TOWARDS DESIGNING ENGAGING AND ETHICAL HUMAN-CENTERED AI PARTNERS FOR HUMAN-AI CO-CREATIVITY

by

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ABSTRACT

JEBA REZWANA. Towards Designing Engaging and Ethical Human-Centered AI Partners for Human-AI Co-Creativity. (Under the direction of DR. MARY LOU MAHER)

Human-AI co-creativity involves a human and an AI collaborating as partners on creative tasks such as generating music or art. This research domain is particularly timely as AI becomes increasingly prevalent in collaborative spaces. With the availability of ChatGPT, DALL.E 2 and other generative AI tools, co-creative AI is gaining popularity. Unlike general human-computer interaction, human-AI co-creation establishes a complex relationship where AI actively contributes, assumes human-like roles, and generates novel content blended with the user's contribution. Therefore, designing engaging and ethical co-creative systems poses challenges due to the open-ended nature of human-AI interaction. This dissertation contributes empirically and theoretically to the design of engaging and ethical human-centered co-creative AI. It focuses on four main areas: designing interaction, the impact of AI-to-human communication, ethical guidelines and understanding users' mental models of co-creative AI in human-AI co-creation. Firstly, this dissertation introduces the Co-Creative Framework for Interaction Design (COFI), which describes the broad range of possibilities for designing interactions in co-creative AI. Additionally, an analysis of 92 existing co-creative AI systems identifies common interaction design trends and research gaps. The analysis reveals a notable gap in commonly employed interaction designs: the absence of two-way communication between humans and AI, where AI cannot communicate with humans, limiting their potential as partners. Inspired by the research gap identified, this dissertation delves into examining the impact of AI-to-human communication on user experience and perception of co-creative AI. Two prototypes of a co-creative system, with and without AI-to-human communication, were developed to facilitate a comparative study. The results show an improved collaborative experience and user engagement with the AI that can communicate. Moreover, the results shed light on emerging ethical concerns alongside increased user engagement. This dissertation further explores the ethical challenges in human-AI co-creation by taking a human-centered approach. A design fiction study is presented to explore several ethical dilemmas and challenges in human-AI co-creation from the perspective of potential users. Findings provide potential users' perspectives, stances, and expectations, serving as a foundation for designing human-centered ethical AI partners in human-AI co-creation. Finally, this dissertation investigates users' mental models of co-creative AI, which is essential to understand designing human-centered co-creative AI. Through a survey study, we delve into users' mental models of co-creative AI and their association with user demographics to identify ways to design value-sensitive co-creative AI. The results obtained also lay the groundwork for future research on personalization in the realm of human-AI co-creation. The findings and frameworks presented lay the groundwork for future advancements in the field of human-AI co-creativity.

DEDICATION

This dissertation is dedicated to my parents, whose unwavering belief in my abilities and their tireless efforts to provide me with the best possible opportunities have been instrumental in my journey. My parents' dream was to see one of their children achieve a doctoral degree. I am grateful for their support and I know they take immense pride in my accomplishment of earning this degree.

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I want to express my sincere appreciation to my husband, Sajid. He stood by me throughout my PhD journey, even as he navigated his own challenges in his PhD pursuit. His support has been the bedrock of my success, and I couldn't have done this without him. I am also deeply thankful to my parents for their constant encouragement and emotional support during the ups and downs of this challenging journey. I am thankful to all my friends who supported me with their positivity and motivation. Lastly, I want to thank my dissertation writing buddies, whose support and shared experiences made a significant difference in completing this monumental task.

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CHAPTER 1: INTRODUCTION

While creativity can take on many forms and definitions, it is commonly defined as the exploration and production of novel and valuable ideas [2, 3, 4]. Creativity is considered a valuable skill and technology can be used to facilitate and enhance human creative capability. Computational creativity is an interdisciplinary field first derived from the field of artificial intelligence that involves computational systems capable of producing ideas and artifacts creatively [5]. Research in computational creativity has led to different types of creative systems that can be categorized based on their purposes: systems that generate novel and valuable creative products, systems that support human creativity, and systems that collaborate with the user on a shared creative product combining the creative ability of both humans and AI [1]. Human-AI co-creativity, a subfield of computational creativity, involves both humans and AI collaborating on a shared creative product as partners [6]. In human-computer co-creativity, both humans and AI agents are viewed as one system through which creativity emerges. The creativity that emerges from collaboration is different from creativity emerging from an individual, as creative collaboration involves interaction among collaborators and the shared creative product is more creative than each individual could achieve alone [7]. Human-AI co-creativity is an important area of study given that AI is being used increasingly in collaborative spaces, including AI in collaborative music [8], collaborative design [9] or even in hospitals as a virtual nurse [10]. With the availability of ChatGPT [11], DALL.E 2 [12], Github Copilot [13] and other generative AI tools, co-creative AI is gaining interest and popularity among the general public. This field has the potential to transform how people perceive and interact with AI. Interaction is a basic and essential part of co-creative systems as both the human and the AI actively participate and interact with each other, unlike autonomous creative systems that generate creative artifacts alone and creativity support tools (CST) that support human creativity [14]. Rather than being perceived as a CST, co-creative AI should be regarded as a collaborative partner in co-creation.

