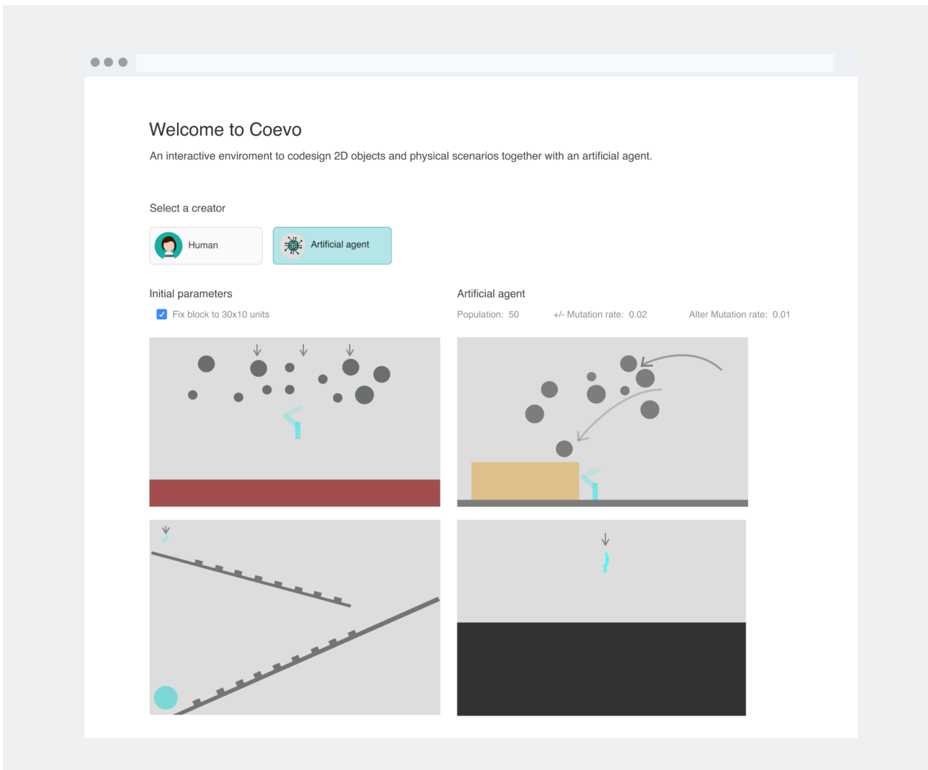

Figure 6.2 From top-left to bottom-right. E0: Collect balls. The objective is to maximize the number of balls collected by its design proposal. E1: Move along an inclined plane. The goal is to define a proposal that moves along an inclined plane until reaching a certain position as fast as possible. E2: Move through a different medium. The proposal is initialized on a free fall position but in this case, it must move from one medium to another until reaching a bottom area. E3: Protect area. In this scenario, creators must define a proposal that minimizes the number of balls that hit a specific area.

Once these scenarios have been defined, we discuss the experiments performed and the design proposals generated both by artificial agents and humans.

6.1.1 Human evaluation

The purpose of this test is to determine human capabilities in generating creative designs. To achieve this aim, we recruited a total of 8 adults, 5 females, age - 25 (SD = 1.49) to complete the experiment using Coevo environment. All participants had a background on design or engineering.

We provided a specific web desktop interface to define and evaluate proposals (Figure 6.3). When the test began, a proposal composed of a unique 2D block was presented to the user within a specific scenario. In each scenario, the initial position and block size (30x10 units) are already defined and cannot be modified by users. Based on that, participants can generate and evaluate design proposals.

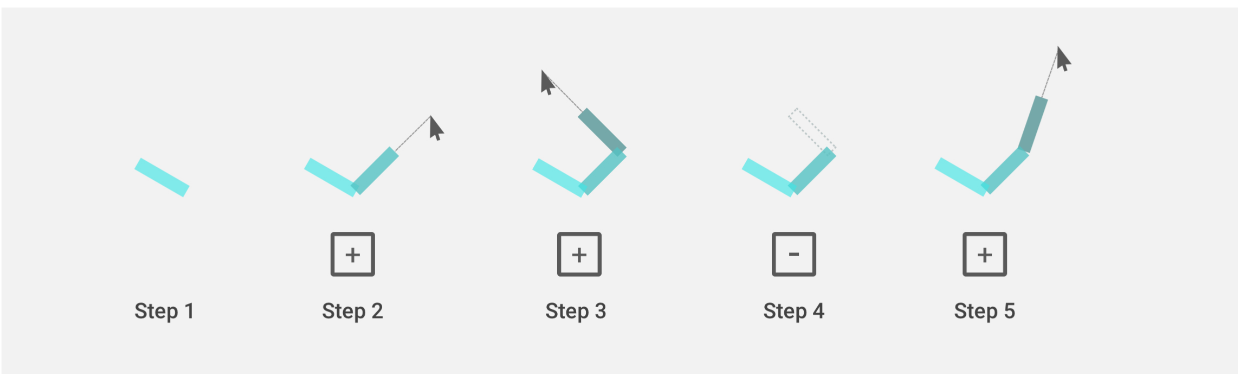

Figure 6.3 Design process example. Given a certain proposal (step 1), the participant can edit it with keys +/- for adding (steps 2, 3. 5) and removing (step 4) and mouse to define a direction.

Once completed, they can select the generated proposal and run a simulation to obtain the score that indicates this proposal's performance within the scenario.

Note that the design tools provided and possible actions within the experiment are the same as our artificial agent. This approach's objective is to minimize the differences between both creative processes and explore how different outcomes can emerge with that constraints.

Experimental design. A total of 5 scenarios have been given to participants with each specific design challenge to be completed. Participants are required to generate shapes using the design tools provided and evaluate their proposals within the simulated environment they are in. An introductory scenario was also presented to the users that included the tool capabilities, the simulation process, and the result evaluation. They were asked to generate solutions for the given scenarios with a time restriction of five minutes. Participants were also asked to create diverse solutions for each scenario.

As a result of this experiment, a design database of human-generated proposals for each scenario has been created. This allows us to perform a design analysis together with the results of agent experiments and explore similarities or differences between the proposals and their creators.

6.1.2 Artificial agent evaluation

Our artificial agent is based on the variable genetic algorithm (GA) presented in Chapter 5 This agent differed from the others by its flexibility to use the design language allowing it to add and remove pieces from the design solution. As described before, this agent was outperforming other algorithms by generating both valuable and novel solutions for each given scenario. In addition, these agent capabilities also mimic humans' creation tools presented previously since blocks can be added and removed without any descriptions.

All design proposals are placed on the same corresponding initial position and evaluated using each scenario-specific fitness function. Then, when all the members of a generation have been evaluated, we compute a mean fitness value of all the proposals, and another generation is created using the operands described before. This fitness value indicates the evolution of a certain population and is used as a measure of performance. Optimization is an open-ended process that constantly generates proposals. However, we decided to automatically stop a certain simulation when there is no indication of progress between multiple generations. To measure this we use the described mean fitness value. Once a simulation is stopped we save all the design proposals generated until that moment in order to perform our future analysis and compare it with human proposals.

6.2 Results

In this section, we discuss the design proposals generated both by humans and our artificial agents in each scenario. Our goal is to evaluate both capabilities of humans and our agents to produce creative designs. We consider Ritchie's approach for evaluating creativity [130] consists of evaluating individual creativity by analyzing the artifacts produced during a certain process rather than the process itself. As described before, in order to reinforce this approach we have prepared an environment where all the creators have the same tools and rules of creation. Then, once they have generated a proposal, a simulation is made. After they have finished, they are given feedback. This process is the same one used on our artificial agent, as it learns through trial and error during a series of generations and evaluations.

Moreover, we have decided to evaluate a whole group of creators by considering each individual proposal to later compare with our agent capabilities. This evaluation is based on Maher [118] proposal for evaluating creative artifacts that consist of three parts:

- **Value**: how well an artifact fits the function for which it has been designed. It is a measure of design performance.

- **Novelty**: how different an artifact is from the rest of the proposals. This similarity analysis will be based on generated shapes.

- **Surprise**: how an artifact can exceed expectations on value and novelty from already defined patterns found in the solution space. In other words, when defining a certain experiment, we have made some assumptions about possible designs that can be created. Then given our fitness function and our assumptions on possible solutions in each scenario, can a creator generate a proposal beyond these expectations?

We have gathered and analyzed all the proposals generated by humans and our agents during the process. Especially in agent experiments, the number of proposals increases a lot since there are multiple generations with a large number of designs. Once valid proposals emerge, the following generations learn from them and create further variations on these original proposals. In Figure 6.4 examples of this process in each scenario are shown.

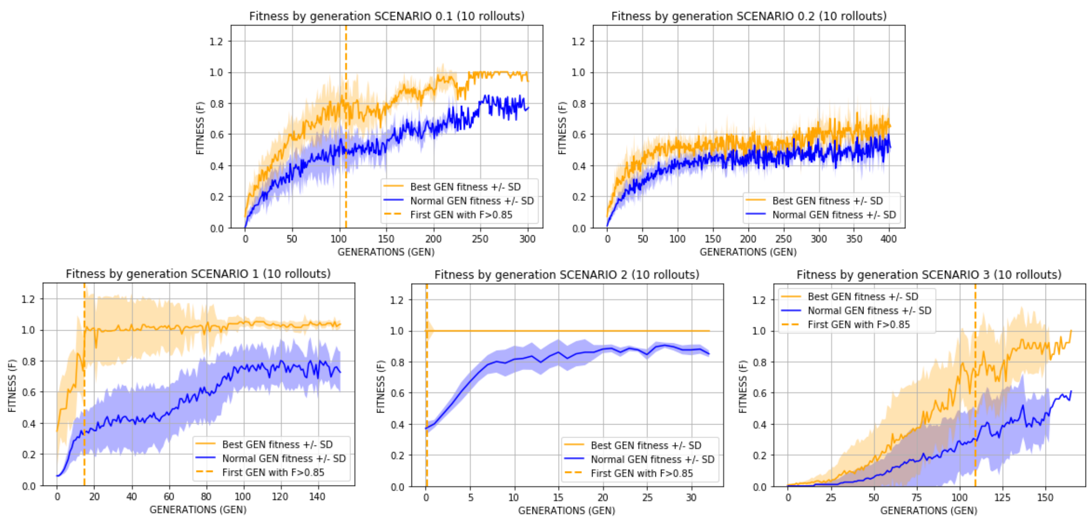

Figure 6.4 Learning process to propose designs with higher fitness (F). In each plot, a proposal with maximum fitness within a generation is shown in orange. By contrast, a median of fitness calculated from all proposals within a generation is shown in blue. The learning rate differs within scenarios until convergence. On Scenario 1 and 2, our agent produces designs with F>0.85 the first time on Gen 15 and Gen 1 (on average) respectively. In contrast, in Scenario 0 and 3, proposals with F>0.85 does not appear until Gen 107 and Gen 109 (on average) respectively.

6.2.1 Performance.

A large number of designs are generated within this learning process. All these proposals are distributed by scenario and creator generating a total of 10 design datasets (2 creators x 5 scenarios). Then we used a selection method related to the concept of value exposed by Maher [118] to evaluate the designs ranking them based on their fitness. To reduce the number of selected proposals we discarded designs with a fitness lower than 0.85. The decision to use a fitness threshold of 0.85 was based on empirical observations and is likely specific to the particular design problem and optimization method used in the experiments. Other design problems and optimization methods may require different fitness thresholds to achieve optimal results. In Table 6.1 there is a summary of the maximum fitness obtained by humans and agents in different scenarios.

Max Fitness Performance comparison					
Creator	**E0.1**	**E0.2**	**E1**	**E2**	**E3**
Human	1	1	1.176	1	1
Agent	1	0.82	1.51	1	1

Table 6.1 Maximal fitness Performance results between humans and our agent. Note that in Movers scenario (E1), both human and agent obtain fitness values higher than 1 due to the proposals are faster than original speed of a free-falling perfect wheel of mass 1.

Regarding human results, we observed that they have proposed valid designs in each one of the scenarios given. By contrast, our artificial agent proposes a large number of artifacts but most of them are discarded until some valid solutions emerge. This can be explained due to its inner learning process, which differs from human already learned experience. As shown in Figure 6.4, our agent only learns through generations based on the fitness evaluations of each given proposal. Thus, a learning process is needed until a valid proposal emerges. However, as shown in Table 6.1, in terms of value, it's able to produce human-level designs in all the other scenarios. In particular, in Movers scenario (E1), the agent's proposals are able to generate proposals with F>1. This particular case happens because our agent outperforms original fitness function defined. This function, as described before, considers an estimated time to complete the experiment as one of the measures to evaluate proposals. A value of F>1 means that the proposed designs are moving faster than the expected time to complete the distance given. Then in terms of surprise, we can consider that some proposals' performance has outperformed original expectations, especially on agent proposals with a maximum F=1.51.

Only in Scenario 0.2, our agent is not able to produce designs with a fitness greater than or equal to one (F=0.82). In this scenario, blocks must be concatenated to create an overlapping path that gathers all the falling balls. Then if the algorithm doesn't create a proposal with a long chain of blocks it cannot reach higher fitness values. In Figure 6.5, this evolutionary process is illustrated in which the algorithm must learn first to collect balls from one side of the scenario and then rotate and overlap itself to collect both sides. During the path overlapping, the fitness of the solution is stuck and this situation causes strong difficulties in the evolution of the algorithm.

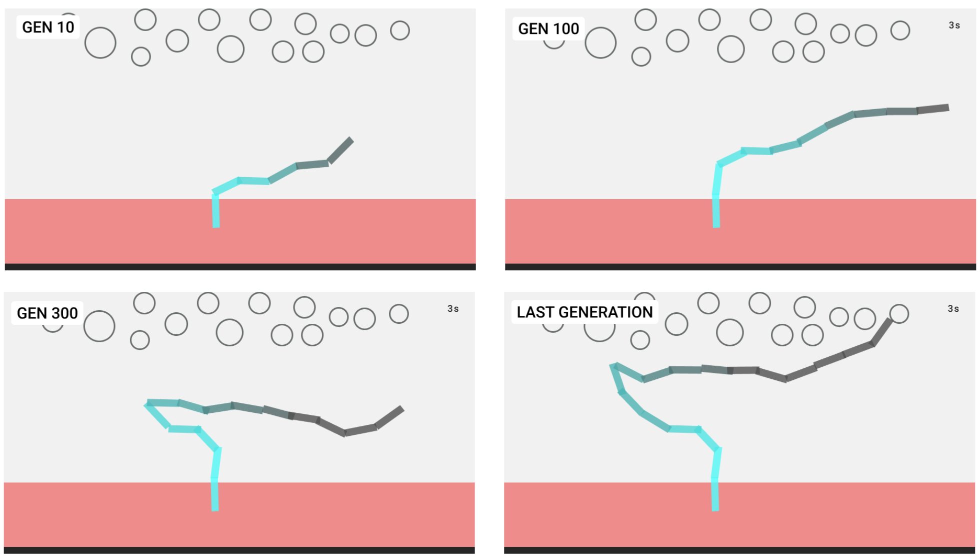

Figure 6.5 Learning process to propose designs for Scenario 0.2. In the beginning, the agent learns to propose a shape that collects balls from one side (top images). Later on, probably due to mutation with blocks in the middle of the chain the proposed shape overlaps itself allowing it to collect more balls (bottom images). However, as observed in the presented results, the agent cannot come up with a shape that collects all the balls

We will not consider the artificial agent's results in E0.2 and compare it with human ones because already fails on generating proposals with F>0.85 given the initial design conditions.

6.2.2 Novelty

From this first selection based on performance, multiple datasets with a large number of valid proposals have been obtained. Then an evaluation of novelty in designs will be performed. This study will help us to understand how similar or different are the design solutions generated by each group of creators. Our objective is to determine the creator's capabilities to generate novel designs in each scenario. We will evaluate novelty capabilities by mapping the proposals in a similarity space. As is described in [118], we will obtain distances between elements and create clusters of artifacts. Unlike Maher and Fisher's [118] approach, we consider both quantitative (analytical) and qualitative (human perceptual) similarity to evaluate a whole group of artifacts. Our model will consist of firstly analytically comparing and selecting a group of representative designs extracted from solution space and later comparing them qualitatively based on pairwise similarity perception from human judgment.

Clustering selection.

To reduce the number of proposals for the perceptual comparison we define a method to select a representative number of designs through an analytical comparison. We measure pairwise correlations between each artifact (F>0.85) present in the solution space. These correlations are measured by calculating the pairwise Pearson correlation coefficient [135] at positions X and Y of all proposed two-dimensional shapes. We associate the mean value of these Pearson correlations coordinates with each pair of artifacts. From this, we can obtain a similarity matrix that allows us to cluster design proposals.

We order the artifacts of each cluster by their performance score. Then, we pick the best artifact score of each cluster. For each scenario, we decided to set the number of selected designs to 15 as a compromise between obtaining enough representative designs and minimizing the number of comparisons that humans will have to perform during the perceptual tests. As a result, our stimuli set consist of 15 designs extracted from design proposals generated by users and agents separately from each environment.

As shown in Collectors's scenario (Figure 6.6) and Movers's scenario (Figure 6.7), each scenario will have two groups of designs generating a database composed of 8 groups (4 scenarios x 2 types of creators).

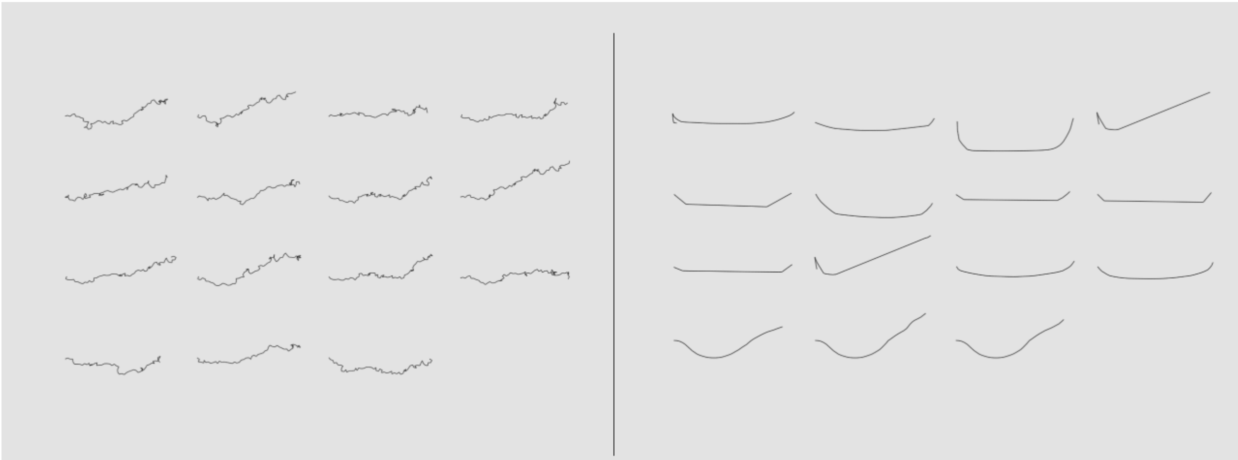

Figure 6.6 Two design sets containing selected proposals in Collectors scenario. On the left, there are artificial agent design proposals. On the right, design proposals are selected from all humans' proposals.

Qualitative similarity and consistency selection.

The purpose of this validation is to understand the human perception of similarity in the proposals generated in each scenario. As stated in [118], novelty can be described as how different a design proposal is from the rest of the solution space. By judging design proposals generated by a creator, we expect to extract information on how novel a proposal is and thus infer the capabilities of this group of creators.

To achieve this aim, an online test to rate all possible pairwise comparisons has been created. After the evaluation, we analyze the distribution of designs based on their similarity and compare the results obtained by artificial agents and users in each scenario.

A total of 156 adults, 78 females, age 27.18 (SD = 6,98) rated a full comparison set composed of 15 design proposals (Figure 6.8) and all the possible pairwise comparisons (120) based on their similarity. All participants were recruited via an online test in which we only captured their age and gender, together with their answers. No background information was captured. In Figure 6.8 we show this test flow.

In the experiment, the stimuli are the proposals obtained from the clustering selection (see previous section). A set of 15 designs from each particular scenario and creator is assigned to

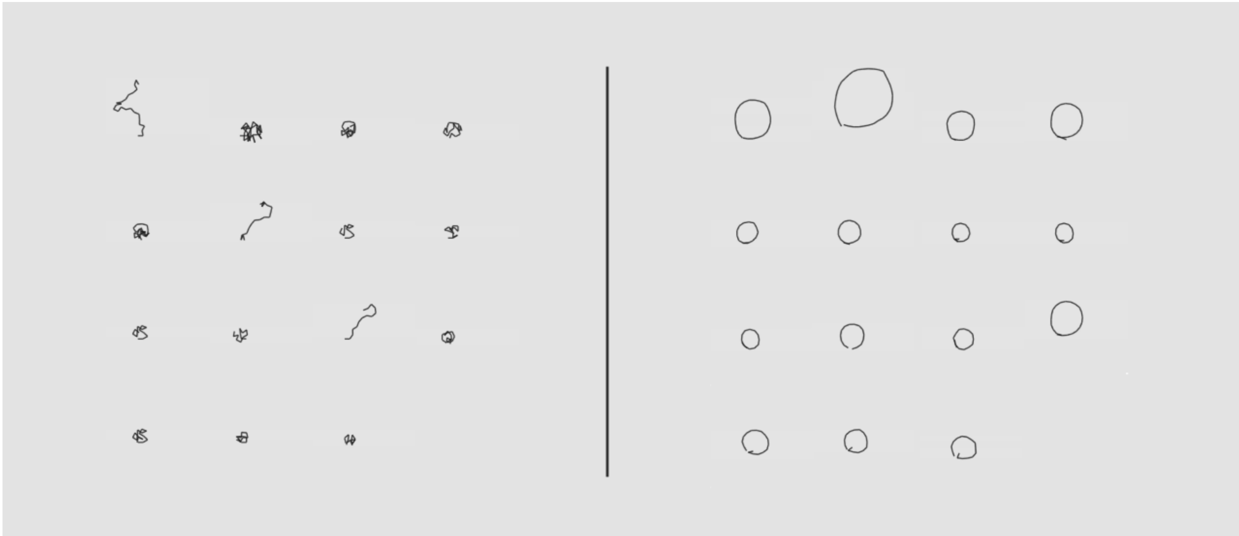

Figure 6.7 Two design sets containing selected proposals in Movers scenario. On the left, there are artificial agent design proposals. On the right, design proposals are selected from all humans' proposals.

each participant and s/he will make 120 pairwise comparisons (all possible combinations). To check participants intra-consistency in their answers we randomly repeat 10% of comparisons. This makes a total of 132 comparisons to be evaluated by users for each set. A completed test will only be considered if all the comparisons are performed.

In the experiment, participants must rate the comparisons on a similarity scale from 1 to 7, being 1 totally different and 7 identical stimuli. Moreover, participants are shown an example of a comparison and then they are exposed to the whole (15) assigned stimuli set for 1 minute before starting. These two pre-test tasks allow participants to determine initial criteria to rate the similarity of two individuals regarding the whole group of proposals.

Two consistency tests have been performed on the participants' responses. Based on the work presented by [136], we aim to determine the consistency in ratings for the same participant (intra-subject consistency) and the consistency between subjects in their ratings on the same scenario (inter-subject consistency).

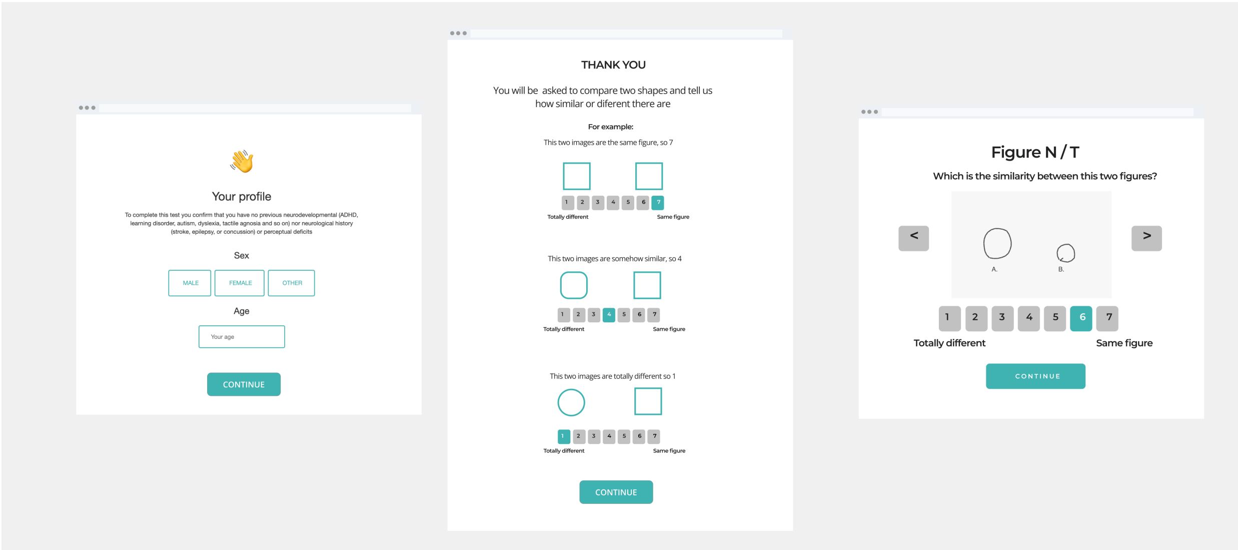

Figure 6.8 Test presented to human evaluations. In each test, we collect some basic demographic data and then we ask them to compare pair-wise proposals

Intra-subject consistency

The intra-subject consistency is obtained by computing the differences while rating the same stimuli during a test session. Since 10% of the stimuli are repeated on a random basis we compute differences in their ratings. We consider acceptable small differences in rating (1-2) given our similarity scale. To obtain participant consistency, we sum all the differences and compute their median value. To be consistent with our criteria, we only accept a median value lower than 2 and a total sum value of 12. This ensures user consistency between repeated values and small variations in participants' perceptions during the test.