Designing and evaluating co-creative systems has many challenges due to the open-ended and improvisational nature of the interaction between the human and the AI agent [15, 16]. Humans utilize many different creative strategies and reasoning processes throughout the creative process, and ideas and the creative product develop dynamically through time. This continual progression of ideas requires adaptability on the agent's part. Additionally, it is not always clear how the co-creative AI should contribute and interact during the course of the co-creative process. For example, sometimes the human may want to lead and have the AI assist with some tasks, whereas other times the human may want the AI to lead to help find inspiration or to work independently. Understanding the mechanics of co-creation is still very much an open question in the young field of human-computer co-creativity. AI ability alone does not ensure a positive collaborative experience for users with the AI [17] and interaction is more critical than algorithms where interaction with the users is essential [18]. Bown asserted that the success of a creative system's collaborative role should be further investigated as interaction plays a key role in the creative process of co-creative systems [19]. The literature also asserts that user engagement is associated with the way users interact with a system [20]. Kantosalo et al. said that interaction design, specifically interaction modality, should be the ground zero for designing co-creative systems [21]. There is a lack of a holistic framework for interaction design in co-creative systems. A framework for interaction design is necessary to explain and explore the possible interaction spaces and compare and evaluate the interaction design of existing co-creative systems for improving the practice of interaction modeling in co-creative systems. Therefore, as a young and fast-growing field, interaction designs should be explored for designing effective co-creative systems that engage users and provide a better collaborative experience.

Communication is an essential component in any collaboration for the co-regulation between the collaborators and helps the AI agent make decisions in a creative process [22]. Stephen Sonnenburg demonstrated that communication is the driving force of collaborative creativity [23]. Two-way communication between collaborators for providing feedback and sharing important information improves user engagement in human collaboration [24]. AI-to-human communication is an essential aspect of human-computer interaction [25]. However, many existing co-creative AI can not communicate with users directly [26]. For example, Collabdraw [27] is a co-creative sketching environment where users draw with an AI. The user clicks a button to submit their artwork and indicates that their turn is complete. The AI in this system cannot communicate with users to provide information, suggestions, or feedback. While the AI algorithm is capable of providing intriguing contributions to the creative product, the interaction design does not focus on a successful human-AI collaboration. In a human collaboration, collaborators communicate to provide feedback and convey important information to each other along with communicating through the shared product and is a major component of the mechanics of co-creation [28]. The literature shows that being able to converse with each other results in an increased engagement level in a human-human creative collaboration [24]. AI-to-human communication is an essential aspect of human-computer interaction and essential for a co-creative AI to be considered as a partner [25]. Additionally, a user's confidence in an AI agent's ability to perform tasks is improved when imbuing the agent with AI embodiment compared to the agent solely depending on conversation [29]. Hence, it is crucial to examine the effects of enabling AI-to-human communication, fostering two-way communication between humans and AI, on user experience in human-AI co-creativity.