Inter-subject consistency

Once this test is completed we also compare the participant's evaluation with other participants in the same comparison set. It is possible that exists a scale shift between the scoring proposals of the participants, this is not breaking the inter-subject consistency. The problem is when the scores of the participants do not correlate (or correlate inversely) for several proposals since this indicates that there is no common difference criterion between them. So we have performed a pairwise Spearman's rank order correlation between all the stimuli ratings (120) per participant for each set of comparisons. The average number of times a scenario has been tested is 14 and therefore 14 correlations are obtained. Then, we find the average correlation coefficients and compare each participant's final median correlation value. A high positive correlation means consistency between the participants when analyzing the similarities.

We decided to accept the 10 participants with a higher mean Spearman's rank for each scenario. So we have excluded outliers from our group of participants. Then, results presented in this chapter have been obtained by analyzing a total of 80 complete evaluations (10 accepted participants x 4 scenarios x 2 design groups).

Table 6.2 shows the final Spearman Rank correlation values for the selected participants. In each case, there is a relevant positive correlation between each participant's responses, with especially strong correlations in human proposals (Mean: 0.74 $\pm$0.04) compared to agent ones (Mean: 0.67$\pm$0.11). This can be explained by the fact that human designs are smoother and easily remembered by participants, unlike agent designs, as shown in Figure 6.7.

Nevertheless, these results show a strong consistency (Table 6.2) between participants answers, so similarity perception can be considered valid for our analysis.

Final Spearman Rank correlation values of participant responses (ρ)					
	Scenario 0	Scenario 1	Scenario 2	Scenario 3	**Global**
Human	**0.78**	0.70	0.71	**0.75**	**0.74**
Agent	0.51	**0.823**	**0.81**	0.63	0.67

Table 6.2 Final correlation analysis. For correlation values higher than 0.7 we can consider a strong correlation between participants answers. Only two Scenarios present a moderate correlation (slightly higher than 0.5). In all cases p-value is lower than 0.05 which allows us to consider our analysis as statistically significant.

Similarity results

We combine two different approaches to evaluate the perceived human similarity between the proposals.

Firstly, we compute the mean value of similarity (from 1 to 7) between all accepted participants' responses in each scenario (see previous section) obtaining the pair-wise similarity of each selected proposal. Then, we obtain a perceptual similarity matrix for each group of proposals and we perform a multidimensional scaling [137] to project similarities down into a 2D space. In all the cases we computed a stress curve to confirm that this representation can be done in this low-dimensional space (Mean: 0.075 $\pm$ 0.035).

The result of these two operations can be visualized in the following set of figures 6.9 which present the final similarity for each scenario.

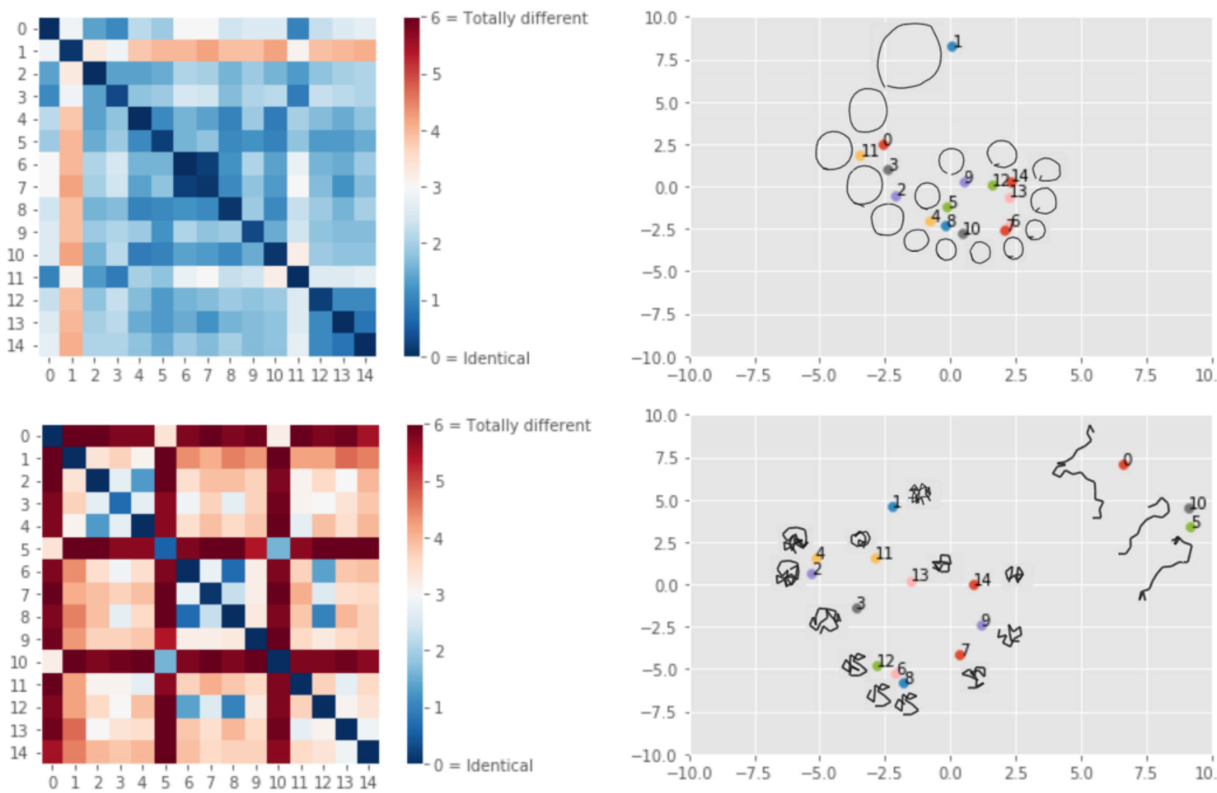

Figure 6.9 Movers similarity perception. On top are corresponding human proposals and on the bottom are corresponding agents. On the left matrix similarities, on the right MDS. As illustrated in the agent's proposal similarity matrix, proposals (0, 5 and 10) which are particularly different from all the others emerge from the evolutionary process

Particularly, in Scenario 1: Movers, we can explore the design space and see how different the human and agent-perceived proposals are. In general, the shapes that emerged from both creators are quite similar. However, this particular scenario shows the biggest difference between humans and our artificial agent. Here the agent is able to generate completely different proposals from the ones proposed by humans. Humans when asked to solve a moving task often recall previous experiences of moving objects. This can result in design fixation, shown in our results as tending towards a single shape, in this case, a wheel, which performs very well in the task. However, once asked to think about different proposals, our participants were stuck on the mental model of a wheel. Therefore, they proposed variations on the size or try to create more circular contours. On the other hand, as the agent is not conditioned by any previous knowledge, it conducts a more varied exploration of possible shapes. This leads to a richer distribution of forms beyond the "wheel shapes", providing new ideas on how to solve this specific problem.

Secondly, we also compute the number of clusters that emerge from each group of proposals. As stated in Maher's work [118], clustering algorithms can serve as a great tool to measure distances from potentially creative designs. Here, we propose a mean shift algorithm (MS) [138]. We decided to use the MS algorithm because it does not predetermine the number of clusters. Clusters in MS algorithm [134] are directly related to pairwise distances between proposals to set an initial bandwidth. To ensure that process bandwidth is the same during cluster generation for human and agent proposals, we computed the mean pairwise distance for each scenario. Despite the fact that the standard deviation of this mean distance can be high, as a consequence of the wealth of different proposals, the average within both perception tests (agent and human) will allow us to establish a common bandwidth (BW) for each scenario. Then, since the bandwidth is shared we can analyze the number of clusters that emerged within the process (Table 6.3) and visually examine the representative proposals for each cluster.

These clustering results show that agent's proposals are perceived more differently than

Metrics distribution with MS Algorithm				
	E0	E1	E2	E3
Human	4	3	3	4
Agent	**8**	**7**	**4**	**6**

Table 6.3 Results of emerging groups with common bandwidths. As can be seen for all scenarios, there is a higher cluster emergence on agent's proposals.

the ones created by humans. These extracted clusters are visually analyzed to access the perception of similarity within the elements in a cluster (Figure 6.10).

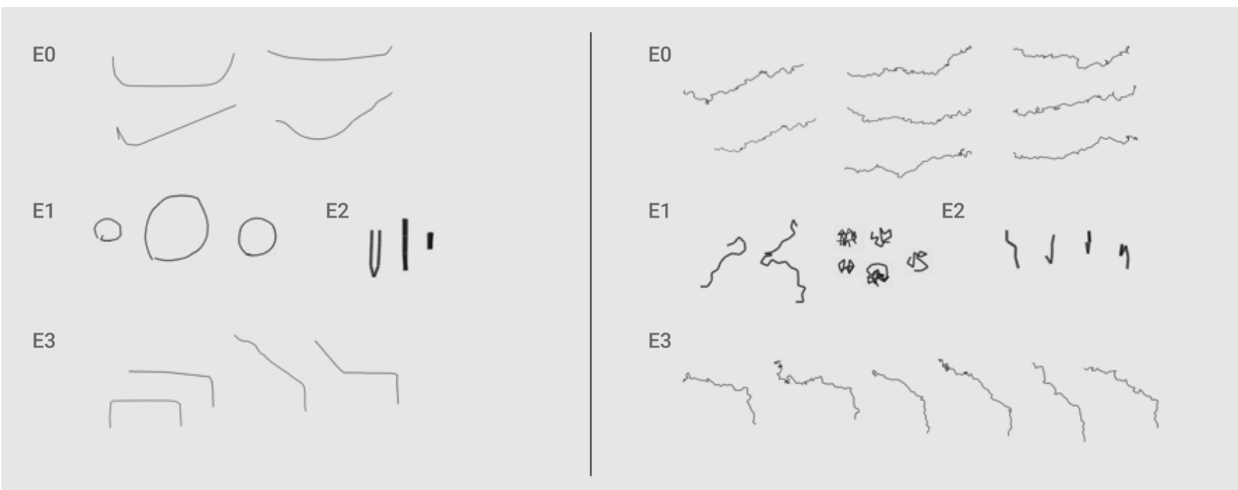

Figure 6.10 On the left a representative from each cluster extracted within our method. On the right the ones corresponding to agent's proposals. Each cluster are marked with the corresponding scenario (E0–E3)

This visualization allows us to notice differences between elements within the same cluster. Especially for Scenario 1, agents' clusters representatives are significantly different from each other. In the other scenarios, these differences are less noticeable when visually inspected, so we can consider that both the novelty of the agent and the human are similar.

However, for the purposes of comparing agent and human capabilities, in terms of performance and novelty, our initial results are encouraging. Our agent has been able to produce human-level proposals in most scenarios. In addition, in Scenario 1, it surpassed human capabilities in terms of novelty by producing a larger variety of shapes that differ from those created by humans.

6.3 Discussion

In this Chapter, we explored how the definition of flexible design tools presented in Chapter 4 can allow both human and artificial agents to generate creative designs in multiple scenarios. Since both are using the same design tools, we measured their creative capabilities by evaluating proposals generated by a group of human designers and our artificial agent. We focused our analysis on comparing them in terms of performance and novelty [118]. After training, our results show that our agent can create designs on a human level in each of the scenarios without prior knowledge. Specifically, in Mover's scenario (E1), the agent is able to surpass human-created designs both in terms of performance and novelty. This is supported by the reviews from our crowd-sourced similarity test, where most human proposals are perceived as less diverse. These results suggest that prior human knowledge of the solution space has limited the emergence of creative designs that performed well in given scenarios. Humans tend to converge on similar solutions for the same design problems. In contrast, our agent is able to explore broadly the solution space by performing actions based on the given tools and rules. This is particularly relevant in Mover's scenario in which a large number of different proposals have been generated, leading to a wide diversity of solutions.

This emergence could also be related to the richness of the scenario and the definition of the problem. However, based on our current number of scenarios and test participants, it is difficult to generalize to many other problems without further research. For that reason, in Chapter 7, the extended version of the Coevo environment (see Chapter 4) allows the definition of new problems and scenarios to be used. We consider that a shared design tool may be beneficial for enabling future collaborative environments where humans and agents would exchange information during the design process. Some previous work has demonstrated the possible benefits of using generative techniques in the early stages of design exploration [41]. However, with our tool, we could explore how real-time modification of the problem space can guide the exploration of AI rather than restart the evolutionary process.

First, an approach can focus on a human guiding the evolution of the system (or imposing constraints) directly modifying the proposals generated by the AI agent instead of selecting the best candidates as shown in Interactive Evolution [90]. This is possible due to the coding of the genotype through an array of angles that maps directly to the resulting phenotype. This relationship could allow humans to contribute at any point during the agent optimization process, fine-tuning any part that comprises the full 2D shape, and then guiding the evolutionary learning process without relaunching the experiment from the beginning while exploring solution space together with an AI agent.

A second extension of the results of this experiment is the co-design of a proposal together with the AI agent. We suggest exploring how humans expect to interact with an AI agent while co-designing a solution, including turn-based mechanics or real-time AI suggestions. In both cases, it is important to use the same tools to edit proposals directly or communicate design intentions while exploring the solution space.

Both approaches are included in the experiments of Chapter 7 where we study the possible relationships and roles between human and artificial agents in the creative process.

6.4 Conclusions

In this Chapter, we presented a comparative study on how both AI agents and humans can use the common language to solve 2D physically-based problems in the Coevo environment. We consider this shared language definition to generate valid designs for humans and AI agents, as a first step towards creating a future collaborative environment. To evaluate the potential of this tool to be used in multiple scenarios, we compared the artifacts produced by an evolutionary-based artificial agent with those generated by a group of human designers. We consider that the evaluation is fair since both use the same tool and each time a simulation is carried out, they receive feedback based on the performance of the proposal. The comparison of the proposals is made in terms of performance and novelty. Based on our results, we can consider that the proposals of our artificial agent are at a similar level to those produced by humans. Also, in one scenario, the agent was able to produce interesting new design solutions that were not originally considered by humans. These preliminary results could indicate how an artificial agent without previous knowledge can produce novel artifacts that were not originally considered by humans. In humans, the knowledge acquired by previous experience in both solution and problem areas can cause design fixation and influence their capacities to generate novel proposals. On the contrary, since no prior knowledge is given to our agent, the design fixation may be mitigated, avoiding a possible initial bias based on valid proposals already known.

In the following Chapter 7, we investigate how our evolutionary-based agent can collaborate with humans together to solve a wider number of design challenges. In addition, we also introduce possible roles that humans and agents can assume in the creative session considering different design conditions such as solution possibility space and difficulty in solving the challenge.

Chapter Seven

Interactive coevolution for exploring solution spaces in Coevo

In this Chapter, we focus on supporting human creativity in solving 2D physics-based problems through collaboration with an evolutionary AI agent. Previous research has investigated various AI tools and their impact on supporting the human creative process [139]. These tools can evolve beyond their traditional passive roles to become active collaborators in the creative process [73]. Some researchers refer to these new interfaces as mixed-initiative creative interfaces (MICIs) [27] or co-creative systems [140]. Interaction design plays an important role when defining co-creative systems, as both humans and AI actively engage and interact in the creative process [140]. For that reason in this Chapter, we introduce a new co-creative version of Coevo, which involves both humans and AI agents generating solutions together for the Coevo environment. This experiment differs from the study of different AI agents acting as autonomous creative systems from Chapter 5 or creativity support tools that merely assist human creativity (such as the ones presented in Chapter 3 or 6). Particularly, we examine the interaction model for communicating with the AI agent and the potential roles humans and agents can take on during a creative session allowing us to explore how a co-creative system can benefit human creativity (Figure 7.1).

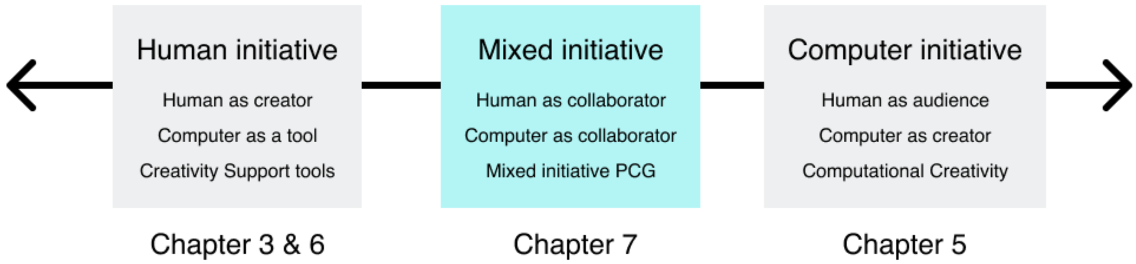

Figure 7.1 Schema adapted describing mixed-initiative creative interfaces (MICIs) [27]. On one end, traditional computer-assisted tools where the human is the initiating and deciding agent and the computer acts as *the designer slave* [141] performing the actions it has been asked for. On the other end, it sits computational creativity [51] which consists of a computational agent autonomously producing work that can be considered creative by a human observer.

Mixed-initiative systems, have been widely explored in the context of Procedural Content Generation (PCG) [142], where MICIs are commonly used to generate game content such as levels, quests, characters, and even game mechanics. For instance, by allowing designers to interact with these AI-powered interfaces, the computer can become the designer's assistant, generating content that meets certain criteria or objectives specified by the designer. This approach allows designers to explore alternative design spaces that would be difficult or time-consuming to create manually and co-create game content with the computer.

In this domain, search-based approaches are often to explore the vast design space and find potential solutions that meet the designer's requirements. These methods are similar to our approach of exploring Sonic Black Holes (in Chapter 3) or Coevo solution space (from last Chapters 4,5,6). As shown in Figure 7.2), the system uses a fitness function to evaluate the quality of each potential solution and guide the search toward more promising solutions. However, one of the main challenges of these approaches is controlling the exploration since these systems often rely on defining certain initial criteria or objectives by the designer and assuming that the algorithm would find solutions matching these constraints.

To guide these explorations and give humans more ways to control the generation, Interactive Evolutionary Computation (IEC) was proposed [90]. IEC combines the optimization process of evolutionary computation with human input to evaluate the generated proposals. Then, using these methods humans can guide evolution based on their subjective preferences rather than only defining initial constraints and evaluation methods. IEC has been widely used in games but also in multiple domains such as art, music, or design amongst others [143]–[147].

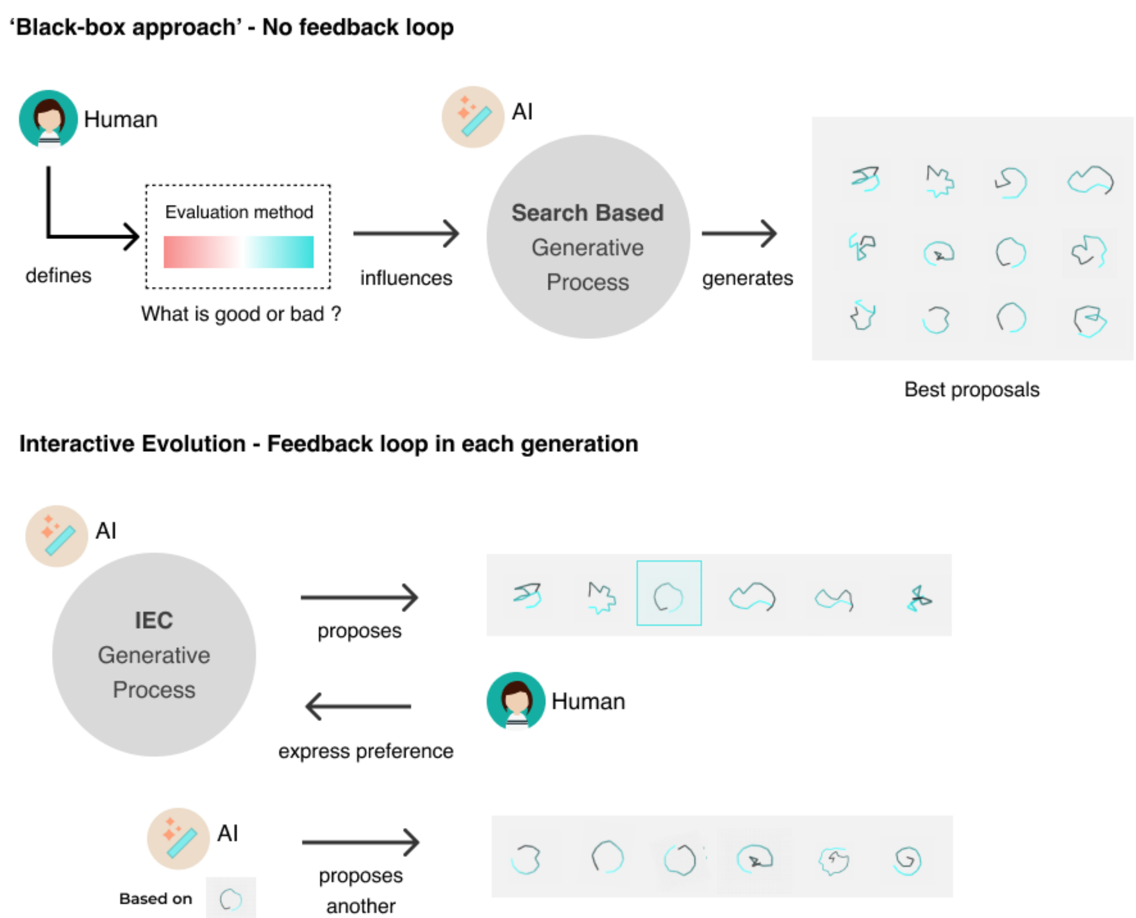

Figure 7.2 Schema of different generative methods. On top, the *Black-box approach* where the humans' role is to define requirements as evaluation methods that serve later on are used as a fitness function for the generative search process. In contrast, Interactive Evolution allows humans to intervene during the generative process and guide evolution based on their needs

However, manually evaluating and selecting all the generated proposals increases the task cognitive load since the user receives a large amount of content, and needs to provide feedback. This can lead to fatigue and frustration [147]. To overcome this weakness, the number of presented proposals can be reduced by clustering similar proposals or reducing the amount of feedback needed by the user while the system generates solutions. A good example of this approach is shown in the video game Galactic Arms Race [146] which maps user's preference considering the interaction with the generated proposal, a weapon. Then, the number of times a weapon is fired is the measure of preference. Finally, in some recent work [148], authors demonstrate how users can quickly explore level design space while having direct ways of controlling the output such as editing latent variables or interpolating points in latent space. Although this combination shows promise for future AI-game level design some of their study participants described the need for more fine-tuning capabilities. This could consist of manipulating design components from each game level rather than latent variables which are not directly related to explainable features.

In co-creative systems, where humans and AI collaborate on a shared creative product as partners, communication is an essential component among collaborators. In many existing co-creative systems, users can communicate with the AI, usually using buttons or sliders, but the AI cannot communicate back to humans, limiting their potential to be perceived as partners rather than just a tool. A study by Rezwana and Maher, explored the impact on user engagement, collaborative experience, and user perception of a co-creative AI [149] by defining two different interaction methods, with and without AI-to-human communication. Their results indicate how incorporating AI-to-human communication can improve the collaborative experience and user engagement with the system. In more recent work, authors also discuss the importance of interaction dynamics and communications, identifying them as the driving forces of the co-creative process in creative collaboration [140].

In this Chapter, we address the challenges of controlling and guiding problem exploration while defining new methods of communication using our human-AI design language. We propose a new co-creative interface that allows collaboration between a human and an AI agent when exploring 2D physically based problems from the Coevo environment (Figure 7.3).

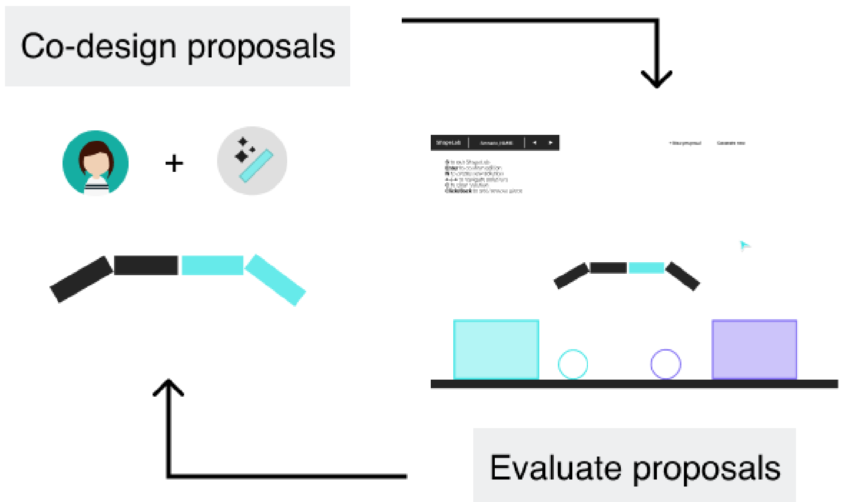

Figure 7.3 Given a problem, both the human designer and AI agent can propose solutions using the defined language (as shown in previous Chapter 6). Then each proposal can be evaluated within the environment to select the best ones. At any point of the loop, the designer can decide to end the creative session and get the best proposals

In contrast to previous Chapters, a new interaction model is introduced in which humans and AI agents jointly take the initiative in the creative act, enabling a collaborative and iterative approach to creative design and problem-solving.

By sharing the same design language, human designers can materialize their ideas through the proposals they generate. Just as when we externalize our thoughts by speaking up or writing them down in a notebook, we can communicate our intentions by using the material and design artifacts that embody our thought process. When human designers use the shared design language, they can effectively externalize their mental models for problem-solving. This not only allows designers to reflect on their own thinking but also enables AI agents to interact with and manipulate the design artifacts, as described in Chapter 4.

Then, by materializing their thoughts as a design proposal and interacting with those proposed by AI human designers can guide the system's responses and manipulate them to meet their needs and preferences. This direct manipulation of proposals represents a form of communication between the human designer and the AI agent, as they work together to achieve a common goal.

This interaction model through the design language can also facilitate the sharing of ideas and insights between humans and AI agents, allowing for mutual inspiration and creative collaboration. As the AI agent generates proposals, it can provide new perspectives and ideas that the human designer may not have considered, opening up new avenues for exploration and creativity. Manipulating the material in this way allows for a more dynamic and iterative creative process, where the human and AI agents can work together to refine and improve the design proposal in real-time. It also allows for more effective collaboration, as both parties can easily communicate their ideas and suggestions through direct manipulation of their proposal.

Given the potential benefits of this interaction model, we are interested in exploring the various roles that both humans and AI agents can assume in the creative process. For example, we want to investigate how the environment affects the expected role of the AI agent. On some occasions, humans may want AI to assist them when they are stuck or they run out of ideas. This can be encouraged if the solution space for a scenario is more diverse (as it happened in the Mover's scenario from previous experiments). On other occasions, maybe the scenario is difficult enough so AI assistance is required at the early stages of the exploration, rather than as an inspiration assistant. These expectations can impact the quality and effectiveness of the final design or affect human designers' speed and efficiency of the design process. By experimenting with different roles, we can also gain a deeper understanding of the strengths and limitations of each party involved, and identify areas where humans and AI agents can complement each other to achieve the best possible outcome. Moreover, as we explore different roles and their impact on the design process, we may uncover new insights and strategies for effective human-AI collaboration in other domains beyond creative problem-solving for physically based scenarios.

Our research hypothesis is that the involvement of AI agents in the creative design process, assuming various roles and degrees of involvement, will significantly enhance the quality, efficiency, and effectiveness of the final design outcomes in comparison to human-only design processes. In addition, this will also provide new insights and strategies for effective human-AI collaboration in creative problem-solving for physically-based scenarios and suggest how these findings can be applied in other domains.

In the study presented in this Chapter we want to investigate the following research questions:

1. How do varying roles and involvement levels of AI agents affect the quality, efficiency, and effectiveness of the creative design process? Which are these roles?

2. How does the environment or context of the design scenario influence the expected role of the AI agent in the creative design process?

3. How do AI-generated proposals contribute to the exploration and discovery of new ideas and perspectives in the creative design process?

4. How does direct manipulation of design proposals facilitate communication and collaboration between the two parties?

This Chapter 7 is organized as follows. Firstly, we provide an overview of the design and development of the interface, highlighting its capabilities and how the generative process works. Secondly, we discuss the methodology used to test the interface, the selection of participants, the scenarios from the Coevo environment, and the tasks performed. Then, a discussion of the study is presented, including an analysis of the efficiency and novelty of the proposed solutions, the influence of AI suggestions on the creative process, and the designers' perceptions of their creative session. This will also be an analysis of the designers' creation flow and their creative paths, identifying any emerging roles during the interaction.

Finally, we conclude this chapter by summarizing the findings of the study, clarifying its benefits and limitations while discussing their implications for other creative domains and future research.

7.1 Co-creative coevo

A new Coevo interface, Co-creative Coevo, has been developed in order to support co-creation with humans and AI agents (Figure 7.4). This new interface allows creators to define their own proposals and evaluate them in each scenario. While creators edit their proposals, they can also ask the AI agent to generate proposals offering them new alternatives and opening up new creative paths for them.

Figure 7.4 Co-creative coevo interface. Through this tool, humans can co-create solutions to 2D physically based scenarios together with an AI agent

These different actions are supported through different modes in the Coevo interface. Each mode provides the creator with different tools to support their current goal.

7.1.1 Creation mode

In creation mode, called Shapelab, humans can create and modify any proposals as they need. This includes adding and removing pieces and modifying each individual rotation to accomplish the goal of the scenario. As commented in Chapter 4, through the design language proposed based on manipulating simple blocks we can define complex structures for multiple scenarios. These proposals are positioned within each specific scenario in order to help the users to visualize their proposals in context (Figure 7.5)

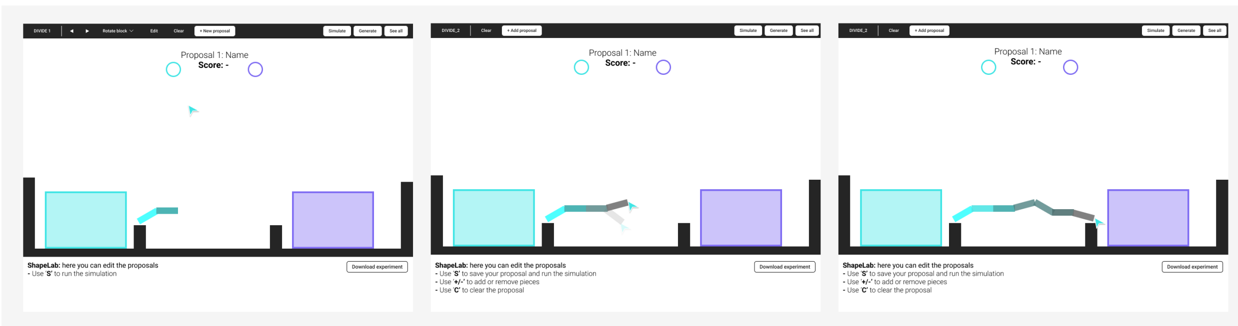

Figure 7.5 Coevo creation mode: ShapeLab. From left to right, we can observe the process of creating one proposal for Scenario Divide 1, in which the goal is to guide each colored ball to its respective container . Using the mouse as a drawing pointer, users are able to create complex shapes by concatenating multiple blocks

In this mode, participants can also navigate through different proposals individually or using a matrix visualization. This last option, supports rapid visualization of proposals and choosing amongst a large set of possibilities. Proposals are prioritized based on user selection and then considering their relative score obtained in the specific scenario. So, proposals that perform better in solving the scenario's challenge will be placed first. This is especially relevant when generating multiple proposals by the AI agent. Rather than analyzing all the AI-generated proposals, the tool encourages humans to focus on the highest-performing ones. In addition, when looking for inspiration, a matrix visualization can be helpful to compare and find new proposals. Switching between the creation and analysis of the solutions can support the exploration of the problem space reducing possible fixation on a certain solution space. Each different proposal can inspire new creative paths and the users can decide where to focus on in each part of the exploration (Figure 7.6)

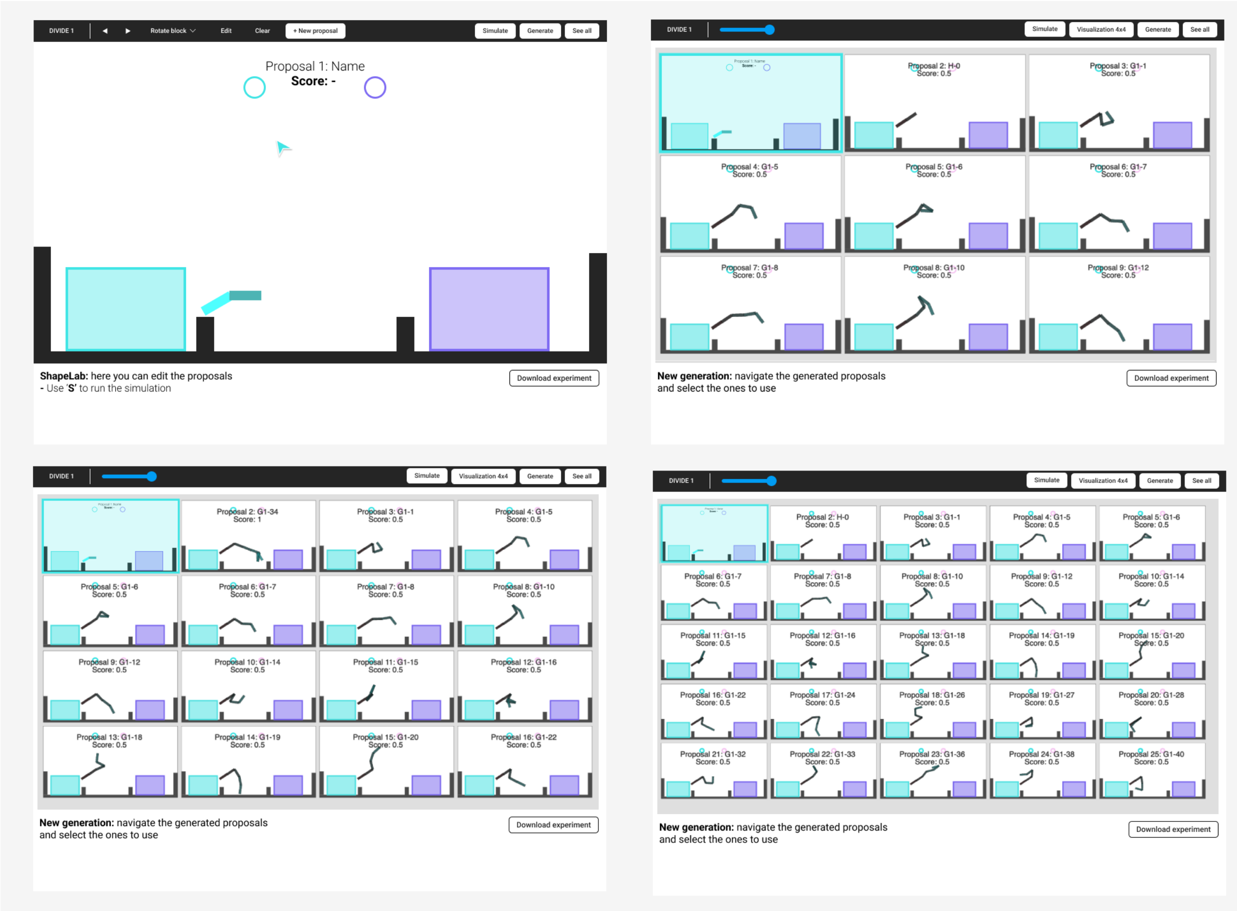

Figure 7.6 Visualization modes. From top left to bottom right: Single proposal, 3x3, 4x4, and 5x5 matrix visualization.

7.1.2 Simulation mode

At any point, users can switch to simulation mode where their current selected proposal is tested within the scenario. The simulation runs until the time of the experiment is finished or the user stops it. If users are working with many proposals at the same time, they can also automate the simulation to evaluate all the proposals via a Fast Simulation mode. In addition, they can also pause the simulation to observe how the different elements of the scenario react to each other and evaluate if their proposal matches their expectations. Finally, after simulation, the proposal is evaluated and a score based on its performance is assigned to it (Figure 7.7).

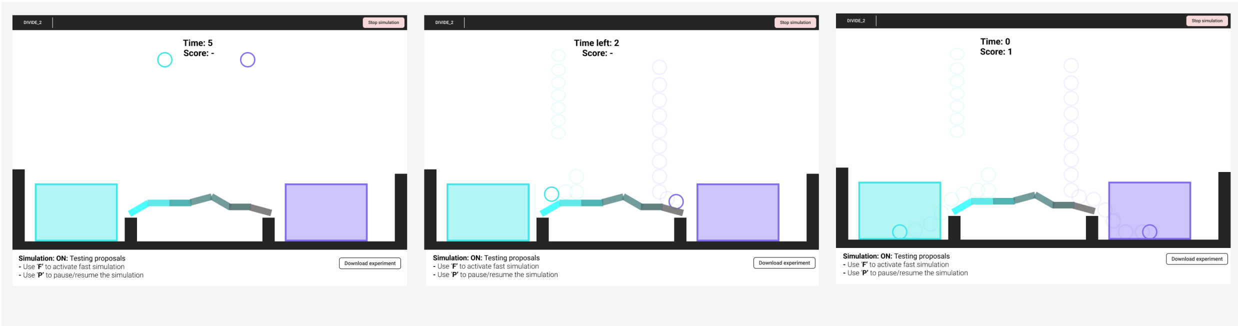

Figure 7.7 Simulation mode. Each scenario runs for a specific time and when the simulation is completed a score is given to the proposal based on its performance (right image). More details on the evaluation method can be found in Chapter 4.

7.1.3 Generative Process

As mentioned in Chapter 5, our evolutionary algorithm has shown in previous experiments that it is able to generate human-level proposals using our design language. For this reason, the generative method has been integrated into the Coevo interface so that users can explore the generated solutions ranked from better to worse performance. This generative process is triggered via the 'Generate' button on the Coevo interface (Figure 7.8.

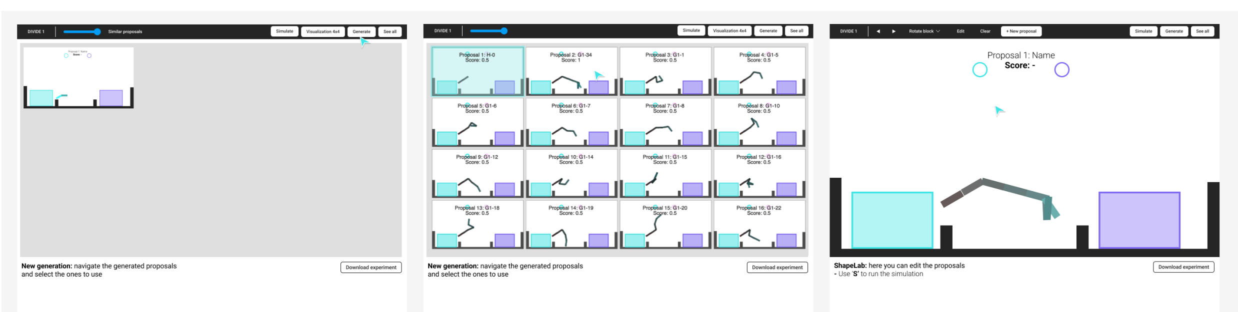

Figure 7.8 Generation process for Coevo. Given a single proposal, users can ask to generate multiple proposals and explore the best-performing ones and easily edit the proposals they consider by clicking on them

Note that the experiments in the previous chapters considered an evolutionary process in which the suggestions were generated entirely by the algorithm. In this new experiment, we explore the collaboration between humans and AI while exploring the Coevo design space.

For that reason, a generative method that enables combining both human and AI proposals has been defined. Two main aspects must be considered when defining this method: user control and exploratory capabilities. On one side, we want to support users' capabilities to define and modify the proposals they consider. This includes guiding the creative process and being able to express their solutions using the given language. In addition, we also want the AI to provide novel creative directions, encouraging users to explore different solutions while reducing their design fixation on a certain solution space. For that reason, we have defined two modes of generation:

1. **Standalone generation**: This mode enables the AI to automatically generate proposals for the given scenario without considering users' feedback or their created proposals. This generation uses the same previous evolutionary algorithm described in Chapter 6 which starts from scratch when exploring a given problem space.

2. **Interactive generation**: This mode enabled the user to select a set of proposals to influence the next generation. To this end, these proposals are used together with the best proposals to generate a new population for the evolutionary algorithm. This approach is inspired by Interactive Evolutionary Computation (see Introduction of this chapter), which uses human input to evaluate content [90].

In Figure 7.9, a demonstration of how these two approaches differ from each other is shown. While Standalone generation suggests a different range of proposals, Interactive generation considers the original proposal from user and provides variations around it.

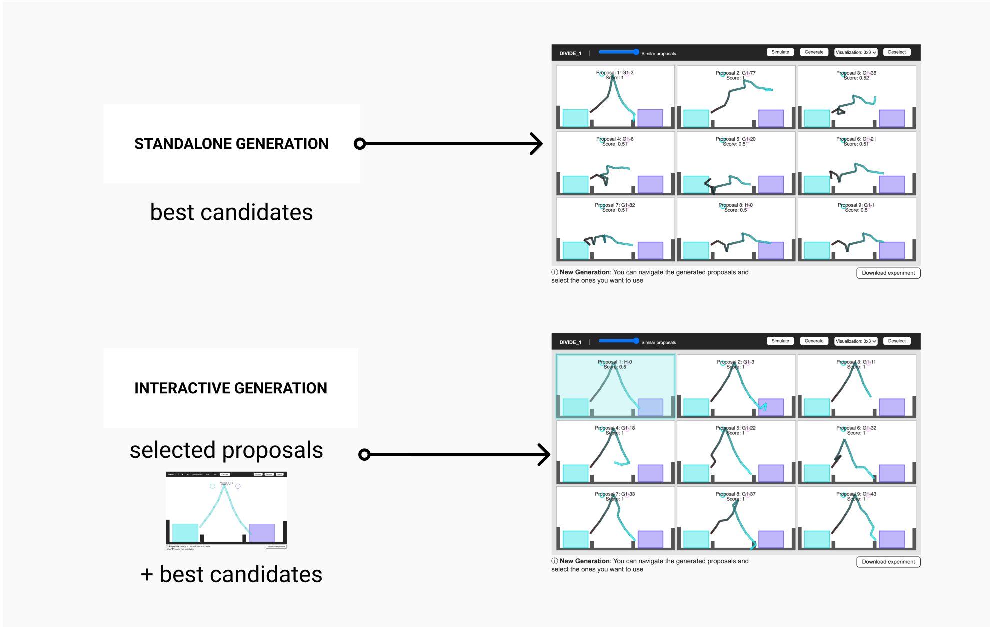

Figure 7.9 Generative methods in Coevo. On top, Standalone generation, provides new directions for participants to explore. On the bottom, Interactive generation, which considers user proposals. In this method, users can select multiple proposals using the provided UI. This proposals are considered together with the ones with highest performance

In addition, to provide users with more control over the evolutionary process, we implemented a similarity slider with 4 levels, which allows users to define their expectations of proposal similarity. The slider ranges from "totally different" to "slightly different", "similar", and "very similar". Users can adjust the slider to communicate their expectations to the AI and guide the evolutionary process accordingly. The slider's design is based on the idea that proposals should be evaluated not only on their fitness but also on their novelty. By allowing users to adjust the similarity level, they can influence the balance between exploration and exploitation in the search process. This feature can help users discover new and innovative solutions while avoiding redundant proposals.

Our algorithm, thus, builds upon the existing proposals selection and breeding algorithm and allows the user to select specific proposals to evolve in addition to adjusting the similarity slider. More specifically, the proposed algorithm, shown in Algorithm 1, is a proposal selection and breeding algorithm based on their fitness and similarity. The algorithm is designed to select the best performing and most novel proposals for the next generation of a population. It first checks for any pre-selected proposals to be added to the population and assigns them if they exist. If not, the algorithm selects the N fittest individuals using a roulette wheel algorithm. The algorithm then selects parents from the fittest individuals and breeds a new population using midpoint crossover. The children are then mutated based on a similarity value chosen by the user. Finally, the algorithm computes the similarity across all individuals in the new population and ranks the proposals according to their fitness and similarity. The top-performing and novel proposals are then selected for user review.

Algorithm 1 Interactive evolution via user selection

for $i = 0$ **to** N **do**
    if any proposal selected **then**
        Assign selected proposals for the next population P
    else
        Get the F fittest individuals for the next population P via roulette wheel
    end if
    Select parents amongst the best fittest individuals P
    Produce a new population P_c using midpoint crossover of the fittest parents
    for each $\mathit{proposal} \in \mathcal{P}c$ **do**
        compute mutation considering similarity value selected by the user
    end for
    for each $\mathit{proposal} \in \mathcal{P}c$ **do**
        simulate scenario and evaluate the proposal based on performance
    end for
    Compute similarity across all individuals of $\mathcal{P}c$
    Order the proposals considering fitness and similarity
end for
Select the top M performing and novel proposals for user review

As mentioned earlier, a major weakness of interactive evolution is potential user fatigue and cognitive overload. To mitigate these problems, we propose a method that presents the user with a subset of the best-performing proposals in the solution space, selected according to both the user's preferences and the simulated performance of the proposal in solving the scenario. Additionally, we calculate pairwise similarities between proposals (See Chapter 6) to cluster them and present users with proposals from different clusters to reduce redundancy. This approach promotes divergence in the creative process, allowing users to explore both novel proposals and the most successful solutions. Furthermore, we allow users to have control over the number of proposals presented and to choose to focus on specific proposals as needed (from visualizing only one proposal to a maximum of 25 proposals at once). Finally, our algorithm offers the user the possibility of providing feedback or guiding the evolutionary process at each step, allowing for flexibility in the generative process. As presented, the algorithm supports both providing feedback via selection or only considering the fitness of the individuals to generate a new population. For this reason, the user can decide whether to let the evolutionary process run over several generations without providing feedback or to control the evolution at each evolutionary step. This generation consist on proposing 100 new proposals based on either current best solutions or considering users preference. Each generation lasts less than 10 seconds (in average in most scenarios). So proposals are rapidly shown to the users for them to evaluate.

In the following section, we describe a user study that was conducted to evaluate the effectiveness of our co-creative interface and the algorithm used to generate proposals. The study aimed to validate our proposed interaction method for exploring the Coevo solution space and to investigate the potential roles of both human users and AI agents in co-creative processes.

7.2 Experimental design

Our study hypothesizes that the effectiveness of human-AI collaboration in the creative process depends on the roles assigned to each party and the solution space of the design problem. In order words, when the design problem has a more diverse solution space, the AI agent's role as an inspiration assistant is more effective in enhancing the creativity and quality of the final design. On the other hand, when the solution space is limited or the design problem is complex, the AI agent's role as an assistant in the early stages of the design process is more effective in facilitating the exploration and generation of ideas. To test this hypothesis, we conduct a series of experiments in which participants work with an AI agent to solve design problems with different solution spaces.

7.2.1 Method and scenarios

The study involved 10 participants with an engineering background (5 females, mean age, SD=24) who were given the task of designing multiple shapes to solve a given scenario using the tools provided.

Participants were presented with 10 different scenarios, with each scenario presented randomly to avoid sequence effects. Each scenario had an average duration of 3 minutes, and the total duration of each co-creative session to explore solutions for the scenarios was approximately 30 minutes. They were asked to complete each scenario in less than 4 minutes. After the presentation of the scenarios, another 15 minutes were allocated for discussion of the experiences with the participants.

The scenarios were categorized into two levels of complexity (easy and hard) considering the difficulty of finding multiple different solutions to that given scenario. Multiple strategies for collecting have been defined in the second version of Coevo, such as intercepting falling elements, dividing elements into different containers, moving elements to create a chain effect, defining shapes to maintain static structures, or uncovering elements (See Figure 7.10). In

Appendix A, a more detailed visualization is provided in order to illustrate the dynamics of the elements of the scenario used to perform our experiments.

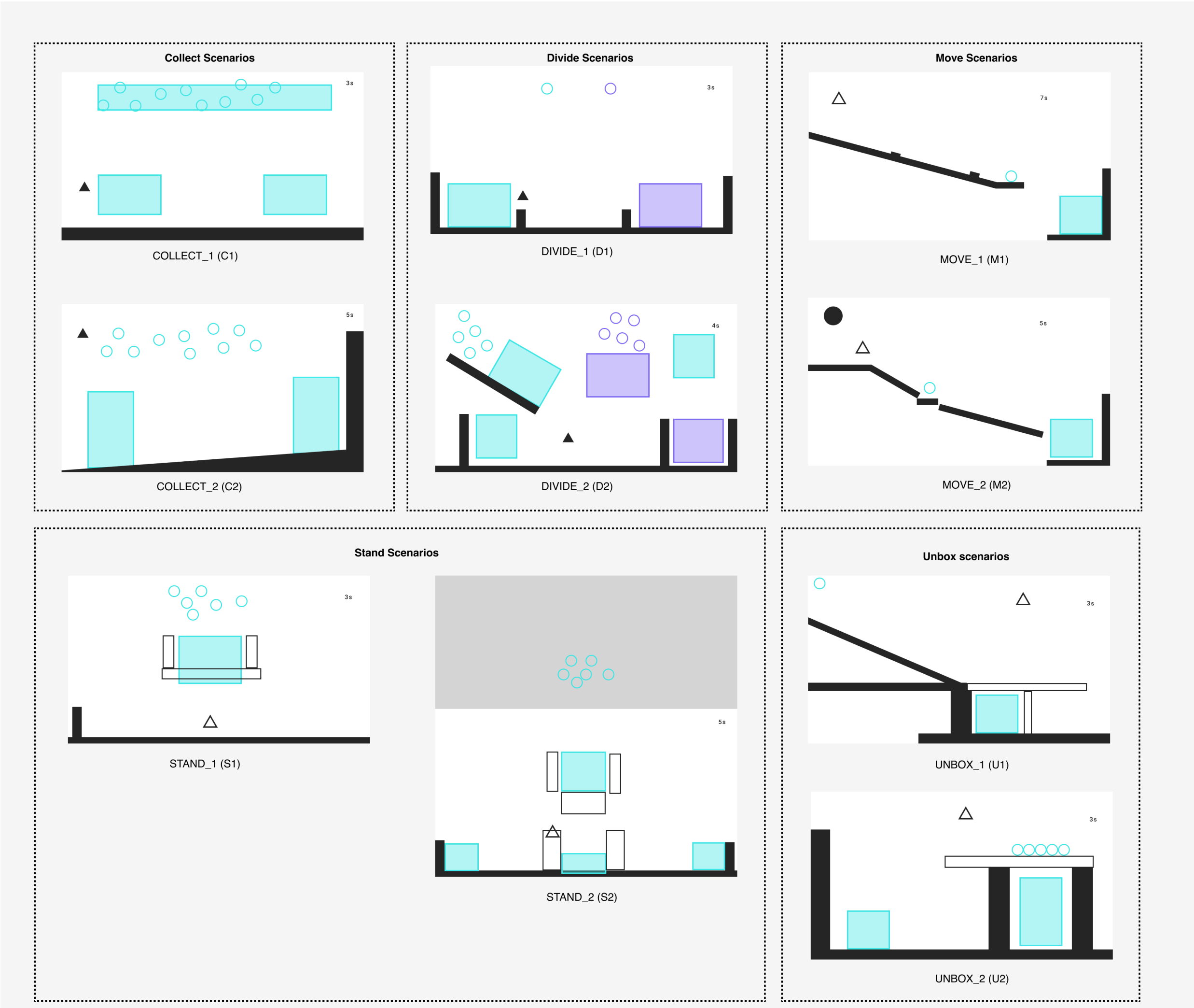

Figure 7.10 Scenarios used in this experiment. From top left to bottom right by topics: Collect, where the user can collect balls in different containers; Divide, which consists in separating the falling balls so that each falls into a specific colored container; Move, in which the proposed shape is also affected by physics so that it falls and touches a static ball so that it falls into the container; Stand, where the proposed shape must support falling blocks in order to sustain a structure; Unbox, where the proposed shape falls by moving an element that blocks the path of the falling ball path.