Increased user engagement and perceived reliability accomplished only through interface design may appear to be a good outcome, but it also raises ethical concerns. People's perceptions of AI's trustworthiness and connection with AI have an impact on their decisions and actions. Because AI optimization can evolve quickly and unexpectedly, the challenge of value alignment arises to ensure that AI's goals and behaviors align with human values and goals [30, 31]. Ethically aligned design is a must for human-centered AI solutions that avoid discrimination and maintain fairness and justice [32]. As artificial intelligence advances, so do ethical concerns that may have a negative impact on humans. These concerns grow considerably more complex and critical as AI begins to collaborate with humans [33, 34, 35, 36]. Therefore, it is essential to anticipate ethical issues and address them during all design stages of co-creative AI [33]. Current human-centered AI (HAI) research emphasizes that the next frontier of AI is not just technological but also humanistic and ethical [32]. While research on ethics in the field of human-computer interaction is growing, there remains a research gap regarding ethics in human-AI co-creation [37]. Unlike general human-computer interaction, human-AI co-creation creates a more complex relationship between humans and AI as 1) AI actively contributes and collaborates in the creative process, 2) AI assumes the human-like roles of partner, evaluator, and generator [38, 39], and 3) AI creates novel content blended with the user's contribution. This complex interaction and partnership raise questions that are difficult to answer; for example, who owns the product in a human-AI co-creation? Therefore, we should not assume that research on general AI ethics and human-computer interaction fully transfers to ethical co-creative AI [40]. A research gap has developed that calls for a better understanding of ethical human-AI co-creativity.

Understanding the impact of diverse mental models of co-creative AI on users' ethical stances is crucial, as user perception of AI influences their ethical stances and concerns regarding the ethical challenges in human-AI co-creation [41]. The research findings underscore the significance of users possessing accurate mental models of co-creative AI, enabling them to be aware of the ethical issues and risks associated with them. A mental model refers to the internal representation that an individual possesses regarding the functioning of something, which is shaped by their real-world experiences. Mental models enable individuals to predict system behavior and act accordingly [42]. Mental models are subjective and based on an individual's beliefs, values and experiences [43]. Another terminology, conceptual model, sometimes has been used interchangeably for the mental model, yet they are quite different. A conceptual model refers to the expert's representation of a system [43]. When the conceptual model of a designer and a user's mental model does not align, it can lead to confusion and errors when using the system. Therefore, understanding users' mental models is crucial to developing effective systems [44, 43]. Llano et al. [45] asserted that equipping co-creative AI with users' mental models not only enables better coordination but also provides a valuable resource for co-creative AI to explain and justify their contributions. To harness the full benefits of co-creative AI, it is crucial to understand how users actually perceive these AI systems and how their mental models may vary across different demographics [46]. However, the existing literature on users' mental models of co-creative AI is notably scarce, leaving several important questions unanswered. By gaining insights into users' mental models, developers and designers can ensure that the AI systems align with users' needs, preferences, and ethical considerations. It allows for the identification of potential gaps, misconceptions, or concerns that users may have, enabling the development of human-centered co-creative AI.

This dissertation makes significant contributions to the development of human-centered, engaging, and ethical co-creative AI by addressing various aspects of human-AI co-creativity driven by the aforementioned motivations.

1.1 Thesis Statement

Interaction Design is an essential component along with AI ability for designing engaging co-creative systems. An Interaction Design that includes AI-to-human communication, facilitating two-way communication between humans and AI, improves user engagement, collaborative experience and user perception of co-creative AI. Ethical issues should be checked when imbuing a co-creative AI with human-like communication abilities, such as the ability to converse and a virtual body. Gaining insights into users' mental models of co-creative AI and exploring their association with user demographics is crucial in developing human-centered, value-sensitive co-creative AI.

1.2 Research Overview

The focus of this thesis is to investigate different aspects of human-AI co-creation to advance the research in developing engaging, ethical and effective co-creative AI. This research addresses this thesis statement by contributing to the following research questions:

- RQ1 - What are the *components of interaction* to consider when designing interaction in co-creative AI?
- RQ2 - How does AI-to-human communication affect the *collaborative experience*, *user engagement*, and *user perception of co-creative AI* in human-AI co-creativity?
- RQ3 - What are the *user perspectives and stances* around ethical dilemmas in human-AI co-creativity?
- RQ4 - What are the constructs of the *conceptual models* of co-creative AI?
- RQ5 - Is there an association between users' *mental models* of AI, *user demographics* and their *ethical stances* in human-AI co-creativity?

We investigate these research questions through a variety of research methods that provide guidelines for designing human-centered engaging and effective co-creative AI. This dissertation contributes empirically and theoretically to the design of engaging and ethical human-centered co-creative AI. It focuses on four main areas: designing interaction, the impact of AI-to-human communication, ethical guidelines and understanding users' mental models of co-creative AI in human-AI co-creation.

Firstly, this dissertation introduces the Co-Creative Framework for Interaction Design (COFI), which describes the broad range of possibilities for designing and interpreting interactions in co-creative AI. Additionally, it provides an analysis of 92 existing co-creative AI systems identifying common interaction design trends and research gaps. The analysis reveals a notable gap in commonly employed interaction designs: the absence of two-way communication between humans and AI, where co-creative AI cannot communicate with humans, limiting their potential as partners.