These scenarios provide a wide diversity of tasks to be completed and possible solutions to the task. Note that we have suggested two variants for each group of scenarios. The first variant is considered easier to solve, while the second may challenge participants by requiring them to define a more complex shape or to consider more elements in the scenario. We are interested to see how new conditions can affect how humans collaborate with our AI agents and how this affects their creative process and the final proposals they produce. For instance, more complex scenarios might demand greater collaboration with AI agents to identify viable solutions, while simpler scenarios with apparent solutions may encourage participants to explore diverse options. In the latter case, the challenge lies in generating innovative approaches to move forward in their creative process.

As an example, in Figure 7.11, a set of valid solutions is presented for some of these scenarios (Stand 1) in order to demonstrate a possible range of solutions.

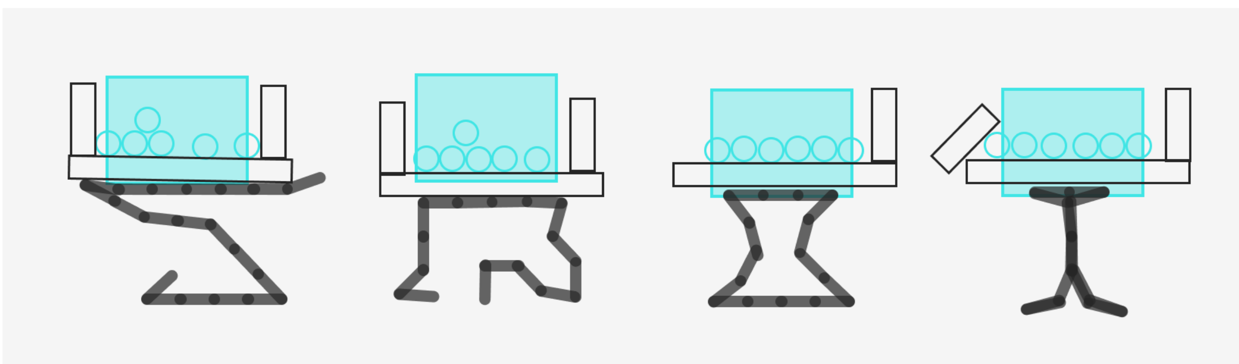

Figure 7.11 Possible solutions for scenario Stand 1. In this scenario, all the elements fall when the experiment is started. Then one of the strategies to complete this scenario is to define a stand to support the current white blocks. From left to right, a set of different stands to support this structure are presented.

Each session starts with a brief simulation of the scenario that allows our participants to better understand how the elements in the scenario work. Then, participants can start using the tool to either generate their own solutions or ask the AI to generate solutions for them.

7.2.2 Modelling user creative output and process

As in previous experiments, we also evaluate the artifacts generated by the participants during the session both in terms of performance and novelty. Participants are required to choose their best candidates at the end of the session, including what they consider to be the most creative and innovative solution. This information allows us to focus on analyzing their 3 top candidates' solutions in terms of performance and novelty. We can assume that a large number of solutions can be generated in each session, so we'll filter them considering the points of view of our participants and analyze these selected proposals.

Apart from evaluating the creative output generated by participants during the session, we are also interested in modeling participants' creative process by capturing their interactions with the system. As stated before, we are interested in evaluating how our proposal can augment human creativity by analyzing both the process and the product of the creative session. For that reason, in this study, a protocol for capturing user interaction with a tool has been defined. This method allows us to later observe humans' creation path and extract both quantitative (e.g.: which actions are performed the most and when) and qualitative data (e.g.: by visually comparing the proposals generated by users) [63]. In addition by capturing these data, we can also know where AI support is needed, its output, and how it influences the creative process (e.g: a proposal suggested by an AI may be accepted by a human changing their exploration). We only capture relevant interactions with the different UI elements within the tool. This includes the following actions:

- Simulation: allows the user to run scenario simulations to test out a proposal.
- Proposal visualization and selection: actions related to choosing the current proposals and selecting and specific proposal.
- Edition mode: editing a specific proposal by adding pieces, removing them, or changing its position.
- Generation capabilities: asking the AI to generate proposals or modifying the parameters of the generation such as specifying the similarity of generated proposals.

This interaction journey is analyzed along with the post-test interview to provide further insight into participants' actions and assumed roles during the creative session, as supported by both their actions and their perceptions of the session after the test is completed.

7.2.3 Post-Interview Questions and CSI

Once participants complete all the scenarios, a post-test interview is conducted. The motivation behind this interview is to obtain user feedback on the participant's experience with the prototype to ensure that the system aligns with their expectations and preferences. Specifically, we are interested in capturing overall impressions and feelings towards the prototype identifying features and functionalities that resonate well with the users while identifying possible areas of improvement. In addition, we also wanted to extract usage and interaction patterns to explore how, when, and why users engaged with AI generative capabilities to later compare these impressions to their creative process extracted from capturing participant interactions with the tool. This analysis includes assessing the system's performance based on user expectations and the tool's behavior preference. Finally, we also introduced the concept of ownership and rights associated with the system-generated content. Our hypothesis states that if participants felt that they were collaborating with the system and their co-creation resulted in useful proposals, creative attribution would be shared with the AI partner reducing the sensation of full ownership of the creative output.

Considering these motivations, our interview questions can be mapped into three main categories:

- Overall impressions and feeling towards the prototype

    1. What do you think of the prototype?
    2. What was good about it?
    3. What could have been better?
    4. What was the most frustrating part about it?

- Interaction patterns for human-AI collaboration

    1. In which moments did you use the generator? Which was the most useful for you?
    2. What did you think of the system responses?
    3. Which responses were more useful to you: those that were similar or those that were different? Why?
    4. What do you think about waiting to get responses from the algorithm, would you prefer to directly edit them or let it run for a while?

- Ownership and creative attribution

    1. What do you think about the ownership of the proposals generated?

After this interview, we'll measure the effectiveness of our system to support creativity using the creativity support index (CSI) [150]. This consists of answering a survey about their experience considering six dimensions of creativity support: Collaboration, Enjoyment, Exploration, Expressiveness, Immersion, and Results Worth Effort. Collaboration refers to the extent to which the system enables effective communication and collaboration in a creative process; Enjoyment is related to delight, engagement, and positive experience from users while using the system for creative work; Exploration refers to the degree to which the system supports exploration and discovering new ideas or possibilities; Expressiveness represents system capabilities to facilitate effective self-expression and communication of intention and creative ideas; Immersion is the level of engagement and concentration within the task; Results Worth Effort is the perceived value and quality of the creative outcomes produced using the system, considering the effort invested.

This index allows us to understand not just how well a tool supports creative work overall, but what aspects of creativity support may need attention.

7.3 Results

As presented, Coevo supports human designers in defining creative solutions for physics-based 2D scenarios through real-time simulation, interactive proposal generation and editing, and a generative method that proposes alternatives based on human feedback. In this section, we analyze the conducted study in terms of participants' experience with the tool, the final solutions they proposed for each scenario, and their creative process in exploring solutions for a given scenario. In total, ten creative sessions were conducted in ten different Coevo environment scenarios. Due to the large number of proposals generated by both humans and AI during these sessions, the results discussed in this section only consider the selected creative output for each session. That is, we evaluate the capabilities of each creator based on their final selection, rather than examining all generated proposals.

7.3.1 Creative outcome

For each creative session, users selected up to three proposals, for a total of 30 proposals. Figure 7.12 displays a sample of these chosen outputs, illustrating the diversity of solutions among participants.

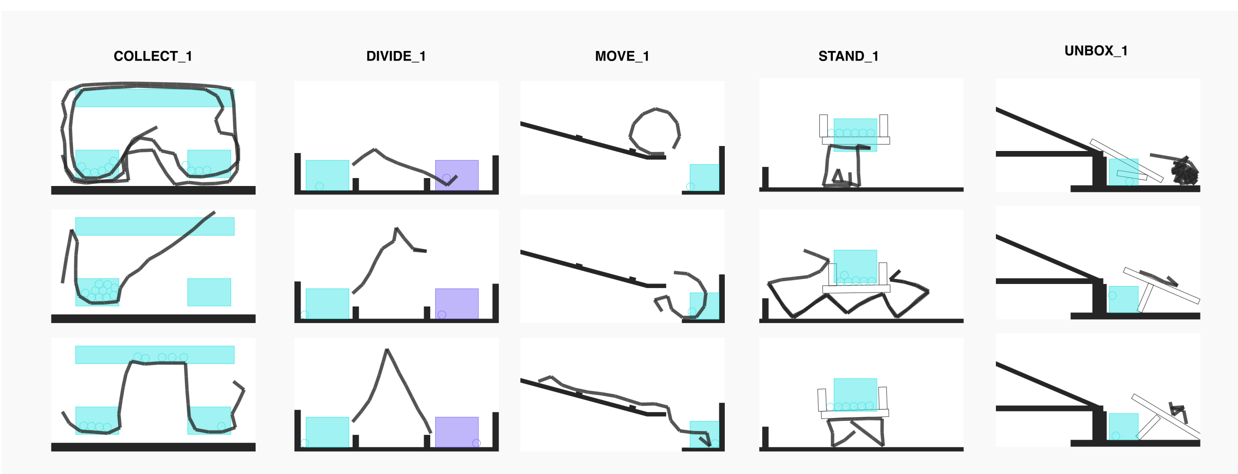

Figure 7.12 An example of selected solutions for each type of scenario in their easy variant. The illustration shows the final state of the simulation, where the fitness is computed

Participants primarily emphasized value and novelty when selecting proposals. Regarding value, since they were asked to achieve proposals with high scores, they chose proposals matching these expectations, considering either a solution they created themselves or one generated using the tool's generative capabilities. Table 7.1 provides an overview of the scores obtained in each scenario. In most scenarios, humans successfully found solutions. The only exception was Unbox 2 (U2), where all participants failed to find a high-scoring proposal without AI assistance. We can also observe that in Movers 1 (M1) the mean score is lower than in the other scenarios.

Scenario	**C1**	**C2**	**D1**	**D2**	**M1**	**M2**	**S1**	**S2**	**U1**	**U2**
Human	0.9	0.9	1	0.9	0.7	0.9	1	1	1	0
Human+AI	1	1	1	0.9	1	1	1	1	1	0.7

Table 7.1 Score comparison for each scenario, with and without AI assistance. Each value represents the mean score of all proposals selected by users in each scenario.

In these two particularly complex scenarios (U2 and M1), the generative process was able to extensively explore the solution space, inspiring users to discover novel approaches to solving the scenario (Figure 7.13). In Unbox 2, for example, the strategy of creating a shape that falls on the cover proved insufficient because the cover is thicker compared to Unbox 1. This led to frustration for most users as they struggled to find alternative solutions. However, the system created a lever-like shape that made the ball fall by applying force from below.

Another example can be observed in the Mover 1 scenario, where the system improved human proposals (Figure 7.13). In this scenario, the shapes proposed by humans did not fall at a sufficient velocity to move the ball to the target due to friction, resulting in the ball falling into the open space. To address this challenge, the generative system proposed two new strategies. The first involved creating a longer shape to form a bridge to the target, while the second introduced a shape designed to strike the ball with greater force at the end, ensuring it landed on the correct target.

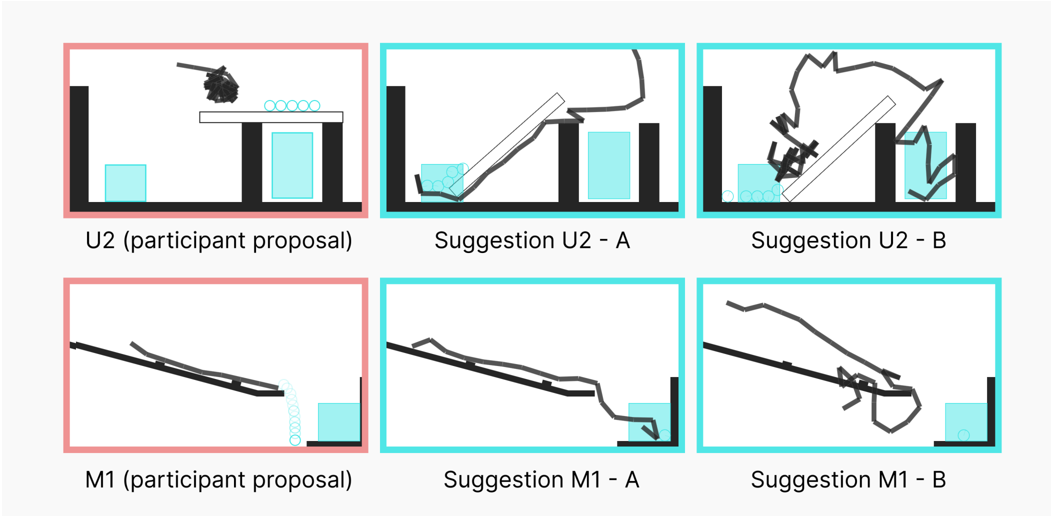

Figure 7.13 Creative solutions proposed by the AI. On top, lever-like shapes for Unbox 2, where the solution involves moving the static blue balls to fall in each respective container. At the bottom, AI-generated variations for humans proposal in Mover 1, where the solution involves creating a shape that moves across an inclined ramp and pushes the static ball at the end of the ramp

AI proposals not only support the creation of solutions better scored than those of humans alone but are also highly valued in other contexts. Table 7.2, demonstrated how all participants have used AI capabilities to explore solutions for each scenario. In addition, in most cases, participants have chosen an AI proposal almost half of the time as an output of the creative session. Particularly, some creators (like P5 or P6) considered choosing AI-generated proposals in most scenarios.

Participant	**P1**	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**	**P9**	**P10**
Overall AI (%)	62.96	63.33	54.17	45.45	72.00	91.67	65.52	50.00	50.00	50.00

Table 7.2 Percentages of generated (G) proposals chosen as a final proposal in all the scenarios.

Furthermore, if we analyze the data by scenarios (Table 7.3), we can also observe the percentage of AI-generated proposals selected as solutions for each scenario. It is noticeable that this percentage increases for more challenging scenarios (version 2 of each scenario type). This indicates a slight tendency to use AI-generated suggestions when humans encounter difficulties or experience a creative block when solving a scenario. For simpler scenarios, such as Collectors or Dividers, this percentage is lower, and humans tend to rely on their own proposals rather than AI-generated suggestions. However, this trend shifts when facing more difficult scenarios, beginning with Divide 2 and Stand, Movers, and Unbox scenarios. We emphasize the results in the Unbox scenarios, where the AI-generated proposals' acceptance rate rises to 74.1% and 93.3%, respectively.

Scenario	**C1**	**C2**	**D1**	**D2**	**S1**	**S2**	**M1**	**M2**	**U1**	**U2**
AI (%)	32.1	45.5	31.0	60.9	67.9	68.0	76.0	75.9	74.1	93.3
Human (%)	67.9	54.5	69.0	39.1	32.1	32.0	24.0	24.1	25.9	6.7

Table 7.3 Percentages of generated proposals (G) accepted by each participant in the study

7.3.2 Creative process

To evaluate the design sessions and creative process, we use a mixed methods approach consisting of three main components. First, we are capturing participants' actions while they interact with the tool to understand which interactions are relevant to the creative process. Second, we use the Creativity Support Index (CSI) and multiple Likert-scale [151] questions to evaluate both the effectiveness of a creativity support tool in assisting users engaged in creative work and participants' preferences. Finally, we conduct a qualitative analysis based on our observations of participants using the tool, and their responses in the post-interview. Our approach provides a deeper understanding of participants' experiences with the tool, including ease of use, support for creativity, and any challenges encountered. Then, this mixed methods approach provides a comprehensive evaluation of the design sessions and creative process while allowing us to gain a deeper understanding of participants' experiences. In the following sections, we delve deeper into each of these topics providing a comprehensive analysis and discussion of each one.

Analysis of Creation Flow and Creative Paths

As introduced before, in our study of the co-creative tool, we categorized possible actions into four main aspects that support creative problem-solving exploration in 2D scenarios:

- *Simulate*: Actions that enable users to simulate and evaluate the performance of proposals to determine the best candidates.
- *Select & View*: Actions related to selecting and viewing current and specific proposals.
- *Creation & Editing*: Actions involving the development of new proposals, editing existing ones, and modifying AI-generated proposals.
- *AI Generation*: Actions that involve requesting AI-generated proposals or modifying the parameters of proposal generation.

We created a visualization that illustrates these actions throughout the session, effectively mapping the creative journey and various user goals. In Figure 7.14, a comparison between participants' creative journeys in Stand scenarios is presented since they demonstrate a vast array of distinct behaviors within the same creative session.

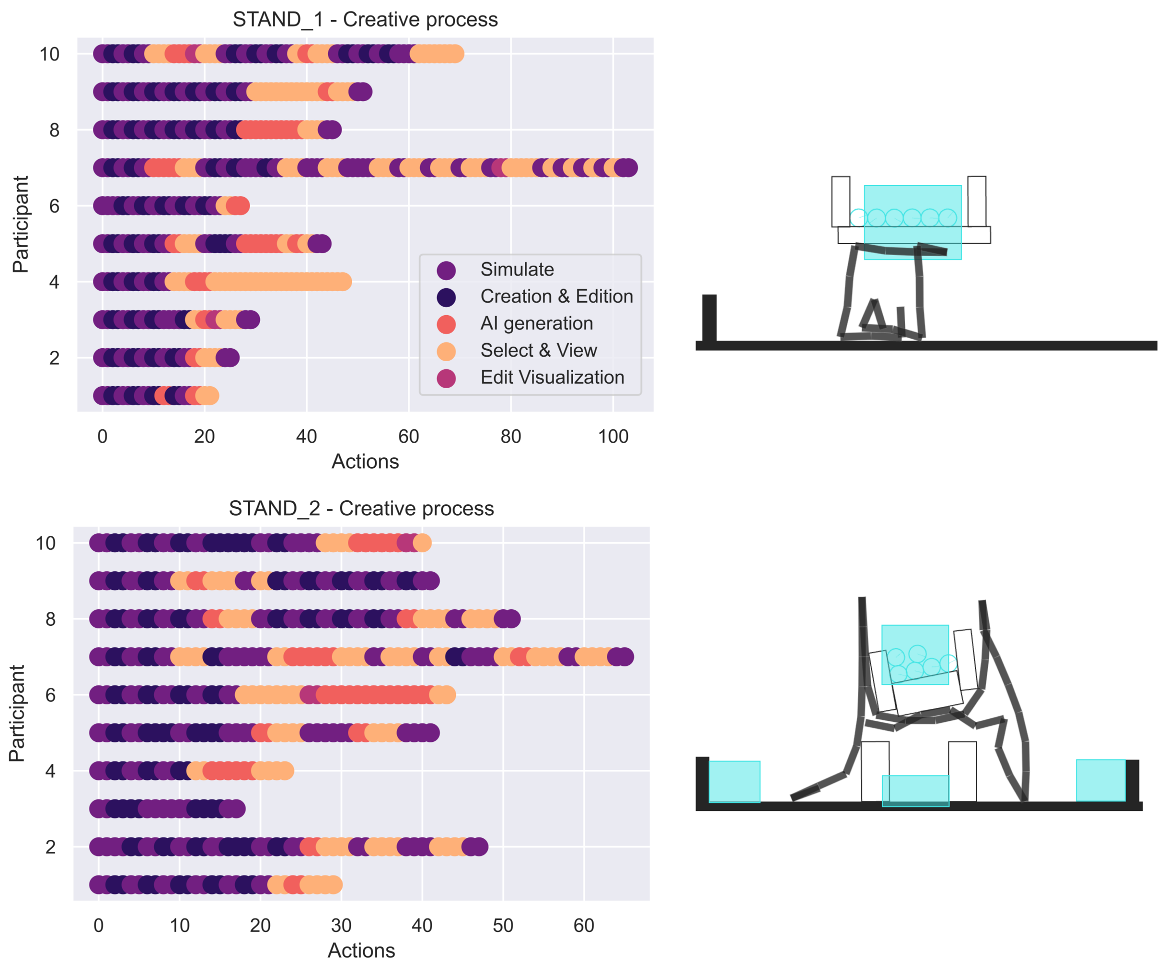

Figure 7.14 Comparison of two creative journeys for Stand scenarios. We can observe that most participants start by simulating and creating proposals to initially explore the problem space (purple pairs). Then, some participants use the generator to explore new design directions or get variations based on their proposals (orange). When this happens, a common pattern emerges among all participants, which is to evaluate AI-generated proposals, often without simulation.

Using these creative journeys visualization we can rapidly observe emergent pattern behaviors across all the participants. Particularly, we can observe that all participants start exploring the problem space by simulating the environment and creating their first proposals (Figure 7.15 - Case A. Creation only). This allows participants to better understand the dynamics of the experiment and how scenario elements interact with each other Similar to the scenarios shown in Figure 7.14, these exploratory phase appears across all scenarios by all the participants. The only difference between users is the time spend in this phase and the repetitions of this Simulate-Create sequence. After there is often a reflection phase where participants view and evaluate current proposals (Figure 7.15 - Case B. Evaluation only). In this phase, participants observe their proposals, select their preferred ones, and often simulate their behavior within the scenario. P7 has the clearest example of this behavior (Figure 7.14). We can observe that in both this participant often combines this pattern of Simulate/Create, then view and evaluate proposals to simulate and create new ones again (Figure 7.15 - Case C). This behavior is present in multiple participants across multiple scenarios such as P2 and P8 in Stand 2 or P10 in Stand 1.

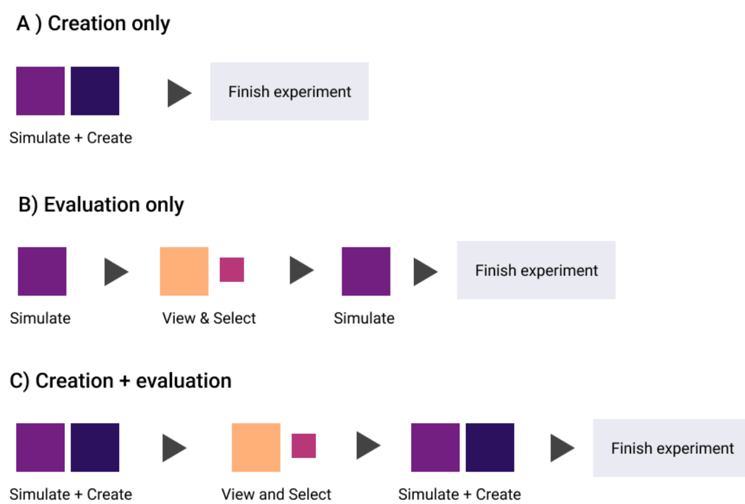

Figure 7.15 Visualization of patterns emerged during creative session

In terms of using the AI capabilities such as the generator, interactive patterns, and AI role expectations are also shared across participants. Most participants prefer AI to support their creative process after their own initial exploration of the problem space. Most participants feel challenged to complete the scenarios at least with one self-generated proposal. For that reason, they often start by finding this first solution without AI help. Then, the role of AI varies across scenarios and even within the same creative session depending on their specific needs. However, participants expect the AI to perform actions that fall into the three main categories introduced previously:

- *AI as an assistant*: when participants have already a clear idea of what they want or once a possible direction is already defined, some participants delegated the task to improve proposals to the AI. This motivation arise from the need to perform repetitive actions that involve trying out the solution or to perform several simpler tasks in order to realize the solution envisioned by these participants. As an example, in Mover's scenario (Figure 7.16 - top), one participant already has decided to solve the problem by creating a falling shape that pushes the ball to the container. However, a simulation and edition phase may be needed to refine this solution until it obtains a high score. Then, participants relied on AI to perform these tasks rather than iterating themselves.

- *AI as an expert consultant*: either if they already found a solution and they want to create new novel ones or generate a new valid solution, participants expect the AI to come up with solutions from scratch. In this category, they expect the AI to act as an expert collaborator that helps them to solve the problem differently. This need is increased in some scenarios such as Unbox 2 (Figure 7.16 - center) where physical relationships between scenario elements make it difficult to predict the scenario behavior. For that reason, as observed in the experiments, participants in this situation specify a high degree of novelty in the similarity slider and rely on AI to suggest solutions without their guidance.