Inspired by the research gap identified, this dissertation delves into examining the impact of AI-to-human communication on user experience and perception of co-creative AI. Two prototypes of a co-creative system, with and without AI-to-human communication, were developed to facilitate a comparative study. The results show an improved collaborative experience and user engagement with the AI that can communicate. Additionally, the results shed light on emerging ethical concerns alongside increased user engagement.

Next, this dissertation explores ethical challenges in human-AI co-creation in a human-centered way. A user study is presented to explore several ethical dilemmas and challenges in human-AI co-creation from the perspective of potential users using a design fiction (DF) methodology, a speculative research method. Findings provide potential users' perspectives, stances, and expectations, serving as a foundation for designing human-centered ethical AI partners in human-AI co-creation.

Finally, this dissertation investigates users' mental models of co-creative AI, which is essential to understand designing human-centered co-creative AI. Through a survey study, we delve into users' mental models of co-creative AI and their association with user demographics to identify ways to design value-sensitive co-creative AI. The results obtained also lay the groundwork for future research on personalization in the realm of human-AI co-creation.

1.3 Contributions

In summary, the contributions of this research include:

- Developing the Co-Creative Framework for Interaction Design (COFI) for modeling, interpreting and evaluating interaction designs in human-AI co-creativity.
- Identifying trends and gaps in common interaction designs by analyzing 92 co-creative systems' interaction designs.
- Demonstrating that including AI-to-human communication improves the collaborative experience and user engagement compared to one-way human-to-AI communication in co-creative systems.
- Determining user perceptions of a co-creative AI with and without AI-to-human communication, highlighting the distinctions such as AI as a partner vs. tool.
- Identifying user perspectives and stances towards several ethical challenges in human-AI co-creation for developing human-centered ethical guidelines.
- Presenting a framework for the constructs of conceptual and mental models of co-creative AI.
- Identifying associations between mental models of co-creative AI, different user demographics and their ethical stances.

1.4 Thesis Structure

The structure of this proposal is as follows: Chapter 2 provides an overview of the background of co-creative systems, interaction design in designing effective co-creative systems, ethical challenges in human-AI co-creativity and mental models of AI. Chapter 3 describes the Co-Creative Framework for Interaction Design (COFI), which describes the possible scopes of interaction design in co-creative systems. This chapter also demonstrates an analysis of interaction designs of 92 existing co-creative systems using COFI to identify trends and research gaps in commonly used interaction designs. Chapter 4 presents a co-creative system, Creative Penpal, for investigating the impact of AI-to-human communication on user experience and user perception of AI. This chapter also presents a comparative study to investigate the impact of AI-to-human communication on user experience and the findings. Chapter 5 presents a design fiction serving as a prototype of a futuristic co-creative AI, which provokes readers to ponder over several ethical dilemmas. It also presents a qualitative study to investigate users' perspectives and stances around ethical challenges in human-AI co-creativity. Chapter 6 introduces the constructs of conceptual and mental models of co-creative AI for investigating users' mental models of co-creative AI. It also presents a study to examine users' mental models of co-creative AI and their association with user demographics and other variables. Chapter 7 presents the general conclusions of this dissertation and future work opportunities.

CHAPTER 2: BACKGROUND

This chapter discusses previous related works in the domain of human-AI co-creativity. It begins by discussing various types of creative systems to establish the foundation and origin of human-AI co-creativity. The chapter then addresses the research gaps in human-AI co-creativity, particularly in the areas of interaction design and communication, highlighting the need for further exploration. It then delves into the concept of creative collaboration among humans and emphasizes the sensemaking of collaboration in shaping interaction design strategies. Additionally, the chapter explores relevant studies on ethical challenges in human-AI co-creativity, user perception of AI, and the background of Design Fiction. Finally, a comprehensive background on mental models theory and mental models of AI is provided.

2.1 Human-AI Co-Creativity

2.1.1 Creative Systems

Creativity is defined as the production of novel and useful ideas [2, 3, 4]. Computational creativity is a field that aims to produce computational systems that can create valuable and novel artifacts. This field discusses intelligent systems that can produce something creative, support the creativity of humans, or collaborate in the creative process. These intelligent systems are considered creative systems in the literature. Wiggins defined creative systems as "A collection of processes, natural or automatic, which are capable of achieving or simulating behavior which in humans would be deemed creative [47]."

Different creative systems have different working methods; some systems work as stand-alone systems, some systems co-create with humans while other systems support human creativity. Davis et al. discussed the three main categories of computational creativity systems [1]: standalone generative systems, creativity support tools, and co-creative systems (Figure 2.1). These three categories are derived from their working process and their purposes. Standalone generative systems refer to fully autonomous intelligent systems that work alone and independently, meaning that they do not interact with humans in the creative process. Creative systems that support the user's creativity are considered creativity support tools (CST). CSTs typically extend or augment the creativity of humans. In co-creative systems, the human and the computer both actively participate in creative collaboration as colleagues.

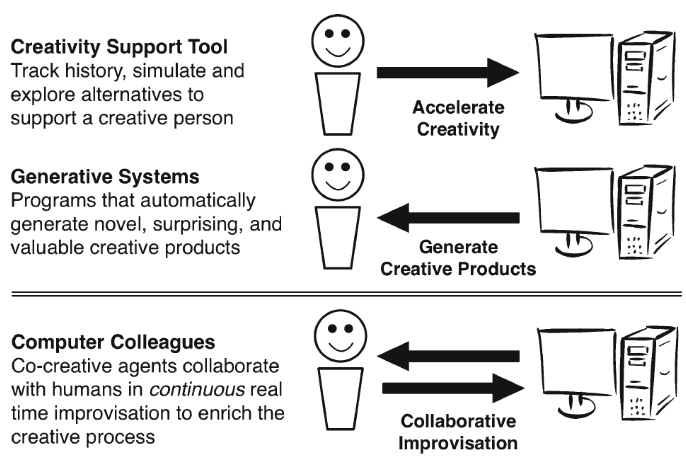


Figure 2.1: Categories of creative systems. Reproduced with permission from Davis et al., 2015 [1].

2.1.2 Co-Creative AI Systems

In 2013, Davis proposed human-computer co-creativity as a way of enabling computers to contribute as creative colleagues in the creative process [6]. Co-creative systems originated from the concept of combining standalone generative systems with creativity support tools obtaining both the generation power of the system and the support (Figure 2.2). In generative systems, only computers take the initiative in the creative process, and in creativity support tools, humans take the initiative in the creative process. In co-creative systems, computers and humans both take the initiative in the creative process and interact as co-creators.

Mixed initiative systems are similar to co-creative systems, and they are often used as a substitute term for co-creative systems. Yannakakis et al. defined mixed-initiative co-creation as "The task of creating artifacts via the interaction of a human initiative and a computational initiative" and discussed the strong links between mixed-initiative co-creation and theories of human and computer co-creativity [48]. Co-creative systems are mixed initiative, but not all mixed-initiative systems are co-creative systems. Mixed initiative systems are a broader category including co-creative systems as well as systems that do not focus on creativity.

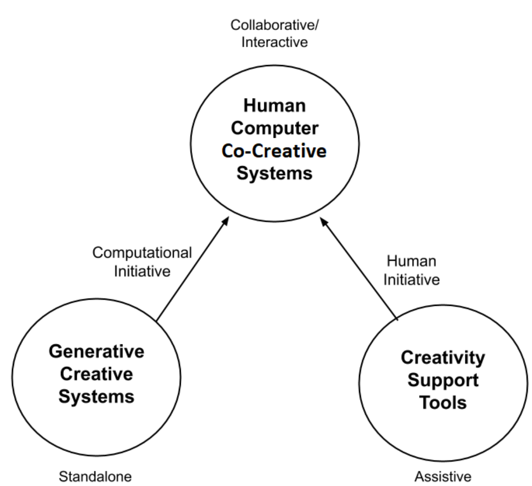


Figure 2.2: Origin of co-creative systems

In a co-creative system, contributions from the human and AI agent to the shared artifact and interaction between them make the creative process complex and emergent. Maher explores issues related to *who* is being creative when humans and AI collaborate in a co-creative system [49]. Antonios Liapis et al. argued that when creativity emerges from human-computer interaction, it cannot be credited either to the human or to the computer alone and surpasses both contributors' original intentions as unexpected, novel ideas arise in the process [50]. Designing interaction in co-creative systems has unique challenges due to the spontaneity of the interaction between the human and the system [15, 16]. The progression of emergent ideas and spontaneous strategies and techniques utilized by humans makes the process of designing a co-creative agent difficult. A co-creative agent needs continual adjustment and adaptation to cope with human strategies. In addition, it is sometimes quite perplexing to decide what an agent should do in a given context in the co-creative process. A good starting point to investigate questions about modeling an effective interaction design for co-creative systems can be studying collaboration and co-creativity in humans [1]. Mamykina et al. argued that by understanding the factors of human collaborative creativity, methods could be devised to build the foundation for the development of computer-based systems that can augment or enhance collaborative creativity in humans [51].