- *AI as an exploration partner*: due to the exploratory nature of evolutionary algorithms, many participants used the AI generation simply to obtain a large number of valid proposals from which they can draw inspiration (Figure 7.16 - bottom). Instead of developing solutions, they relied on AI capabilities to generate and evaluate many proposals and waited for the AI to present them with the best proposals. As mentioned earlier, overcoming creative fixation is one of the most important intrinsic motivations of the participants. Therefore, the possibility to generate a wide range of proposals to choose from is highly appreciated by the participants as they mentioned during the session.

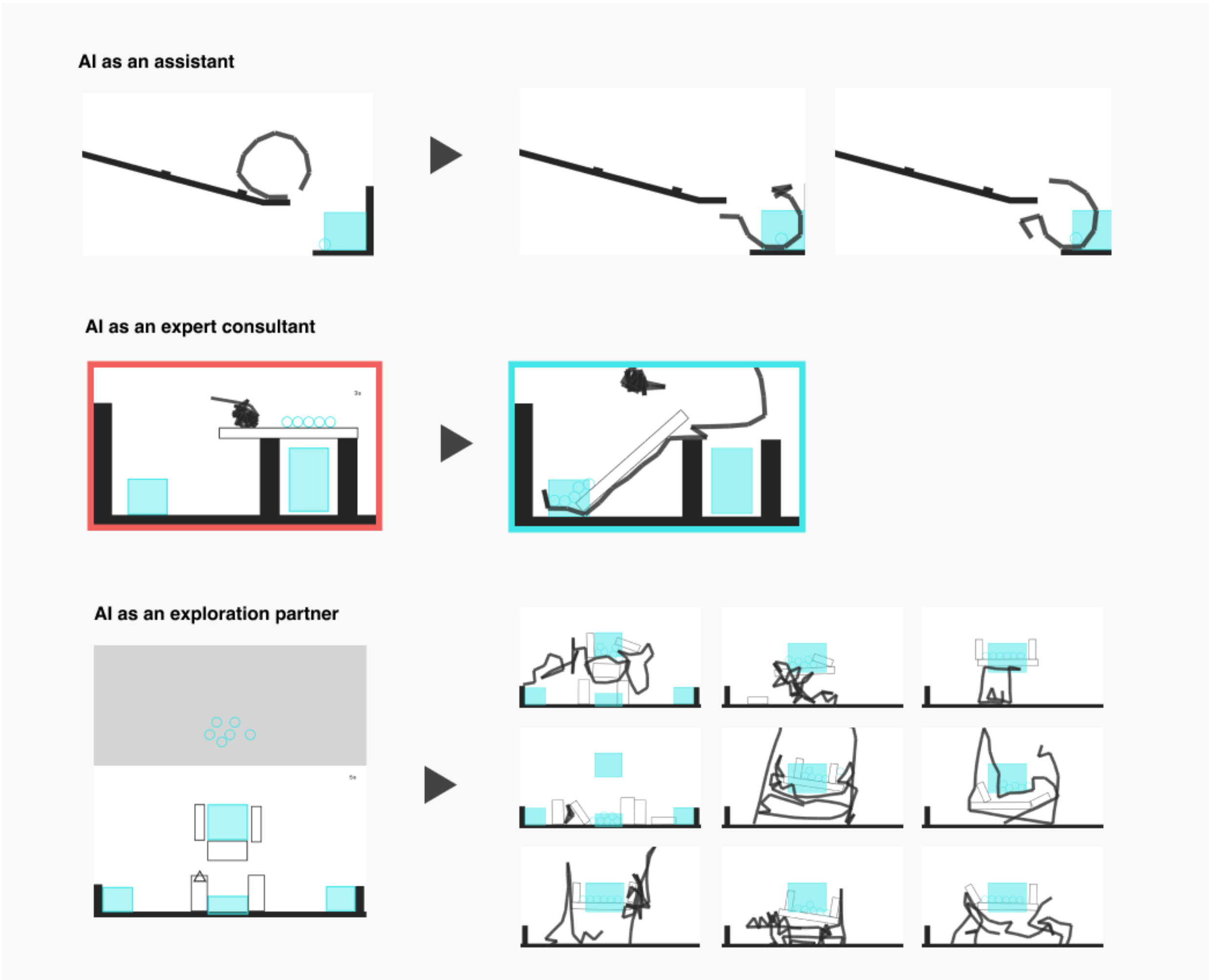

Figure 7.16 Three main AI roles during creative problem-solving in Coevo scenarios. From top to bottom: AI as an assistant to refine and improve human ideas; AI as an expert consultant that explores the solution space and proposes valid solutions; AI as an exploration partner that guides the user by providing possibilities to explore a particular problem space.

For each of these roles, we can also observe some specific actions performed together across multiple scenarios and users (Figure 7.17).

Figure 7.17 Comparison of creative journeys and usage of AI generator in different moments of the creative session. As an example of opposite behavior in the top journey, participant 10 used the AI generator initially in the session to come up with possible ideas. Then he iterated across these proposals and later on asked again the generator to create other proposals. In contrast, the bottom journey shows how P2, did not use AI at all and proposed solutions without AI assistance.

In most cases, participants began with their own proposals, enlisting the AI to serve as an assistant by refining or enhancing solutions based on their initial ideas. This pattern is prevalent in many of the documented journeys, as sequence A from Figure 7.18 frequently occurs during the early stages of the creative process. This interaction loop consists of the human participant defining initial proposals, followed by the AI generating and evaluating a set of new proposals, and concluding with the user editing these proposals before deciding to generate more or conclude their exploration. In this context, both humans and AI agents act as creators as they mutually respond and adapt to each other's proposals.

Additionally, we have observed that users often follow a pattern of evaluating proposals and generating new ones without making alterations to the existing proposal. This leads to pattern B from Figure 7.18, which is characterized by a generation-evaluation loop. Here, the participant takes on the role of a curator for the AI-generated suggestions, while the AI continues to produce new ideas based on the human's guidance.

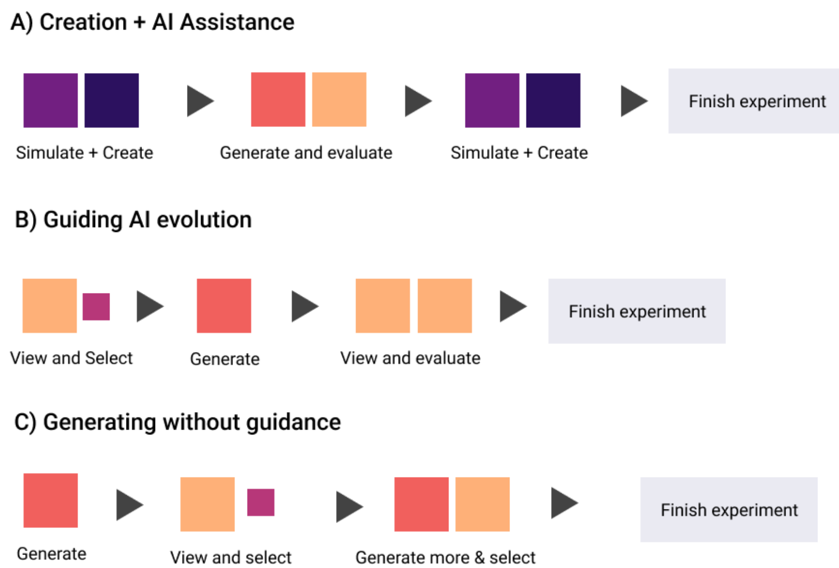

Figure 7.18 Visualization of series of actions involving interacting with AI.

Finally, there are instances where participants generate solutions without offering any examples (as seen in Pattern C from Figure 7.18). In these cases, participants are primarily seeking inspiration and guidance to discover new perspectives on the problem. Figure 7.17 shows multiple instances of these interaction patterns within a single session, indicating that the role of the AI can shift during the creative process.

Although the majority of participants use AI-assisted capabilities in all scenarios, there are a few cases where they prefer to simply define and simulate their proposals rather than be inspired by proposals that have already been created. This is the case with P2 from Collect 1, where the participant does not use the generator, visualizer, or proposal selection features. This phenomenon is only observed in the Collect 1 scenario, which is probably due to the relative simplicity of the scenario and the participants' ability to come up with several valuable and novel solutions themselves.

In the subsequent section, we compare the data gathered during participants' sessions with their own perceptions of the task and their creative processes within Coevo.

7.3.3 Qualitative analysis

We have discussed the output of the creative sessions while describing various interaction patterns observed between participants and the AI during the creative process. These patterns offer insights into how users engage with AI-powered tools to generate, evaluate, and refine proposals. We highlight the possible changing roles between humans and AI based on their creative needs.

With this understanding of the interaction dynamics, we now shift our focus to analyzing user perceptions of the AI's role and the tool itself. To achieve this, we draw upon post-test interviews conducted with the participants and the CSI score which can provide us insight into the overall user experience and the effectiveness of the AI as a creative collaborator.

In Figure 7.19, we examine user perceptions of the co-creative system using a survey where participant rate their agreement or disagreement with each statement using a Likert scale.

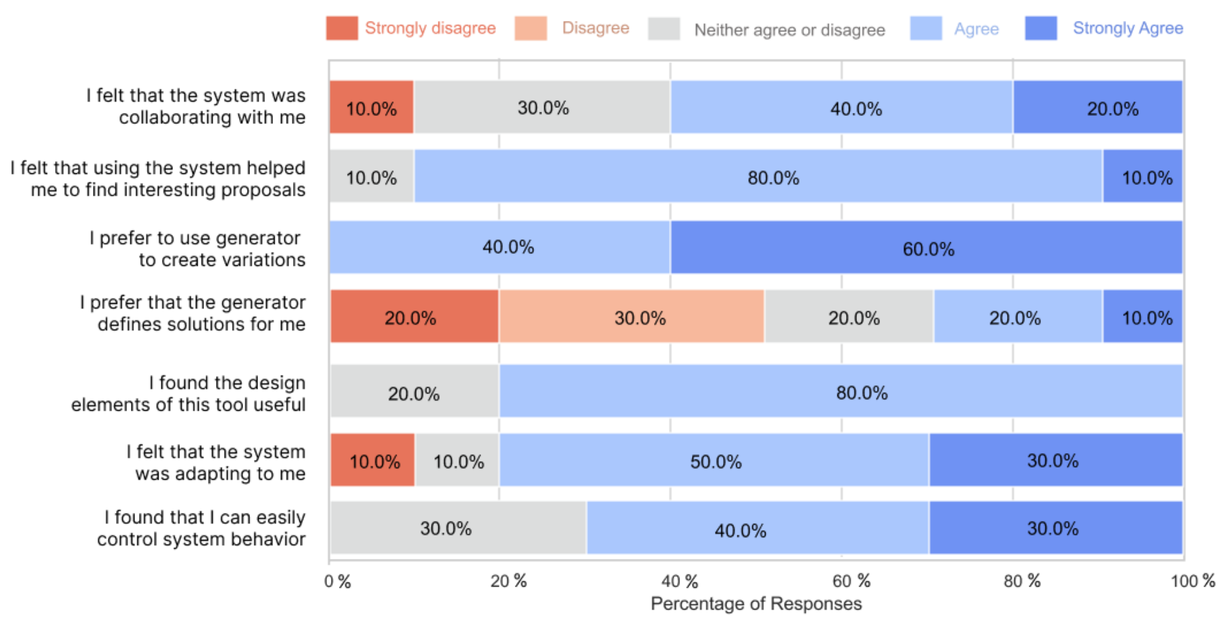

Figure 7.19 Visual representation of user responses to post-test interview questions, highlighting agreement and disagreement levels for various aspects of the system.

We analyze responses based on the previously described question within multiple categories, including system collaboration, proposal generation, the usefulness of design elements, system adaptation, system control, user preference for the human initiative, and user preference for AI-generated solutions.

- *Collaboration*: A majority of participants, with 20% strongly agreeing and 40% agreeing, felt that there was a collaborative relationship between them and the AI. On the other hand, 30% of the participants remained neutral regarding collaboration. However, one participant, P9, strongly disagreed, as they believed they were managing the tool to achieve the desired outcomes. These responses reveal a general consensus among participants that there is a collaborative aspect in the interaction with the AI, although one participant expressed a strong opinion against it. This sense of collaboration aligns with the perceived ownership of the creative output.

  The majority of participants (90%) believed that if a proposal was inspired by one of their ideas or they modified a system-generated proposal, the creation was a joint effort, with both humans and AI sharing responsibility. In certain cases, participants attributed total creative responsibility to the AI when they couldn't solve a scenario. For example, P1 claimed that only the Collector's scenario result was solely their own creation, while the others were collaborative efforts. Similarly, P3 acknowledged that the AI's proposals led to finding a solution, and thus attributed part of the ownership to the system. P5 expressed that the AI collaborated with them when help was needed, and P8 emphasized that the AI's assistance in some scenarios indicated a shared effort, indicating a shared ownership of their creations. In contrast, P9 maintained its stance on collaboration, as they were the only participant who claimed full responsibility for the ownership of the creations in all scenarios. However, as they engaged with the AI and influenced the generated proposals, the participants felt the usefulness of the tool in exploring the problem given and finding creative solutions in multiple scenarios.

- *Helpfulness*: In comparison to the opinions on collaboration, a majority of participants (80% agreeing and 10% strongly agreeing) believed that the system was helpful in finding interesting proposals. When asked about the positive aspects of the prototype, 8 participants emphasized the generative capabilities of the tool. P1 mentioned how the AI proposed various ideas based on their input, being especially useful when they ran out of ideas. Similarly, P3 and P6 highlighted the generator's impact on accelerating their creative process, as it allowed them to begin with a range of proposals instead of a blank canvas. P10 also acknowledged that they could not have solved all the scenarios alone, and the system assisted them in overcoming their creative block.

  These findings illustrate the importance of AI in providing new creative directions and facilitating progress in the creative process. By offering users novel perspectives and suggestions, the AI-powered tool demonstrates its value in enhancing human creativity, especially in overcoming creative blocks and design fixation within this process.

- *Preference of the generator*: Regarding the generator, most participants preferred system responses that closely resembled their own generated ideas (60% strongly agree and 40% agree). In these cases, they adjusted the Similarity slider to 'Similar values' to influence and guide the generation of new proposals. P1 detailed their iterative process of proposing a shape without being overly concerned about the final result and then using the generator to refine it. P7 emphasized how they used the generator to combine two proposals they liked.

  In most situations, they didn't want to start using the generator from scratch and define solutions for them (half of them strongly disagree and disagree with this statement). Two participants agree and one strongly agrees with this statement. Only when participants felt stuck did they adjust the similarity slider to generate more novel proposals, seeking inspiration from new creative paths. P4 explained that this option encouraged them to think differently about the solution. P5 also noted how some variations surprised them, revealing alternative ways to solve the scenario. P8 described how this approach assisted them in finding proposals when they were unsure of what to do.

Based on the participants' testimonials, it becomes apparent that providing human users with tools to control the AI's role and influence the generation of diverse results within a session is crucial. Offering users the ability to customize the AI's output according to their needs, preferences, and creative challenges allows for more effective collaboration. In this experiment, by enabling users to choose between similar or novel proposals, the tool matched different stages of the creative process, adapting to a wide range of scenarios and problem-solving approaches. In conclusion, the design of AI-based creative tools should prioritize user control and flexibility in order to foster successful human-AI collaboration and enhance the overall creative experience.

- *Design language and tool elements*: The majority of participants responded positively to the design language implemented in the tool, with 80% expressing agreement and 20% remaining neutral. Several participants described the creative session as enjoyable and engaging, as they found the tool to be intuitive and user-friendly. They felt challenged by the different scenarios and believed that the design language enabled them to effectively express their ideas. P1 explained how they explored various solutions by sketching ideas and using the visualizer to compare and iterate on their preferred options. P9 appreciated the tool's intuitiveness, which allowed them to focus on defining solutions rather than spending time understanding the tool's functionality.

  However, some participants expressed a desire for more expressive capabilities. A few participants would have preferred to directly draw their solutions rather than concatenate blocks, citing limitations in the current block size that hindered their ability to accurately define a solution. P2 desired a more pencil-like experience with the capacity to draw multiple lines rather than just one. P10 mentioned the constraint of starting from a specific point and expressed a preference for drawing from any location.

Some participants also suggested incorporating additional generative capabilities and AI suggestions. P8 wished for the AI to propose ideas based on the user's ongoing creation rather than solely when prompted by a button press. P2 wanted to visualize AI proposals overlaid on their own solutions to directly learn how they could be improved.

In conclusion, the design language and tool elements implemented in the study received predominantly positive feedback from participants. They appreciated the intuitive and user-friendly nature of the tool, which allowed them to focus on solving problems and expressing their ideas effectively. The enjoyable and engaging creative session also demonstrated the tool's potential to facilitate a seamless and productive human-AI collaboration. While some participants expressed a desire for more expressive capabilities and additional generative features, the overall response highlights the success of the design language and tool elements in fostering a positive user experience and enhancing creative problem-solving.

- *Adaptation & Control*: Regarding adaptation, despite users being able to influence the system's behavior only through defining their own proposals, selecting them, and using the Similarity slider, most participants felt that the system adapted to them effectively (50% agreed and 30% strongly agreed). These results align with the perception of system control, where most participants found it easy to manipulate and influence the AI's behavior. P6 noted that, even though they initially did not understand how the generator worked, the proposals provided were in line with their expectations. P2 explained that the Similarity slider was related to the level of creativity they wanted in new proposals, using it as a means to control novelty and explore different directions. P8 appreciated the ability to view multiple solutions and decide when to focus on a particular one, which facilitated exploration and the discovery of new solutions. Only one participant felt that the system did not adapt to them, as the generated solutions were not valid for their scenario and they expected the system to propose only valid solutions.

Although participants are generally positive about system control, some participants expect the AI to offer only valid, high-scoring solutions. P2 suggested that the AI could take more time if it could not find solutions quickly or perhaps request more user feedback. Considering that in most scenarios the generations take less than 10 seconds, they are willing to wait more time for getting better results. P5 mentioned that some generated solutions were unusual, attributing this to the generator "going crazy." However, they appreciated this aspect as it inspired them to think outside the box and discover new ways to solve the problem. This highlights two perspectives on the importance of novelty and value in AI responses: some participants expected high-scoring solutions when refining their proposals, while others appreciated less performant proposals if they inspired new problem-solving approaches during exploration.

In relation to the AI's response time, most participants described it as fast or fast enough, as it offered numerous proposals to explore within seconds. P3 noted that the generator's speed helped them stay in a creative flow and quickly explore multiple directions. P6 appreciated being able to visualize solutions while the generator was running, giving an idea of the time remaining. P1 suggested running simulations in the background or showing proposals in a side panel while the user explored a solution, instead of "blocking" the system during generation. When asked if it would be acceptable for the generator to take more than a minute, most participants expressed concerns about breaking their creative flow. They preferred rapid interaction with the system and modification of its responses over receiving more refined solutions at the expense of time.

These findings reveal a balance between exploration and exploitation in the creative process, with participants valuing both novelty and high-scoring solutions from AI.

While some users appreciated less performant proposals that inspired new problem-solving approaches during exploration, others expected high-scoring solutions when refining their proposals. Participants' responses also manifest the importance of maintaining creative flow. Participants preferred rapid interaction with the system and quick modifications of its responses over receiving more refined solutions at the expense of time. This indicates that low latency in generating solutions is crucial to support the user's creative flow and facilitate a seamless, engaging experience with the AI tool.

Creative Support Index

Finally, participants evaluated the system's capabilities to assist them in the proposed creative task using the Creative Support Index (CSI) [150].

In Figure 7.20, the final CSI scores from our experiment are presented. Participants generated an average score of 78.47 (SD: 4.42) out of 100 for creative problem-solving in Coevo scenario. This score indicates that our tool can be considered a good creativity support score ("B" grade), but not excellent.

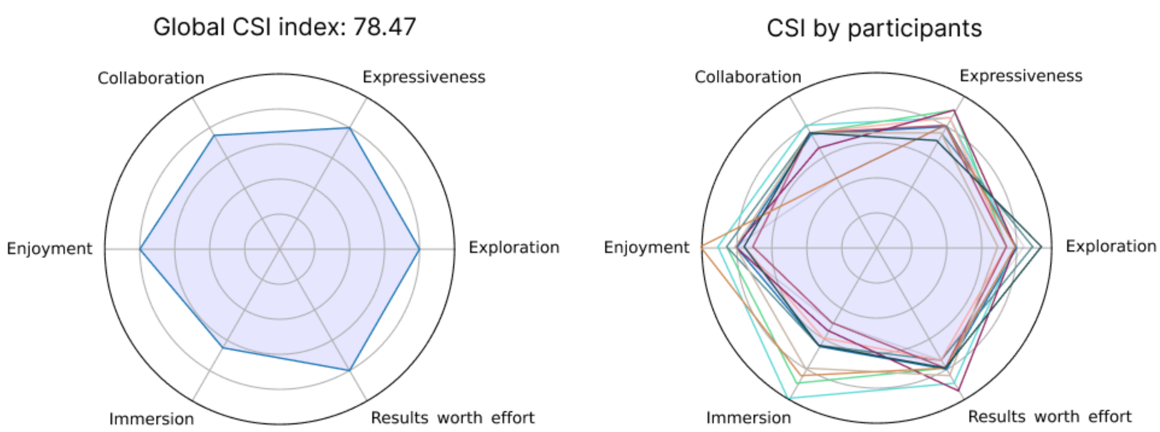

Figure 7.20 CSI Scores overview. The chart has six dimensions, labeled along the axes: *Exploration*, *Expressiveness*, *Collaboration*, *Enjoyment*, *Immersion*, and *Results worth effort*. On the left is the mean value of each dimension; on the right, CSI scores for all participants in a study

To better understand what we should focus on when designing creativity support, we can further examine the individual factors and their ratings, as suggested by [150]. In addition, we explore which dimensions are particularly important to participants in creative problem-solving tasks. This factor is presented in the table 7.4 where the average factor count indicates importance of each dimension (out of 5)

Exploration	Effort	Collaboration	Enjoyment	Immersion	Expressiveness
3.70 (0.95)	2.30 (1.42)	2.30 (2.11)	2.40 (1.35)	1.50 (1.27)	2.80 (1.81)

Table 7.4 Dimension Scaling Factors. These values are obtained by pair-wise comparisons across all the dimensions. Each participant is asked if they prefer a certain dimension over another one. As an example, if a participant values exploration over all the dimensions, the factor obtained will be 5 out of 5 comparisons (corresponding to each other dimension)

In this specific context, we found that *Exploration* **(3.70)** was the most significant aspect for participants, followed by *Expressiveness* **(2.80)**. Furthermore, participants highly valued *Enjoyment* **(2.40)** of the task. Interviews revealed that the majority of participants felt challenged by the scenarios, leading them to consider the enjoyment of the task as an important factor.

Subsequently, participants deemed *Collaboration* and *Results Worth Effort* as equally significant factors **(2.30)**. In terms of *Collaboration*, participants considered AI to be their collaborator and rated this dimension accordingly. It is important to note that there were significant differences in *Collaboration* scores among participants, as their perception of *Collaboration* depended on their interpretation of the term. Finally, the majority of participants did not consider immersion to be a crucial aspect in this creative context.

Having analyzed the importance of each dimension, we focus on the overall scores achieved in each of them. This information is present in Table 7.5 together with each individual CSI score. As we can observe the highest scores of the tool perfectly match the most important dimensions, regarding *Exploration*, *Expressiveness*, and *Enjoyment* (8.1, 8.2, and 8.3 respectively). This indicates that participants rated our tool higher in their most important dimensions.

	P1	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**	**P9**	**P10**	**G**
Exploration	8.0	7.5	9.0	7.5	7.5	8.0	7.0	8.0	8.5	9.5	**8.1**
Expressiveness	8.5	9.0	7.5	8.5	8.0	9.0	7.5	8.0	8.0	7.0	**8.2**
Collaboration	8.0	7.5	7.5	7.5	7.5	6.5	7.5	4.5	4.5	7.5	**6.9**
Enjoyment	9.0	8.5	8.5	7.5	7.0	8.0	8.0	10.0	8.0	7.5	**8.3**
Immersion	10.0	9.0	6.5	6.0	5.0	5.5	8.0	8.5	5.0	6.5	**6.9**
Effort	9.0	8.0	7.5	7.5	8.0	9.5	8.5	8.0	7.5	8.0	**8.0**
Overall CSI	**86.0**	**81.3**	**79.7**	**76.7**	**72.3**	**78.0**	**75.7**	**84.0**	**73.0**	**78.0**	**78.5**

Table 7.5 Participants' scores in various categories, their Global CSI score, and the Global average scores for each dimension

- *Exploration*: the average count for the exploration factor is **3.7** and **8.1** as its global score, indicating great importance for users in creative problem-solving. As observed in the participants' creative journeys, they explored the solution space by testing out multiple proposals and using the generator when they needed inspiration or could not solve the scenario. One way to improve the current score in this dimension could be to combine better generative skills and new visualization methods. Some participants mentioned that it could be very interesting to see suggestions while they are editing proposals, or better ways to visualize and compare proposals in the scenario at the same time, which could support participants in their exploration needs.

- *Expressiveness*: this dimension is directly related to how design language contributes to the definition of proposals and their expressive capabilities. Also in this context, the participants rated the tool highly (**2.8** as a factor and **8.2** as a global score), which shows that the language was flexible enough for them. However, there is still room for improvement in this dimension as well and we can rely on the participants' feedback by improving our constructive system and replacing it with a continuous drawing canvas without restrictions on placement.

- *Enjoyment*: the average score for this dimension is **8.3**, indicating that participants found the system enjoyable to use. This supports previous qualitative analyses in which they indicated that they enjoyed finding solutions to challenging scenarios and suggesting new ways of solving them.

- *Collaboration*: as commented before, there is a high standard deviation in this score (**2.11** from a mean score of 2.3), which is mainly caused by the participants' perception of their collaborator. This also affects the global score **(6.9)**, suggesting that we could consider different possibilities or try new ideas for collaborative dialogue. As mentioned earlier, P9 scored poorly in this area because they felt that there was no collaboration with anyone. For this reason, we need to be cautious in interpreting these results. Considering this aspect, and based on the participants' feedback rather than this score, we could explore other interaction techniques for communicating with an AI-driven system, such as turn-based communication or reactive suggestions that allow the AI to interactively suggest and show solutions without the user having to press the 'Generate" button.

- *Effort*: with a global score of **8** and an important factor of **2.4** participants felt that the effort required to propose solutions for Coevo scenarios was good for them. Again, the use of direct drawing instead of manipulating blocks can be a way to reduce the complexity of defining solutions and can probably improve this score. Another way is to provide better opportunities for participants to define solutions or generate variations of already defined solutions. Participants mainly struggled when they ran out of ideas. Therefore, suggesting options to them directly during the design could be a good approach.

- *Immersion*: this dimension has the lowest score in the scenario and its importance is also the lesser for creative problem-solving. Nevertheless, we can also offer up some improvements that can help users to stay in the flow while using the tool. Based on participants' feedback, we can improve the speed of generation and the quality of suggestions, because in some cases waiting for results or getting bad results can make participants stop participating in the activity.

Overall, the analysis of the Creative Support Index together with participant feedback tells us that the system is generally well received by participants, with strong scores in the dimensions of Exploration, Expressiveness, Enjoyment, and Effort dimensions. These scores suggest that the tool is beneficial for creative problem-solving. It provides them with flexibility while reducing complexity by using a common design language and supporting exploration and inspiration through generative skills. Participants found the system and experiment enjoyable and stimulating as it challenged them to come up with innovative solutions. They were generally satisfied with the AI capabilities and most of them considered it as another collaborator in the creative process. These results suggest that the role of AI in creative problem-solving is to support exploration, provide creative direction and be an assistant to help them to refine and improve their solutions. The AI role is not expected to be static, but rather dynamic and adaptive. It should evolve in response to the current state and their creative needs at any point during the session.

7.4 Conclusions

In this Chapter, we explored human-AI collaboration in creative problem-solving. We mainly focused on the human creative process and the potential roles AI can play during this process. To do this, we have presented a new version of Coevo, where humans can co-create with AI to find innovative solutions in multiple scenarios.

We observed that in most situations, participants were able to propose multiple novel solutions to the challenges presented. Only in more complex perceived scenarios (Unbox 2 and Move 2) participants required AI assistance to find high-scoring solutions. All participants included AI-generated solutions in their final proposals, leading to over 50% of the final solutions being AI-generated. Some participants even had a majority of AI-generated solutions in their selections (P5: 72% ; P6: 91% ; P7: 65%). Furthermore, all participants, except P9, saw AI as a collaborator to the creative process and acknowledged that they share responsibility for the solutions developed in collaboration with AI.

In terms of the creative process, most participants started by defining solutions on their own and sought AI assistance in three key situations:

- *Creative block*: when participants had difficulty finding new solutions, they turned to AI. This behavior occurred mainly in simple scenarios with obvious solutions (Collect scenarios).

- *Refinement needs*: when participants already knew a possible solution by visually analyzing the scenario, but they were not able to reach high scores when simulating the scenario. Mainly observed in scenarios with multiple objects affected by the physics such as Divide 2 or Stand Scenarios.

- *Complex scenarios*: when participants struggled to find a solution at all and they asked the AI to propose effective solutions. Prominent behavior in complex scenarios such as Unbox 2 or Move 2.

These needs directly influenced the expected role of the AI which, using the same design language, could directly modify and propose new solutions for participants. These roles during the process include:

- *AI as an Exploration Partner*: The AI generated a range of solutions from which the participants could draw inspiration. This helps with creative block and fixations by exploring different ideas and offering up-ranked solutions that humans can choose from, which improves the breadth and depth of the creative process.
- *AI as an Assistant*: In this role, the AI refined and improved participants' ideas, reducing manual effort and increasing efficiency. Particularly useful when repetitive tasks or trial-and-error iterations are required.
- *AI as an Expert Consultant*: Here, AI generates novel solutions from scratch when participants needed fresh ideas or are faced with complex scenarios. This promotes innovative thinking and potentially increases the quality and effectiveness of the solutions.

These varying roles and involvement levels of AI agents have significantly enhance the quality, efficiency and effectiveness of the creative design process. This created a more flexible and dynamic problem-solving environment, where the AI can support the human participant based on their current needs and creative state. In addition, participants were able to influence AI's responses through a similarity slider and by interactively selecting solutions, which allow them to control the generative process.

As observed, context (scenarios) greatly influenced the role of AI. In simpler scenarios or when participants have a clear idea, the AI might serve as an Assistant, improving and refining the initial idea. In complex situations, where predicting the outcome is challenging, participants might expect the AI to act as an Expert consultant, proposing innovative solutions. And when participants want a broad set of ideas for inspiration, they might rely on the AI as an Exploration Partner. Thus, this context together with the exploratory process directly influences the level and type of AI involvement. Then, the role of AI is expected not to be static but rather dynamic and adaptable. It should evolve in response to the human collaborator's current state and their creative needs at any given point during the session.

In addition, participants showed patterns in their interaction with the AI agents. After their individual exploration, participants required AI assistance in multiple situations. Then a process of validation and evaluation of these solutions started, which consisted of either visualizing multiple solutions at once or even using these to generate more variations based on their preferred ones. Participants found it helpful to have the AI-generated solutions ranked by score and to choose the number of solutions displayed at once. This helped them decide where to focus without having to evaluate a large number of solutions. AI-generated suggestions have greatly enhanced human exploration and discovery of new ideas. It provided new perspectives, which was the most important factor and the better value for them when we analyzed the CSI index in multiple dimensions. As expected, the AI produced novel solutions that participants might not have considered and quickly generated a wide variety of valid proposals. Participants used these proposals as inspiration, refined them, and built on these initial ideas.

In that aspect, direct manipulation of design proposals enhances communication and collaboration by providing a shared medium for interaction. It allows for immediate feedback and iteration, making the creative process more efficient and effective. Participants can directly interact with and modify AI-generated proposals by making their intentions, ideas, and feedback explicit. This direct manipulation also benefits the understanding of the AI's logic and reasoning, enhancing collaboration. Finally, it fostered a sense of co-creation, where both humans and AI contribute to the evolution of the design proposal. This was evident in the sense of shared responsibility for the solutions generated in all scenarios, showing that most participants felt they were collaborating with the AI rather than using it as a tool.

Regarding the limitations of the system, some participants wished for more expressive capabilities, such as drawing directly on the canvas, or they expected more autonomy in the AI, which could propose solutions while we create our own solutions, instead of using a button to generate them. However, in general terms, most participants showed a positive attitude towards the tool's capabilities, which was also reflected in the rating of the system, which received a good score of 78.47 (B grade) in the Creative Support Index. Particularly, this new version of Coevo scored higher on key aspects such as *Exploration*, *Expressiveness*, and *Enjoyment* support.

These findings support our initial hypothesis that creative-problem solving processes can be augmented through a dynamic human-AI collaboration during the whole process. As an answer to our initial hypothesis, three main aspects should be considered when defining co-creative systems for creative problem-solving:

1. AI's contribution to generating a diverse range of solutions significantly facilitates the discovery of new ideas and enhances efficiency. This leads to a majority of the final solutions being generated in collaboration with AI.

2. Direct manipulation and editing of AI-generated proposals can augment the creative process. This shared medium encourages immediate feedback and iteration, fosters a sense of co-creation, and improves understanding of the logic of AI, leading to a sense of shared ownership of solutions.

3. AI's role in the creative process should be dynamic and flexible depending on the scenario context and the creator's needs. It can serve as an Exploration Partner, an Assistant, and a Expert consultant with its involvement greatly influenced by the knowledge of the scenario and the participant's current creative state.

In the following Chapter 8, we conclude this thesis detailing our research findings on creativity-support tools and co-creative systems and their implications on human-AI co-creativity. We discuss how this learning can be applied to other creative domains that require future human-AI collaboration.

In addition, we propose some design guidelines for developing new AI-powered creativity-support tools or co-creative systems, taking into account the diverse needs during a creative session and the emerging roles during the collaborative process.

Chapter Eight

Discussion and conclusions

The goal of this thesis is to show how a computational system can augment human creativity in problem-solving scenarios in different domains. Our approach focuses on fostering creative exploration through interaction with the shared design materials that are co-created during the creative process. This perspective is closely aligned with theories of design practice and creativity research that view the design process as an iterative process where reflection on understanding problem and solution spaces plays an important role in exploring the design situation and the emergence of creative designs. This alignment can support this thesis's applicability in other domains such as design and creative practices.

In this Chapter, we discuss our perspective on human-AI collaboration in creative problem-solving processes and suggest design principles for human-AI co-creation, considering both the expected AI role and the interaction techniques needed to communicate with the AI system. We discuss our findings providing further pieces of evidence on how computational support can be applied in different design situations. In addition, we propose some design principles to create future AI-powered tools or co-creative systems. Finally, we expose possible future directions of this work.

8.1 Summary

This thesis contributes to multiple aspects of human-AI co-creativity. In this section, we detail these contributions together with some pieces of evidence presented during this thesis work.

The creative spark: supporting creativity through valuable and novel proposals

At the beginning of this thesis, we stated the following general research question:

> *"How can a computational system augment human creativity by interacting with shared design material and lead to more novel and useful solutions than those generated by individuals working independently?"*

The notion of this creativity augmentation is supported by the proposals generated during the various experiments conducted as part of this work. We provide clear examples of how both historical (*h-creativity*) and personal (*p-creativity*) creativity can be augmented in distinct domains [114].

In Chapter 3, we started by investigating how a semi-autonomous computational system could support *h-creativity* through the optimization of Sonic Black Hole (SBH) profile designs. These SBHs are commonly employed to control and dampen vibrations, especially in thin structures. The creation of these structures usually involves designing a structure that eliminates vibrations reflection, typically in a duct termination. In Chaper 3, our goal was to improve the performance of the standard power-law designs, which are widely used in this field. This problem encapsulated the essence of *h-creativity.* It required a high degree of expertise and domain knowledge to formulate solutions, given the complex concept involved. Additionally, the solution must be novel, not just for the individual, but within a broader historical and societal context (scientific community). Our results, discussed in Chapter 3, show that the system-generated proposals surpassed the optimum power-law profile across almost all frequencies. Furthermore, we have developed new combined techniques utilizing evolutionary algorithms for optimizing profiles in duct terminations, which included the use of damping material in the tapering section of the duct, further enhancing the effectiveness of the designs.

While these experiments illustrated how a *h-creativity* problem could be supported by computational means and how AI can contribute to advancing knowledge of the field [114], we aimed to explore systems that can collaborate with the user on a shared creative product. This differs from computational creativity approaches in which a system exhibits creative behaviors alone [27], [51]. This sense of collaboration could not be fully explored in the first domain due to the complexity of simulating and evaluating the creative product generated by the system.

To explore a co-creative scenario where both humans and AI contribute together, we defined a new environment in Chapter 4. This environment was designed for creative problem-solving and included a language to generate solutions. This approach allowed us to demonstrate how *p-creativity* could be enhanced through real-time interaction with generated materials within the design situation. This environment reduced computational complexity, enabling rapid interaction and manipulation of system-generated proposals.

Using this environment, in Chapter 6 we compared proposals generated by an artificial agent with those generated by humans. The results demonstrated our AI agent's capability to generate proposals at a human level in multiple scenarios. Then, in Chapter 7, we demonstrated how through human-AI collaboration, participants were able to propose multiple novels and valuable solutions to the challenges presented. Evidence of AI's impact was observed in the final proposals selected by participants, with over half of the solutions being generated together with an AI. Some participants even had a majority of AI-generated solutions in their selection (P5: 72% ; P6: 91% ; P7: 65%). Furthermore, participants considered the AI agent as a collaborator in the creative process and acknowledged shared responsibility for the developed solutions.

Most participants suggested that the AI's capabilities enabled them to explore novel solutions that they might not have considered, thereby quickly generating a wide variety of valid proposals. These proposals served as inspiration, allowing participants to refine and build on these ideas, advancing their thinking processes.

This demonstrates the significant impact of AI in generating a diverse range of solutions, aiding the discovery of new ideas, and enhancing human *p-creativity* through the exploration of the problem space.

The role of language in facilitating human-AI collaboration

One of the key aspects that enhanced communication and collaboration between human and AI agents has been providing a shared language for directly manipulating the shared proposals and exploring the solution space. As discussed in this dissertation, externalizing our internal cognitive processes in a shared material can influence others' exploration leading to new potential solutions and a fresh perspective on the problem space.

Initially, we posited the concept of computational assistance in creative tasks as a reflective dialogue mediated via the design material. As outlined in the introduction, this implies the need for a language that supports iterative creation and modification of proposals while fostering exploration and the simultaneous evolution of problem and solution spaces in the design context. Subsequently, we postulated two research questions concerning the language's definition and its implications for human-AI collaboration.

> *"What impact does the design and use of the design language have on the emergence of creative proposals, and how do these tools support exploration?"*

> *"How does communication mediated through the creative product influence human-AI collaboration? Which benefits and limitations it presents?"*

In the Coevo environment, we examined how a continuous iterative process of design proposals was generated using our proposed language. We first validated how different evolutionary algorithms could leverage the language to suggest solutions in multiple contexts

(Chapter 5), and compared the most effective solutions to those conceived by humans (Chapter 6). This comparison showed how our AI agents were able to produce human-level solutions thereby enabling us to integrate these agents into the co-creative system showcased in Chapter 7. There, we investigated human-computer co-creativity [152] which involves real-time improvisation based on shared creative products between humans and AI. This collaboration strategy is evident from the previously presented analysis of the creative output presented in Chapter 7. In terms of their creative process, most participants started by defining solutions on their own and later used the AI as an assistant by refining or enhancing solutions based on their original ideas. In contrast, when participants run out of ideas they required AI assistance in generating possible design directions and later modifying systems proposals to match their own creative needs.

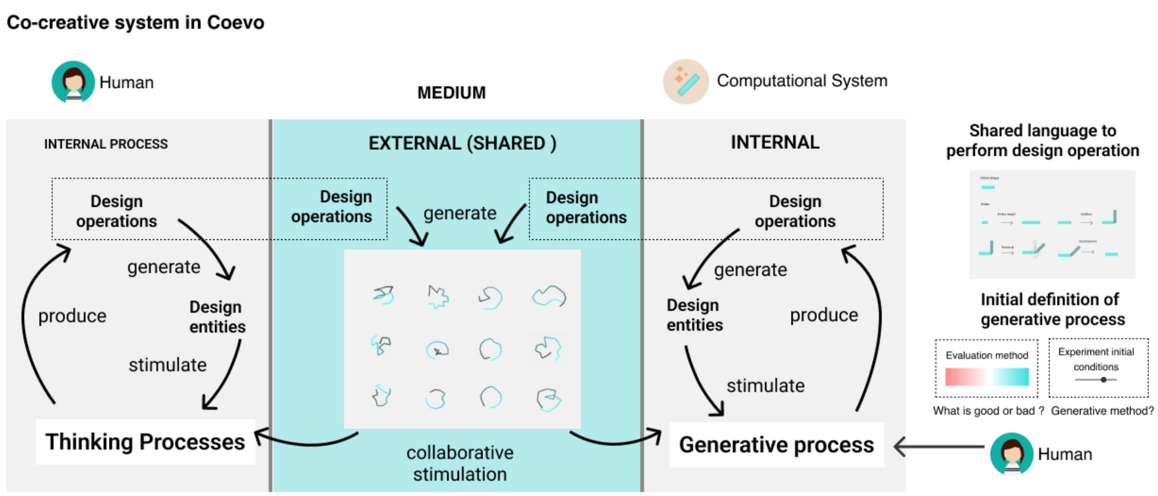

Figure 8.1 Schema of human and AI role in a Co-creative system. In Coevo, the initial human role is to define the design language and the initial generative method and conditions. Once the creative session starts, both actors contribute to the exploratory process by iteratively creating, sharing, and modifying each other's proposals. Schema adapted from [18], [119]

This interaction was possible because both human and AI agents shared the same design language for manipulating proposals. This demonstrated how AI suggestions influenced the human exploratory process and how our participants also influenced the AI output, embodying the nature of collaboration (Figure 8.1).

In contrast, as illustrated in Figure 8.2, in autonomous systems, the language's primary function is to drive exploratory processes rather than to serve as a catalyst for collaboration. In the experiments from Chapter 3, the human role was confined to setting the experiment's initial conditions, including defining the evaluation function and analyzing the computational system's output. Then, an expressive design language enables the system to define complex solutions clearly, thus defining proposals that can subsequently be evaluated by the system.

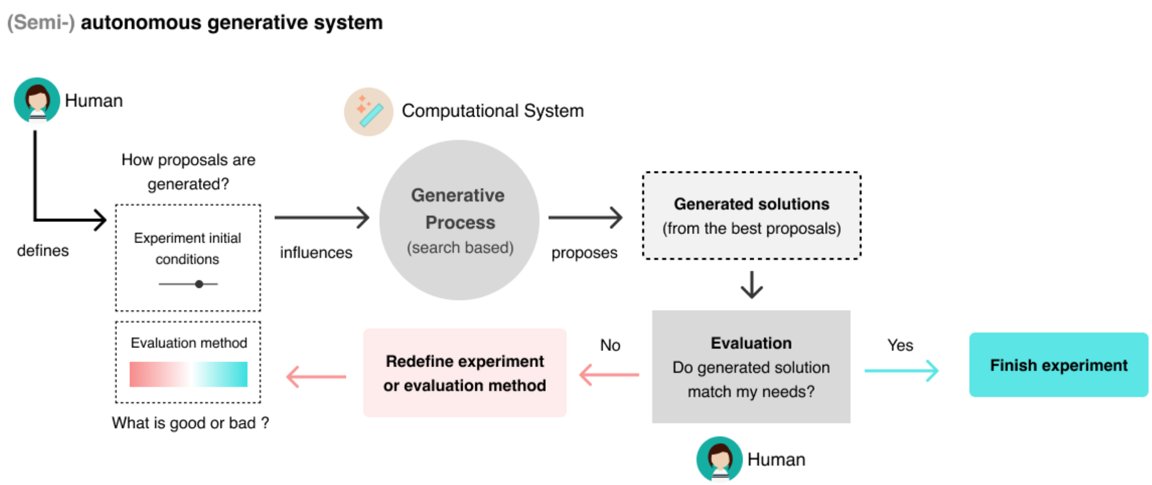

Figure 8.2 Schema of human and AI role in a (semi-)autonomous generative system. Humans' role in this type of (semi-)autonomous systems is focused on defining the initial experiment conditions and later on evaluating the final proposals of this system. If the proposals don't meet their criteria, they must change the design conditions and run the experiments again which is a tedious task.

Furthermore, since the generative process and language are human-defined, a mutual understanding of how a proposal is created is established. This enables the autonomous system to explore the solution space while incorporating human insights, leading to more effective and creative outcomes. For instance, during the experiments in Chapter 3, we selected a promising novel design that was proposed by the system. Then, we modified a part of the proposal based on our knowledge of how this proposal can behave in a real scenario. This illustrates how interaction with the final outputs of a generative system can also lead to the definition of a novel profile with one of the highest performances in a particularly complex problem space.

Finally, this approach of exploring the solution space through a design language aligns with the essence of design activities, which often involves finding solutions to ill-defined problems [6], and the design process predicated on concurrently refining the problem and solution [8], [10]. As stated in earlier chapters, the interaction between the designer and the environment influences the designer's perception of both solution and problem spaces, expanding the designer's initial understanding and knowledge of the given domain [18]. An expressive language can facilitate a better representation of internal mental processes while increasing the AI's expressive range in presenting solutions. This can improve understanding and collaboration while enabling better fine-tuning of the solution to match the human mental model.

Navigating solution spaces: evolutionary algorithms as powerful search engines

In this thesis, we explored the potential of AI-assisted creative problem-solving via multiple evolutionary algorithms to navigate distinct problem spaces. Our initial research question aimed to identify the most effective computational methods for creative exploration:

What types of computational methods can be integrated into different creative processes? How do they impact the exploratory process?

Throughout the course of this thesis, we have integrated a variety of evolutionary algorithms across all conducted experiments.

In Chapter 3, we introduced how *Covariance Matrix Adaptation-Evolutionary Strategy* (CMA-ES) could be used to optimize sonic black hole profiles. Later on, we also proved how this approach could be combined with a *genetic algorithm* (GA) responsible to improve these profile results by exploring different absorbent configurations for a specific profile design.

In Chapter 4, we combined an evolutionary algorithm with shape grammar, thereby creating a powerful tool for automated exploration of Coevo solution space and the generation of a wide diversity of designs. Particularly in Chapter 5, we showed how this type of algorithm is less influenced by initial design considerations by providing more flexibility in the design. This flexibility aids in discovering unique solutions, as initial considerations can often encapsulate solution details or restrict solution space exploration. For instance, one design condition for AI agent involved using a specific number of blocks. This requirement forced the designer to initially state these design constraints and prematurely contemplate a possible solution. In contrast, we proved that by letting the algorithm optimize this number, it was able to find valuable and novel solutions without this design constraint. This suggests that the algorithm can lead to better results in terms of value and novelty if it is given an expressive language for exploration (our shape grammar). This implies that not only the algorithm definition influences the creative output but also how the problem space is explored. We provided more pieces of evidence of this concept in Chapter 6, where we showed how using a single AI agent combined with shape grammars provided a powerful solution search tool for exploration in multiple scenarios, matching human-generated proposals in terms of novelty and value.

In Chapter 7, we introduced a novel evolutionary technique inspired by interactive evolution that allowed our participants to direct the generative search by selecting proposals based on their criteria. This method merges the exploration capabilities of evolutionary algorithms with human guidance, resulting in more targeted outcomes.

This dynamic interaction between humans and AI encourages more effective exploration of the solution space while preserving human control. In this context, we also examined how different definitions of fitness functions guide and influence the exploratory process. This is a common occurrence in many design problems where complex constraints must be satisfied. Evolutionary algorithms can manage these constraints effectively by incorporating them into the fitness function. For instance, in Chapter 3, one of our goals was to reduce the number of absorbent-filled cavities created by the algorithm, so we penalized solutions that used more than the ones intended. Another example, from Chapter 4 involved defining a more open fitness function that rewarded solutions that exceeded the initial expectations of the experiment. Particularly in the Movers scenario, participants were asked to generate solutions that moved through a ramp and reach a goal within a specific timeframe. This timeframe was set based on the average speed of a wheel-like proposal to reach a target. However, when defining the fitness function, we favored solutions that were faster than this average speed, leading to the discovery of unexpected new designs that surpassed our initial understanding of the solution space.

By defining a fitness function, we also facilitate the exploration of the solution space while directing the AI algorithm towards a certain direction. The algorithm can modify its search strategy based on the fitness landscape it explores. As the landscape changes (i.e., if the problem is dynamic), the algorithm can adapt to those changes. Therefore, whether by defining initial fitness functions and design constraints or by guiding the algorithm's exploration through interactive evolution, humans can steer the creative session based on their preferences or intuition, while entrusting the exhaustive exploration of the solution space to the AI.

Our experiments demonstrated how these algorithms performed open-ended tasks that required extensive solution space exploration. While traditional AI/ML methods are typically effective at finding solutions to well-defined problems, in creative work there is a need for adaptation and open-ended exploration. As shown in previous work [80], evolutionary algorithms can both explore to find novel and surprising solutions and exploit a more defined solution space - both essential conditions in creative work.

For that reason, the evolutionary algorithms as search engines in the creative domain support a flexible and adaptive exploration that combines the strengths of both human and AI systems. This closely resonates with human design processes where we often start with a vague problem definition and we gain a deeper understanding of the space by generating solutions and reflecting on their performance. Utilizing these algorithms also supports various roles in creative exploration depending on our creative needs and involvement in the creative process. On one end, we can either become the audience or the curators of final proposals presented by these algorithms since they will likely align with our expectations defined through our initial design constraints and fitness function. On the other end, we can leverage the algorithm's optimization capabilities to enhance our own designs and solve complex scenarios based on our design intuitions, as exemplified in the SBH optimization from Chapter 3. Finally, we can share the initiative with these AI agents becoming active collaborators in our design exploration. In this context, we can either guide the evolution by interactively providing examples of our creative expectations or use these algorithms to provide us with novel directions to explore and later modify them to match our needs.

To meet these different expectations, we need to consider these creative needs into account when defining the algorithm. It is crucial to provide the algorithm with sufficiently expressive language (such as the one presented in this thesis) to explore and manipulate solutions to the given problem space. This ensures that the algorithm is a flexible and efficient tool that can adapt to a variety of creative scenarios and design requirements.

New interaction patterns and AI roles for co-creative systems

In human-AI creativity, the interaction dynamics between the human and the AI system [140] and its roles during the creative process [73], [74] are essential components to consider for effective co-creative systems. In Chapter 7, we have presented different interaction techniques to communicate with the AI, beyond pressing the 'Generate' button. These techniques included influencing the generation via selecting proposals or using the similarity slider to express their expectations of the generated output. As we commented, when analyzing the proposals generated and the creative journeys of the participants, we found that one of the most important aspects of collaboration was that they could manipulate each other's proposals by using the same language. This shared language allowed participants to express their intentions visually while reflecting on AI responses through the shared product of their creative process (Figure 8.3).

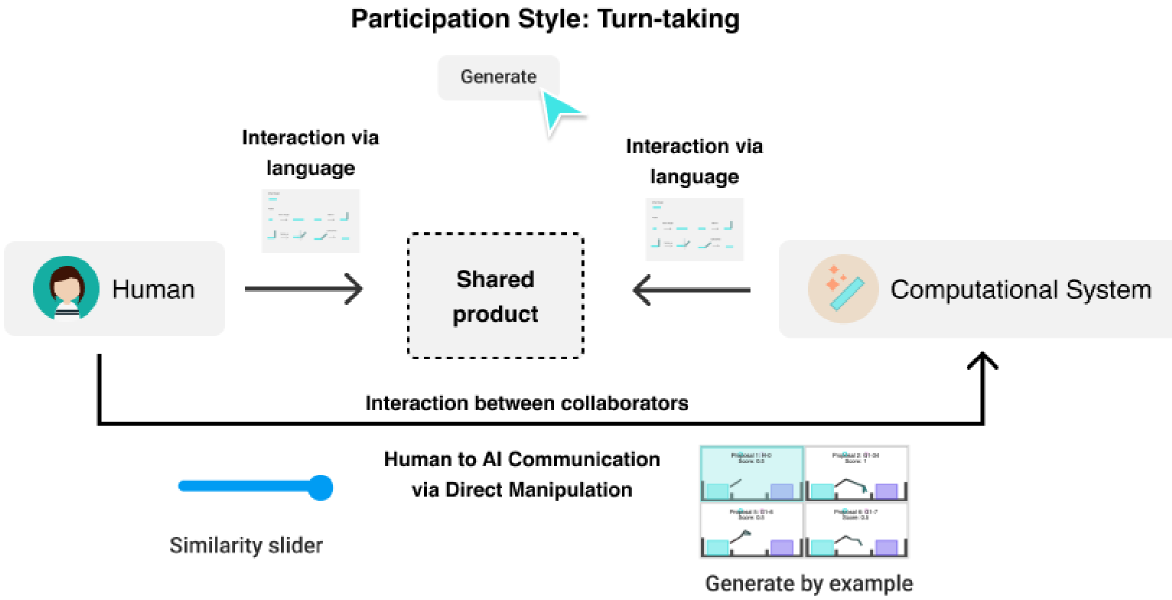

Figure 8.3 Interaction style present in Coevo based on modeling interaction in human-AI co-creative systems from [140].

This interaction style resembles other generative co-creative AI agents, where one of the roles of the AI is to be inspired by human proposals and generate similar ones or to evaluate, improve and contribute to the shared creative product as a generator [140]. These two roles match with our *assistant role*, where the AI is responsible for contributing to the creative process by reducing manual effort and increasing process efficiency through iteration. In addition, our findings indicate another type of AI role in their creative problem-solving process where AI acts as an exploratory curator helping participants to overcome creative block and fixation. These 'provoking' agents are rare in the literature according to [140] and represent a way to support divergent thinking in scenarios where more exploration and perspectives are needed. In addition to this, participants also described their need to use *AI as an Expert Consultant*, creating novel solutions and concepts from scratch to help them start to face more complex scenarios. This type of AI agent also lacks in the co-creative systems literature and can help humans in finding creative inspiration at the beginning of a creative journey, promoting innovative thinking and potentially increasing the quality and effectiveness of the solutions.

In addition, as mentioned by our participants a more active role is also found in co-creative systems literature [140]. This corresponds to an improvisational AI agent that allows working on the same task in parallel. In the Coevo environment participants envisioned this interaction method in two possible directions: sharing the same space (Figure 8.4) and as a side panel with suggestions (Figure 8.5).

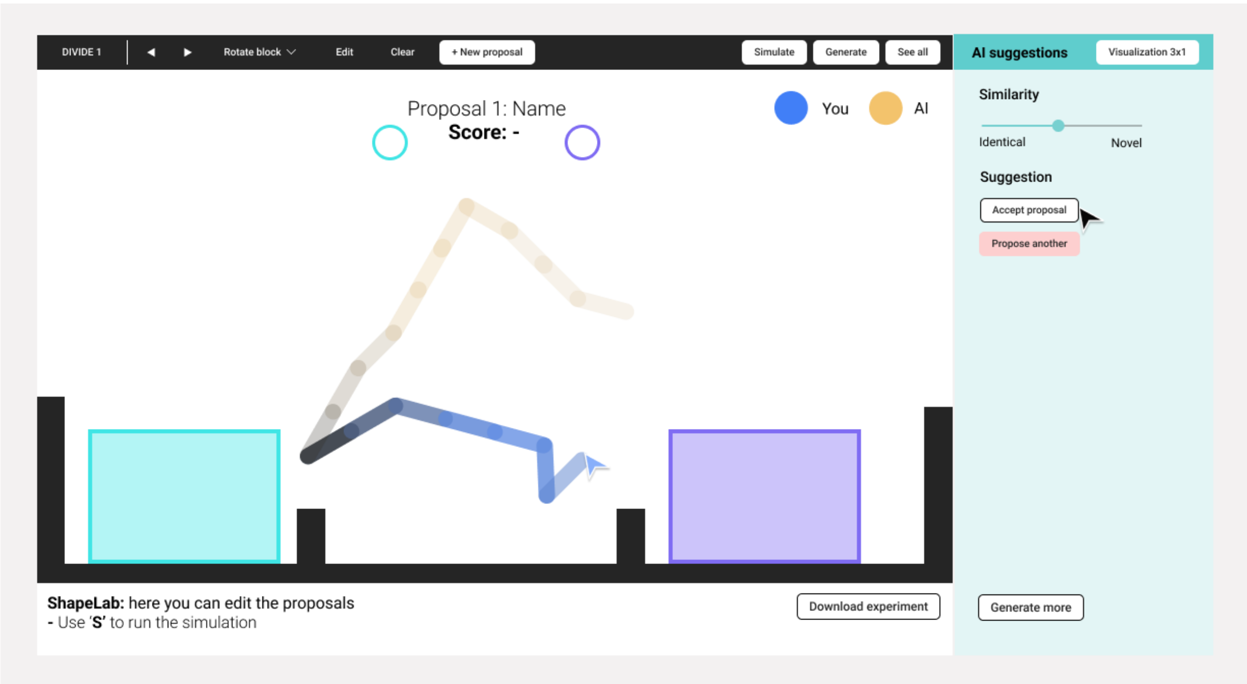

Figure 8.4 AI suggestions placed live on canvas allowing the user directly visualize them in context.

In the initial approach, positioning AI responses above the human proposal within the shared interface can enhance the user experience by offering immediate feedback exactly where required. It eliminates the need for a turn-based interaction between the user and the AI system, allowing both entities to contribute simultaneously to the creative process. Humans can influence these AI suggestions based on their needs, following methodologies and interaction methods employed in previous experiments. This strategy is particularly effective in minimizing user fixation and providing guidance in complex scenarios. An adaptive system could detect that a solution is not found and offer up one when needed without user intervention.

Although this model could augment visual thinking capabilities in humans and assist in formulating more effective solutions, it can be perceived as a disruption of the flow since it can shift human attention to the proposal. Furthermore, the user's focus is often close to the action so any suggestion that appears or changes while actions are being performed (e.g: adding or subtracting blocks) could result in shifting their attention back and forth, disrupting their interaction with the system. Therefore, AI suggestions should always be designed to be minimal, non-disruptive, and easy to disregard, allowing humans to focus on the task they are performing without interruption.

For that reason, it is generally better to present AI suggestions in a way that is minimally disruptive, such as in a separate, dedicated area of the interface (Figure 8.5). In Chapter 7, participants highlighted how visualizing these AI-generated proposals helped them to explore and find new solutions to the given problem spaces. These proposals ranked by their relevance or effectiveness scores, served as a repository of solutions they could leverage. The multiple visualizations used, allowed users to compare multiple proposals at once, draw inspiration, refine their ideas, or incorporate elements from that list.

Here, we propose improving this past experience by offering up a dynamic site panel that allows users to view and interact with AI suggestions while they are creating their own proposals in the canvas. This helps them to understand how the suggestions relate to their current work or problem. This context can be less explicit if users have to switch between different views or if they have to wait for the system to generate responses. This immediate feedback loop can enhance user engagement and facilitate a more interactive and iterative problem-solving process. As an example, users can quickly notice a change in the side panel and choose to incorporate an AI suggestion or modify it as needed. This can speed up the decision-making process and make the interaction with the system more efficient. This also allows to increase users' perception of control over their experience. They can choose when and how to engage with these AI suggestions. In contrast to the previous approach, a separate panel can also reduce the cognitive load of users since they can concentrate on their main tasks without distraction.

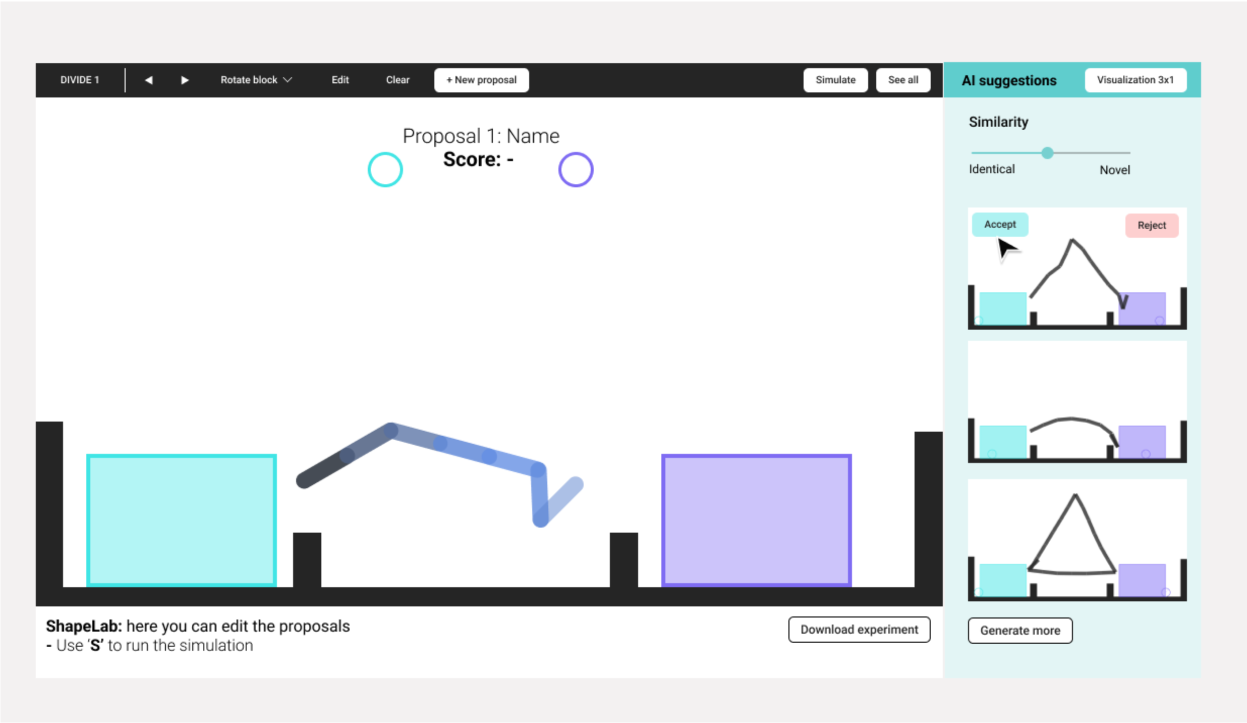

Figure 8.5 Placing AI responses and parameters into a dedicated side panel allows humans to focus on their creative work. When needed, they can engage with the AI system via directly interacting with the proposals generated, without leaving their context window.

Furthermore, these suggestions can also be generated based on specific user preferences or responses to specific events in the creative process. For instance, suggestions can be updated after a scenario simulation, offering alternatives that perform better or providing novel solutions based on creative needs. To facilitate exploration, the 'Generate' button can also be included for users that want to request new proposals asking the AI to lead the initiative of the exploration.

The combination of both approaches can also be employed, allowing for contextual visualization while enabling users to maintain focus as needed. For instance, this could involve displaying a solution on the main canvas when a user hovers over a particular AI suggestion from the side panel. These novel interaction methods build upon existing techniques for interacting with AI in creative problem-solving scenarios presented in this thesis and expand the expressive range in human-AI collaborative scenarios.

Wearing Many Hats: The Dynamic Roles of AI in creative processes

> *"Which is the main AI role in the creative process? How do AI-generated proposals contribute to the exploration and discovery of new ideas and perspectives?"*

Our research findings in Chapter 7, suggest that there is not one prominent AI role in creative problem-solving but rather a combination of multiple roles responding to different creative needs. This indicates how AI's role in the creative process should be dynamic and flexible depending on the scenario context and the creator's needs.

This illustrates the importance of language definition and its flexibility across all phases of the interaction, from the pre-session setup of parameters to the iterative co-creation, selection, and modifications of the shared creative product generated during the creative session, and finally to the post-session edition of final proposals. In Figure 8.6, we illustrate these different dimensions involving the creative process and the possible human and AI roles in each phase based on our experiments.

1. **Pre-session Phase**: In this initial stage, humans define system capabilities to generate responses and initial conditions for the experiment. This can involve defining a creation language, determining which artificial intelligence method to use, and training it by providing context or setting some preliminary conditions as needed. The system's responses to given problems are shaped by these preliminary settings. In addition, an evaluation mechanism is also defined at this stage to determine the system's ability to deal effectively with the problem at hand. This evaluation system provides the opportunity to assess the success of the system's responses, ensuring that they are not only creative but also functional. Note that this phase can be conducted by the future participants of the creative session or an external agent that prepares the AI system

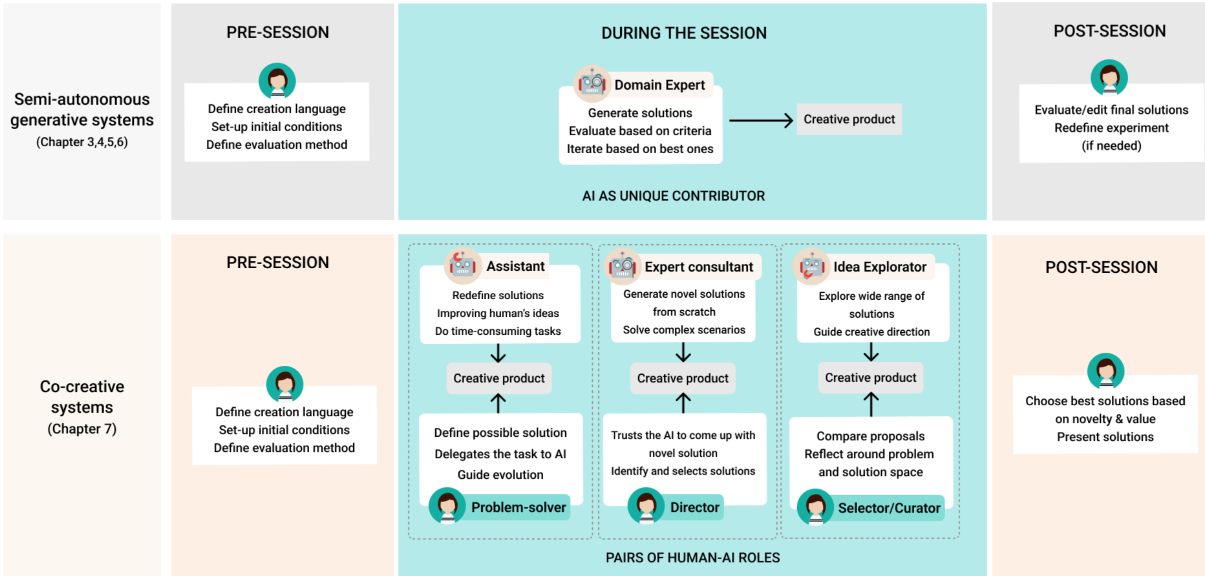

Figure 8.6 Mapping human and AI roles across different phases of the creative flow. Note how in co-creative systems multiple pairs of roles emerge responding to multiple creative needs during the session

for a specific context. In any case, human roles and actions within this phase deeply influence later generative process.

2. **Creative session Phase**: This stage is the creative process itself, where both actors can contribute to generating solutions to a given problem space. Within this phase, humans can steer AI responses following different interaction techniques:

   (a) **Via Direct Modification**: by directly modifying the product or outcome that the system generates, within the boundaries of the shared design language pre-defined in the pre-session phase. This active engagement allows for real-time adjustments and fine-tuning of the creative product.

   (b) **Via Selection**: as presented in Chapter 7, our interactive evolutionary approach allows us to select and offer up the system the proposals that it should take into account. This iterative process enables the system to learn and adapt, improving the relevance of its subsequent proposals.

(c) **Via output expectation**: in this case, using a similarity slider, users can articulate their expectations with respect to the system's outputs. They can specify whether the desired outputs should be analogous to or different from the ones that the system has already generated. This flexibility allows them to control the system's output to meet the specific creative needs of the user.

3. **Post-session Phase**: Once the creative process is completed, humans evaluate the final proposals generated by the system or via co-creating solutions together with an AI agent. Then, they can decide to alter the initial conditions and generative methods in order to investigate their impact on the system's creative output.

In addition, within the creative session phase, multiple pairs of human-AI roles emerged supporting different creative needs and demands of the creative task requiring different approaches and skill sets at different stages. According to our findings, this emergence is mainly attributed to the complexity of the task and the co-evolution of understanding both problem and solution spaces. In creative problem-solving, users started by testing out and refining one initial idea on how to solve the problem. Then, once this solution was tested out, participants either generated variations around that solution (AI as an assistant) or explore novel directions (AI as an exploration partner). In the first case, human directs the design situation by providing feedback and AI contributes to creating a more efficient design process. In contrast, in the second pair of roles, AI directs the design situation presenting new opportunities to explore. This possibility space stimulates reflection-in-action from human partner which compares and contrast solutions. This allows humans to get a better understanding of both problem and solution spaces while encouraging the exploration of potential novel solutions. Finally, in the scenario where AI acts as an expert consultant, AI is more autonomous, generating solutions from scratch without needing user guidance. Then these provided solutions can also serve as a spark for reflection-in-action, offering up new ideas or revealing non-obvious aspects that can also expand the human designer's original concept.

Finally, we must consider how the creative process is often non-linear and iterative involving multiple phases of divergence and convergence within the same session. This complex nature forces AI systems to have a high degree of flexibility and responsiveness to be able to adapt and respond to these multiple needs. Despite the fact that human-AI interaction is especially difficult to design [29], our findings make clear that AI can significantly contribute to a collaborative and creative problem-solving scenario by assuming multiple changing roles within a creative session. However, the effectiveness of the collaboration between human and AI systems is intrinsically linked with the interaction models used in their communication. Therefore, highlight again the importance of a shared design language to communicate via the shared product of their creative session together with the different techniques to influence both the initiative and the generative process of the AI system.

For that reason in the following section, we introduce some design principles for defining co-creative systems for human-AI collaboration based on our findings. These principles focus on supporting and amplifying human creative problem-solving abilities while ensuring system adaptability to changing tasks and needs.

8.2 Design principles for human-AI co-creative systems

In this section, we propose a set of *design principles* for human-AI co-creative systems based on our work. In the literature we find further design guidelines for AI systems [140], [153], [154] or creative support tools [26], [47], [155]. We consider these principles to interact with AI-powered tools and creativity support tools systems and we focus on co-creative systems. Particularly, in co-creative systems where there is an expectation of collaboration between humans and AI agents to explore a given problem space by creating, interacting, and modifying the creative product or material generated during the session by both participants.

Language as an interface

In order to explore a certain problem space, humans and AI should use a common set of symbols, terms, and concepts that serve as a mutual design language for defining solutions. Then, when defining a new tool to support creativity, establishing a shared language forms an important part of this process. This language should encapsulate the parameters and design variables to be used by both human users and the AI system which will later influence the creative exploration. This definition serves as an interactive interface for creative exploration enhancing communication, mutual understanding, and effective collaboration between humans and AI.

Design expressive tools

The interaction design of a tool plays an important role in the future exploration of the solution space. A more expressive tool allows better communication of intention and externalizing concepts more accurately. In our experiments, we showed how the flexibility of the tool allowed both humans and AI agents to generate solutions in multiple scenarios. The design language used by this tool to define solutions influences the generative process and the way the problem space is explored. As expressed by some authors [156], systems for supporting creative processes need to enable users not only to compose artifacts but also to think of what to compose as artifacts.

Support exploration in multiple directions

One of the key aspects of creative problem-solving is exploring widely the solution space. Within this exploration, the space of potential solutions that satisfy our intention grows, allowing us to better understand our knowledge of the initial problem and define better our solutions requirements [11], [18], [37]. We showed in our experiment how *talking through the design material* generated supports reflection and helps users to find more creative solutions.

For that reason, AI should be a source of inspiration and assistance, offering novel ideas and perspectives when the user needs creative stimulation.

Aim for latency-zero responses

Especially in the early stages of the creative process, it is important to keep the user in the flow [17] so that they can fully engage with the task. In this exploratory phase, human is 'forming' their perspective on the problem and solution spaces while defining their creative intention through interacting with the material generated during the session. By providing instant feedback, we support creative flow while allowing a more fluid and continuous interaction between humans and AI systems while ensuring fewer interruptions and distractions during this exploration. Based on our experiments, participants preferred to be offered a wide range of more *imperfect* solutions rather than waiting that the system generated a perfect solution. By rapidly providing outputs to users, AI can inspire new directions and encourage us to reflect upon the problem and solution spaces while maintaining user creative [17].

Communicate AI outputs when needed

Generative systems are capable of providing a vast range of solutions in a short amount of time. There is an expectation that the quality of the output and the speed at which these systems operate will improve greatly over the next few years. For that reason, we must control which information we show to the user in order to reduce cognitive and information overload. If a user is being presented with too much information, they can feel overwhelmed to process it which generates frustration to them. Providing tools to explore, rank or select these generated solutions based on specific criteria can help users better interact with these generated results and select and act on the most relevant ones. For that reason, we must choose human & AI spaces carefully, identifying opportunities to share the same space for rapid interaction or providing a separate space when more possibilities and user actions are required

Support multi-modality

In order to communicate our mental models and internal thought processes, we use different strategies to reinforce our intention through different channels [19]. This can also allow to make information more accessible and provide more expressive capabilities to the interlocutor. Having multiple ways to communicate with AI can give you a better picture of what we intend. For example, when users selected examples of what they wanted to generate, along with the similarity slider, they were able to control the AI generation process and meet their expectations. Future AI-powered systems should support both our language and our visual thinking capabilities for communicating.

Human often drives, AI follows

Typically, humans often prefer to lead the initiative of the creative process. Their expectation can range from defining initial experiment conditions or defining a design intention to even exploring potential solutions by themselves. For that reason, we must empower humans to articulate this initial intention and perspective. Then, AI should adapt to a range of user needs and tasks, being flexible in its role, switching from active participants when needed to stay as a passive observer based on the situation.

AI taking initiative

There's also an opportunity to explore new ways to provide enhanced autonomy to AI agents. When AI has ways to communicate its decision-making process and offer up human explanations, a more dynamic exploration can occur. In cases where the AI has high confidence that a specific solution could advance the human thought process, it can take the lead. By dynamically identifying solutions, the AI has the potential to engage in a dialogue with the user, steering them toward a new creative direction. This differs from traditional AI systems which have generally been reactive rather than proactive. For that reason, there is an area of future research for the field of co-creativity in creating AI agents that can actively engage with humans, initiate actions, and make independent decisions within predefined boundaries as noted also by some authors [140].

Encourage a reflective dialogue rather than a single order

Design and creative processes revolve around exploring problem and solution spaces. As we navigate these spaces, we better understand the situation, which refines our intent and enhances our capacity to articulate our needs. This exploration can be enriched within the context of human-AI collaboration, where the materials generated during a session serve as touchpoints for shared understanding. Especially, when our intention is ambiguously or ill-defined, it's likely that an AI's initial responses may not align perfectly with our expectations. However, we can gain clarity about our goals by examining diverse solutions and reactions from the AI system. For that reason, it becomes essential to establish an iterative feedback loop, which can continually refine the understanding of both humans and AI regarding the problem at hand. We should thus actively encourage these rapid feedback cycles as they benefit both humans and AI systems by leading to more effective communication and better results.

Support interaction based on different AI roles

When designing AI-enhanced systems, it is important to anticipate the prospective AI role within a creative session. Sometimes, AI's role might involve generating a multitude of solutions (e.g.: a tool to brainstorm ideas around a topic). Under such circumstances, we have to provide spaces and tools to guide this exploration and evaluate AI responses. Ideally, these spaces and tools should exist in a distinct space or context to prevent unnecessary distractions to the user. In contrast, in other situations, AI can offer up a single concise solution to improve our current proposal (e.g.: a tool to support writing). In this scenario, we would probably want AI suggestions closer to the action, requiring minimal interaction for the user to either accept or reject it. For that reason, is important to consider how the AI role and capabilities influence the design decisions of the tool.

8.3 Limitations

The research presented in this thesis provides a valuable contribution to understanding the dynamics of human-AI collaboration in creative problem-solving. Despite our focus on iterative interaction and reflection through the design materials, the study carries a set of limitations that should be highlighted.

First, our definition and evaluation of creativity are centered on the product generated from the creative session and the participant's perception of the process. This approach may not encapsulate all facets of creativity, leaving out elements that could significantly influence the creative flow such as the context of the creator or the environment where the creative session is conducted. Moreover, the language defined to navigate the solution space inherently constrains the expressiveness of both human participants and the AI system. This language definition highly influences the creative processes since it directly affects humans and AI capabilities to articulate comprehensive solutions. Communication between humans and AI, particularly through the design material, presents another challenge. There can be moments when human may not be able to fully express their intention, potentially leading to misinterpretation or misunderstanding of the user's intentions by the AI.

Another limitation has also been mentioned by some participants regarding how the AI proposals were presented to users. Our system, though designed to support real-time collaboration, may disrupt the creative flow of users due to the need for mode switching between viewing AI suggestions and employing the creation tools. Future iterations could consider integrating a dedicated panel to seamlessly display AI suggestions alongside the creation tools.

Finally, our research focuses on two specific domains: sonic black hole profile designs and the Coevo environment. This specificity may limit how our findings generalize across different creative domains. Consequently, further explorations may be necessary to apply these concepts to new contexts. Moreover, our computational approach to supporting creativity is mainly based on using evolutionary algorithms. This decision was influenced by these algorithms' exploratory capabilities and how they are able to find solutions without any previous knowledge of the solution space. Despite their exploratory capabilities and ability to discover solutions, may not represent the full potential of other AI techniques to support creative exploration such as reinforcement learning or large language models. Furthermore, current AI models' ability to fully understand, interpret, and act upon human intentions is limited to the design language defined and the different interactive methods to influence AI responses, which might constrain the depth and efficacy of the collaboration.

Future research should concentrate on exploring more expressive methods and exploring novel AI techniques to better articulate intentions during AI-human communication in the creative process. Furthermore, a promising area of research involves enhancing the autonomy of the AI collaborator. While our study outlined various flexible AI roles, there is vast potential for the AI to assume additional roles and increased autonomy given more expressive capabilities and improved means of communication with humans.

8.4 Future directions

The work presented in this thesis highlights the importance of human-AI collaboration in creative domains and it opens new opportunities for future research in multiple directions.

Large Language Models: communicating with natural language with computers

One of the most promising future directions of this work is related to exploring creative domains using large language models (LLM) within creative sectors. Recent research highlights the far-reaching impact of LLMs across numerous industries, attributed to their general-purpose applications [157]. Generative AI technologies, many of them based on LLM [158] find applications in diverse fields ranging from general chatbots like ChatGPT [159], to creative writing [160], [161] or image generation technologies such as DALL-E [162], Stable Diffusion [163] or Midjourney [164].

The success of these models lies in their adaptability to a variety of tasks via the use of *prompts* - natural language directives specifying the expected system output. Therefore, the clarity of intention expressed through natural language significantly influences the system's performance.

This aligns with the work presented in this thesis since we propose that creativity can be augmented with AI throught a reflexive dialogue with the material generated during the creative session. LLMs, as creative collaborators, can also engage in an iterative creation process and reflective dialogue. For instance, they generate responses based on the inputs they receive, creating a dynamic, feedback loop and exchange of ideas that allows exploring both an evolving problem and solution spaces. Furthermore, they enable real-time collaboration, similar to our co-creative Coevo version. These models can offer immediate feedback, and suggestions, or generate new text based on user input.

However, while language is a powerful tool for communication and expression, it has its limitations when it comes to describing certain concepts or ideas. In the case of image generation, natural language can be inadequate for a number of reasons. First, natural language is inherently ambiguous. A single sentence can have multiple interpretations, which can lead to unpredictable or inconsistent outputs when generating images based on language descriptions. This ambiguity can arise from factors such as the use of metaphors, idioms, or cultural references that may not be universally understood.

To mitigate this, one common technique is prompt tuning or engineering. The idea behind prompt tuning is to provide the model with a specific text prompt, which serves as a guide for the model to generate content that is more aligned with the prompt. By adjusting the prompt, users can control the style, tone, and content of the generated text. For example, by providing a prompt that emphasizes a specific topic or theme, the model can generate text that is more focused and relevant to that topic. Some researchers equate prompt engineering with programming in natural language, given how rewriting a prompt significantly impacts a language model's task performance [165].

Despite these advances, natural language can fall short in conveying visual information due to its limited expressiveness. Language may not be able to fully capture the complexity and richness of visual data, leading to a loss of detail or fidelity in the generated images. For example, it may be challenging to describe the texture of a particular object, the way light falls on a scene, or the subtle nuances of color. Then, the problem of not being able to express a concept or idea can also arise when communicating our intentions to generative models. In order for a generative model to create an image or output that matches our intended concept or idea, we need to be able to effectively communicate that intention to the model. When we are not able to find the right words to articulate our thoughts, these models may not be able to produce a matching output.

A potential solution for this problem is considering exploration as a dialogue involving multiple commands to the AI model rather than a single command that will produce a unique single output. This closely aligns with our approach as human-AI collaboration being a reflexive dialogue between humans and AI through the material they produce in the creative session. Interacting with the output and material produced by generative models can support our exploration by providing us with new insights and inspirations, even though we may not know exactly how to express our intentions. By experimenting with various inputs and parameters, we can discover unexpected and novel outputs that can inspire new ideas or perspectives. Then, by actively engaging with the outputs of generative models, we can uncover new insights, generate novel ideas, and explore new areas of interest in a creative and innovative way. For that reason, exploring new methods to interact with these systems and control their outputs can help us to better express ourselves and co-create with

AI-powered systems in creative flows.

New interaction paradigms for supporting creativity in multiple domains

Through this thesis, we highlighted the importance of defining expressive tools and establishing clear communicate methods between humans and AI during a creative process. As previously noted, less work has involved exploring to present AI responses and embodying their capabilities within the interface. In future work, we want to explore and compare different approaches for presenting AI responses and investigate a more proactive role in the creative session.

Our study participants indicated that collaboration with an AI to meet their creative needs was highly valued. However, there's an opportunity to enhance this collaboration further. For example, AI suggestions could be provided closer to the action, allowing for direct sharing of the creative space between humans and AI, or through a side panel for suggestions. Future work could investigate how different ways to present AI suggestions can impact the user's creative flow and facilitate more effective communication human-AI communication by eliminating the need to switch modes to visualize AI suggestions.

Our current approach provides specific evidence on how AI can support creativity by assuming different roles. However, the AI is positioned in a relatively passive role during the creative session, only generating solutions at the human's request. Our works suggest there are many opportunities for AI to take the initiative and stimulate the human creative process, particularly when detecting potential creative blockages or pauses in solution development. At that moment, the AI could lead the initiative and suggest possible next actions that humans can either accept or ignore. Exploring how AI can assume a more active role without disrupting the creative process is one of the most interesting future lines that can be explored.

Finally, while this study examined two creative domains, further exploration across a wider variety of creative fields can be explored such as writing, art and image generation, or music generation amongst others. In this work, we have described different design guidelines for future co-creative interfaces. For that reason, it would be beneficial to investigate how these guidelines can generalize across multiple creative domains and compare user expectations of human-AI collaboration in these varying fields. This could inform the development of new communication strategies for AI, including exploring implicit human-AI communication, thereby expanding our understanding of human-AI collaboration in creative domains.

Our research presented through this thesis, highlights the need for new interaction methods for human-AI co-creation. Future work could focus on designing, testing, and evaluating these methods, such as novel interfaces or protocols that facilitate efficient, effective, and enjoyable collaborations.

The era of personal AI agents

In the research conducted in this thesis, we illustrated some examples of how different AI roles can emerge during the creative session. While the artificial agent in Coevo can support creative problem-solving by using a shared design language, this assistance was constrained by the initial language definition and the agent's exploration of the solution space via an evolutionary algorithm. Even though this exploration didn't incorporate any prior knowledge, the evaluation function and initial experiment conditions influenced the exploration trajectory.

Future AI agents will have more capabilities to explore problem spaces and employ a broader set of tools to accomplish tasks. As an example, the earlier definition of an LLM-powered system demonstrates how novel language capabilities can increase both human and AI agents' expressiveness. Recent research suggests that chaining multiple AI agents together can improve task responses. [166]. The possibility of including multiple AIs or humans in the creative process could also be an interesting area for future research. This can explore the dynamics of multi-agent collaboration and its impact on creative outcomes and AI possible role in supporting creative teams.

One important aspect to consider in this future lies on the ethical implications of these systems. As AI evolves into a more active participant in creative processes, it is key to investigate and comprehend the social, cultural, and legal aspects of human-AI co-creation. Most of these systems are trained on extensive data sets, which significantly impact their outputs. As more AI-powered systems emerge, investigating system bias and exploring how to influence and guide their responses to incorporate diverse perspectives becomes increasingly important.

Finally, we can assume that future AI research in intelligent systems will involve fine-tuning and customization of AI agents and models for specific contexts. This will empower users to create their own data sets and influence AI agents output supporting greater personalization of AI creative collaborators. Recent studies on retraining generative image models exemplify how new fine-tuned models can be easily defined [167], [168] tailoring the AI to individual users' creative styles, preferences, or even different moods.

In this thesis, we show the importance of expressivity and control in creative exploration and how AI can augment human creative capabilities through a reflexive dialogue with the material generated during the creative session. We hope that this work will inspire the future development of co-creative systems and creativity-support tools.

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APPENDIX

Appendix One

Coevo scenario dynamics

The following appendix presents a comprehensive collection of visualizations that depict the sequences and dynamics in the Coevo scenarios across this thesis. In each visualization, a sample proposal has been placed in the scenario as an example.

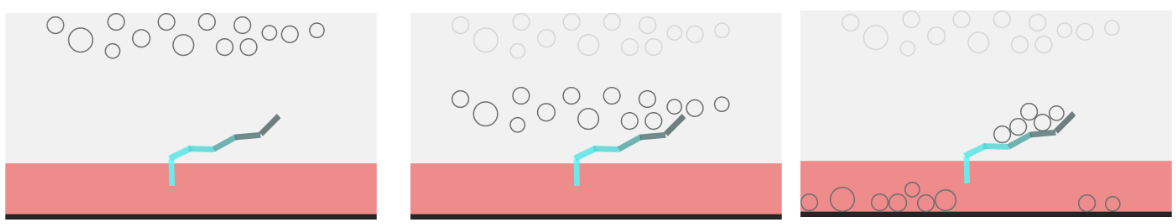

Figure A.1 Sequence of Collector scenario from experiments in Chapter 4, Chapter 5 & Chapter 6

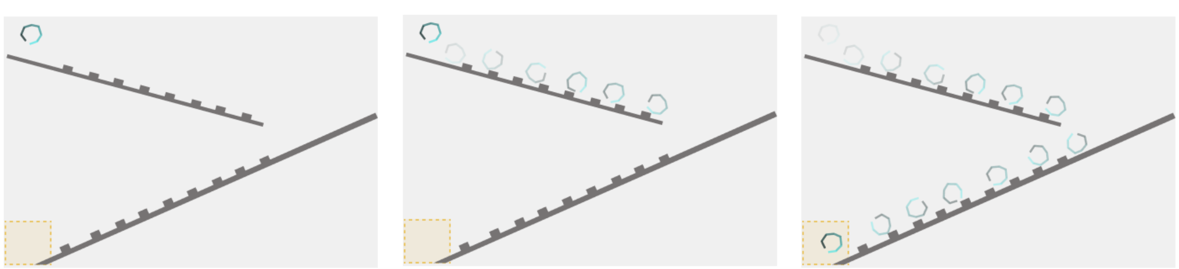

Figure A.2 Sequence of Movers scenario from experiments in Chapter 4, Chapter 5 & Chapter 6

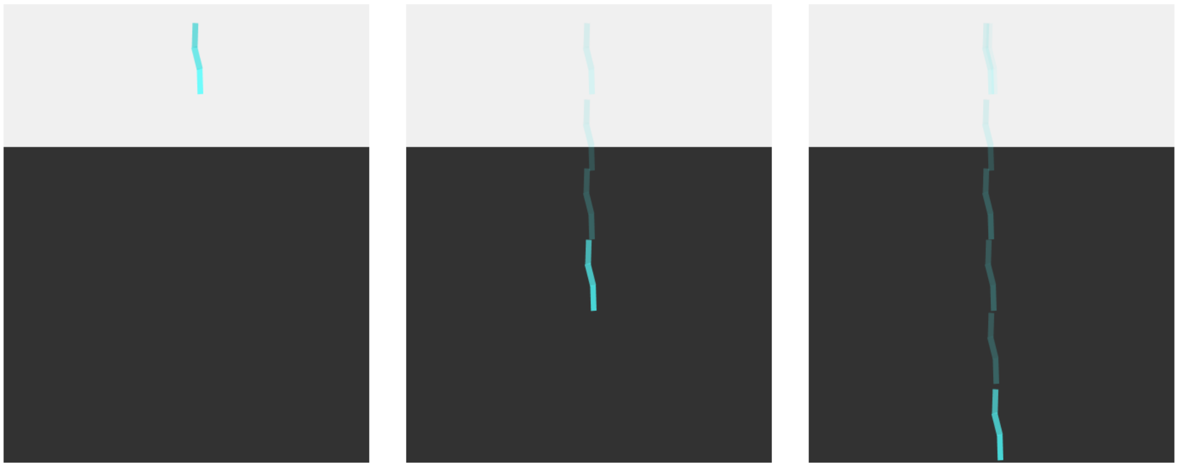

Figure A.3 Sequence of Cutters scenario from experiments in Chapter 4, Chapter 5 & Chapter 6

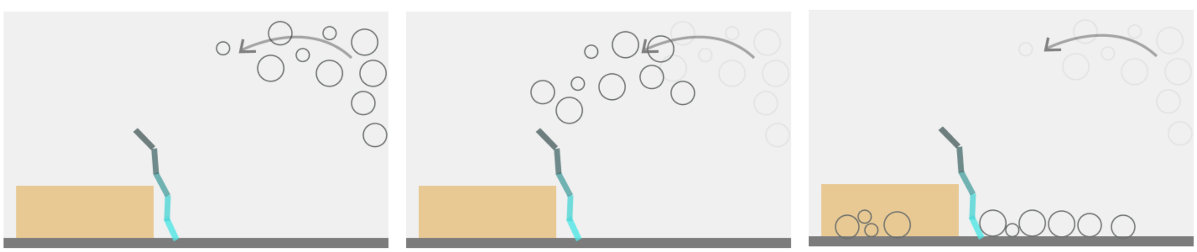

Figure A.4 Sequence of Protectors scenario from experiments in Chapter 4, Chapter 5 & Chapter 6

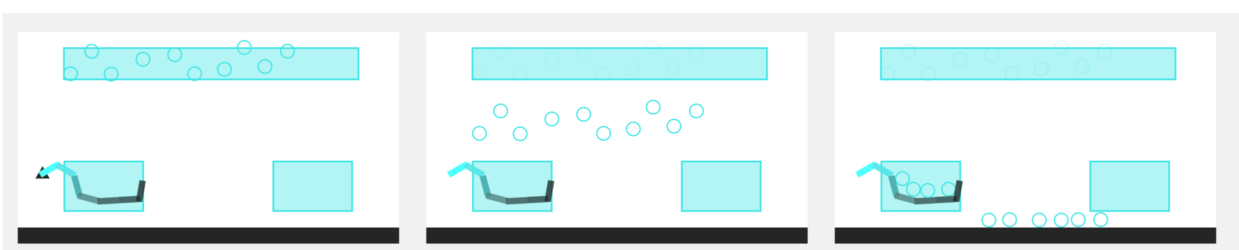

Figure A.5 Sequence of Collect 1 (C1) scenario from experiments in Chapter 7

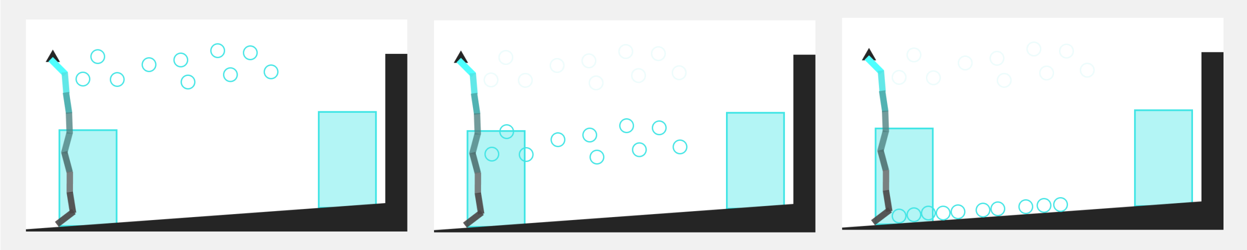

Figure A.6 Sequence of Collect 2 (C2) scenario from experiments in Chapter 7

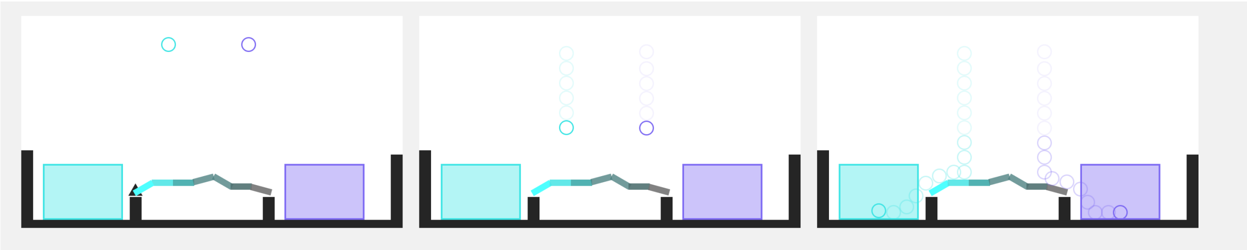

Figure A.7 Sequence of Divide 1 (D1) scenario from experiments in Chapter 7

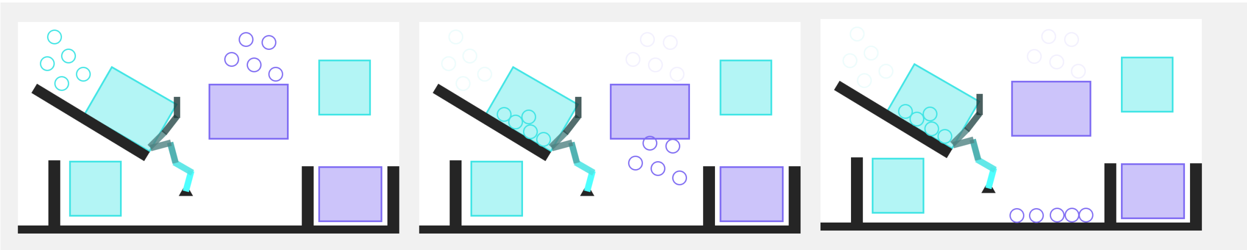

Figure A.8 Sequence of Divide 2 (D2) scenario from experiments in Chapter 7

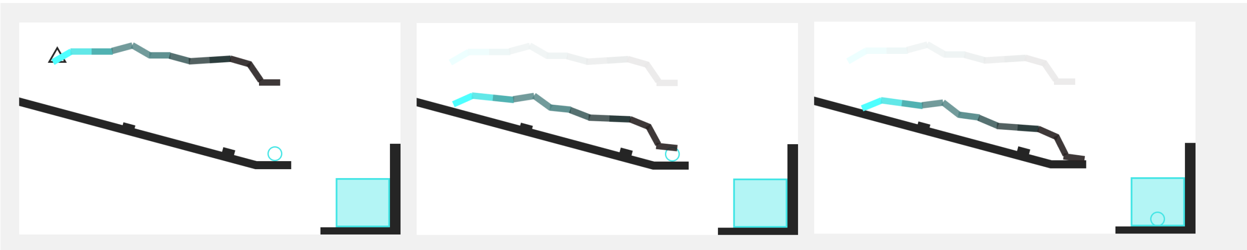

Figure A.9 Sequence of Move 1 (M1) scenario from experiments in Chapter 7

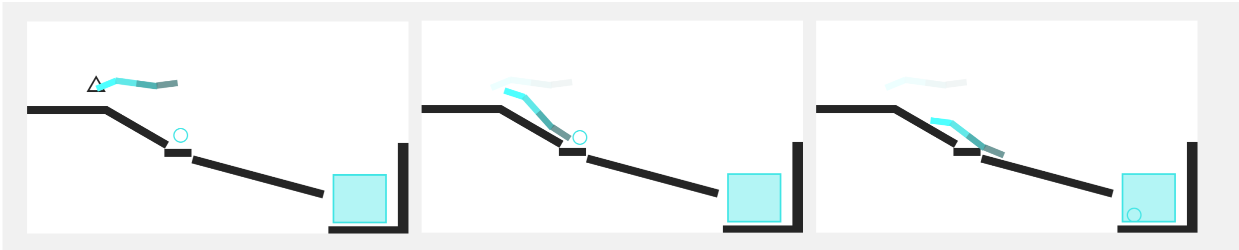

Figure A.10 Sequence of Move 2 (M2) scenario from experiments in Chapter 7

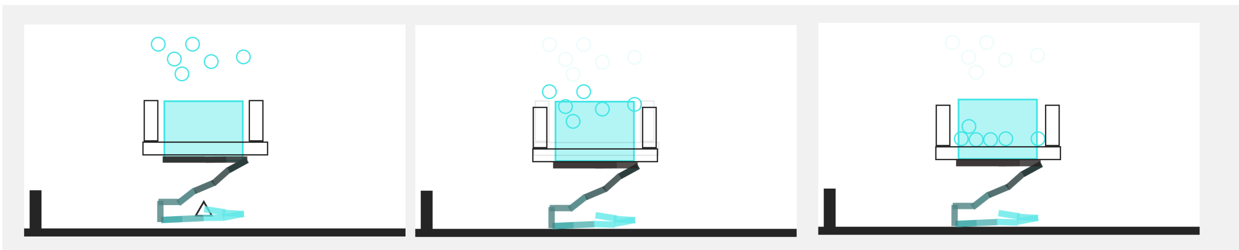

Figure A.11 Sequence of Stand 1 (S1) scenario from experiments in Chapter 7

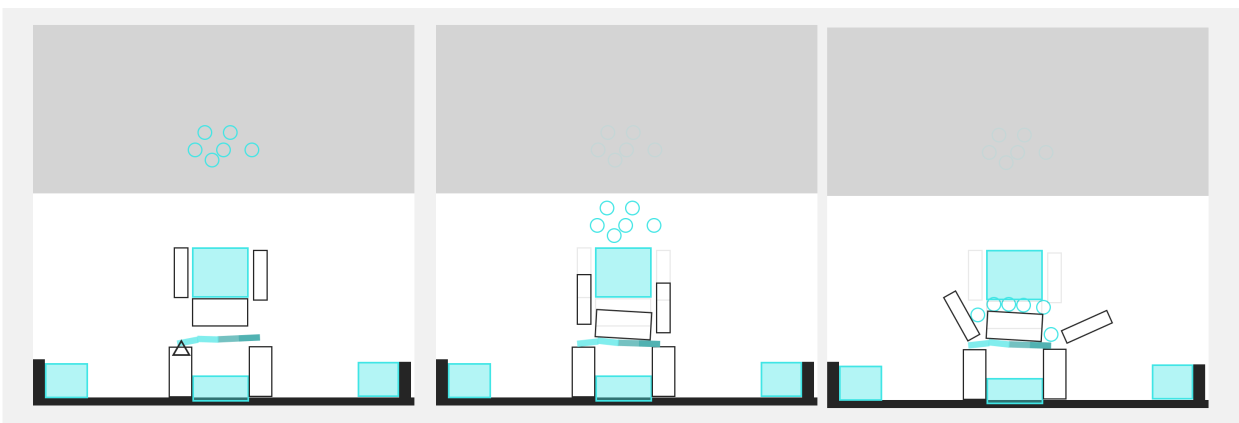

Figure A.12 Sequence of Stand 2 (S2) scenario from experiments in Chapter 7

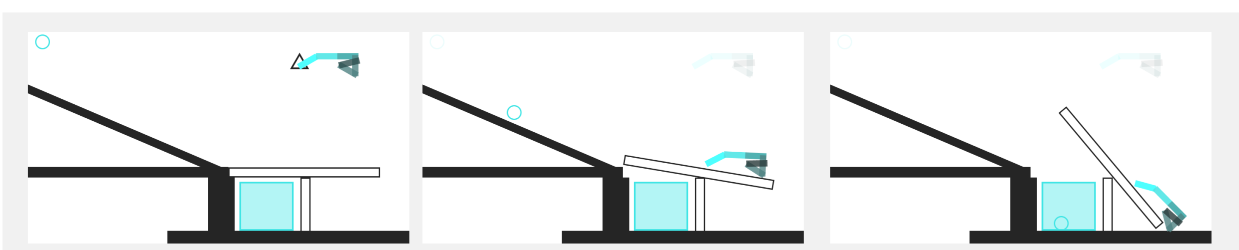

Figure A.13 Sequence of Unbox 1 (U1) scenario from experiments in Chapter 7

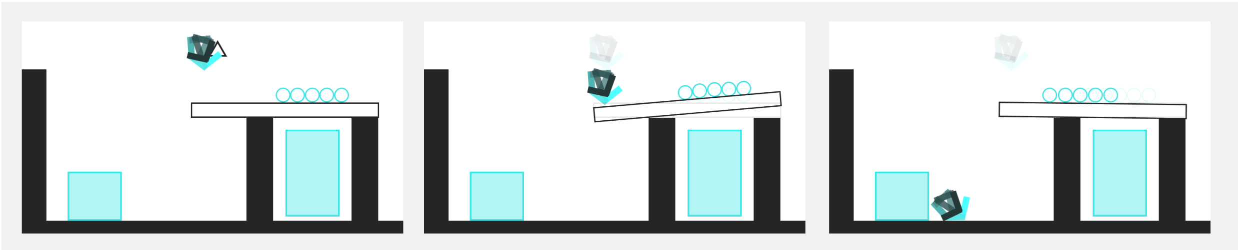

Figure A.14 Sequence of Unbox (U2) scenario from experiments in Chapter 7