2.2 Interaction Design

2.2.1 Interaction Design in Co-creative Systems

Regarding interaction design in interactive artifacts, Fallman stated: "Interaction design takes a holistic view of the relationship between designed artifacts, those that are exposed to these artifacts, and the socio-cultural context in which the meeting takes place [52]." In the field of co-creativity, interaction design includes various parts and pieces of the interaction dynamics between the human and the AI, for example - participation style, communication, roles, mimicry etc. Now the question is how researchers and designers can explore the possible spaces of interaction design. For instance, turn-taking is the ability of agents to lead or follow in the process of interaction. While designing a co-creative system, should the designer consider turn-taking or a concurrent participation style? Turn-taking models work well in many co-creative systems but may not fit well for all co-creative systems. Lauren and Magerko investigated whether the user experience is improved with a turn-taking model applied to Lumin AI, a co-creative dance partner, through an empirical study [53]. However, their results showed a negative user experience with a turn-taking model compared to a non-turn-taking model. The negative user experience resulted from the dislike for the leading AI agent.

Bown argued that the most practiced form of evaluating artificial creative systems is mostly theoretical and is not empirically well-grounded and suggested interaction design as a way to ground empirical evaluations of computational creativity [54]. Yee-King and d'Inverno also argued for a stronger focus on the user experiences of creative systems, suggesting a need for further integration of interaction design practice into co-creativity research [55]. There is a lack of a holistic framework for interaction design in co-creative systems. A framework for interaction design is necessary to explain and explore the possible interaction spaces and compare and evaluate the interaction design of existing co-creative systems for improving the practice of interaction modeling in co-creative systems.

There are some recent works regarding interaction design in co-creative systems. Kantosalo et al. proposed a framework to describe three aspects of interaction, interaction modalities, interaction style and interaction strategies, in co-creative systems [21]. They analyzed nine co-creative systems with their framework to compare different systems' creativity approaches even if they are within the same creative domain [21]. Bown and Brown identified three interaction strategies - operation-based interaction, request-based interaction and ambient interaction in metacreation, the automation of creative tasks with machines [56]. Bown et al. explored the role of dialogue between the human and the user in co-creation and argued that both linguistic and non-linguistic dialogues of concepts and artifacts are essential to maintain the quality of co-creation [22]. Guzdial and Riedl proposed an interaction framework for turn-based co-creative AI agents to better understand the space of possible designs of co-creative systems [57]. However, their framework is only for turn-based co-creative agents and it only looks at contributions and turn-taking.

2.2.2 Communication in Human-AI Co-creation

Communication is an essential component in any collaboration for the co-regulation between the collaborators and helps the AI agent make decisions in a creative process [22]. A significant challenge in human-AI collaboration is the development of common ground for communication between humans and machines [58]. Previous work shows that two-way communication between collaborators is essential in computer-mediated communication [25]. AI-to-human communication represents the channels through which AI can communicate with humans, and this is essential in a human-AI co-creative system [59]. AI-to-human communication is an essential aspect of human-computer interaction [25]. In a co-creative setting, the modalities for AI-initiated communication can include text, voice, visuals (icons, image, animation), haptic and embodied communication [60]. Bente et al. reported that AI-to-human communication improved both social presence and interpersonal trust in remote collaboration settings with a high level of nonverbal activity [61]. However, recent research has revealed that the majority of existing co-creative systems do not include AI-to-human communication, although it is critical in a human-AI collaboration for the AI to be considered as a partner rather than a tool [26]. Many co-creative systems include only human-to-AI communication through UI components like buttons/sliders, and the AI does not directly communicate to the human user [26]. For example, Image to Image [62] is a co-creative system that converts a line drawing of a particular object from the user into a photo-realistic image: the user interface has a single button that users use to instruct the AI to convert the drawing. However, the AI cannot directly communicate with the user.

Chatting with each other or using other types of communication channels increases engagement in a creative collaboration among humans [24]. Research shows that the way users talk in a human-AI conversation is similar to human-human conversation [63]. Bown et al. explored the role of dialogue between the human and the user in co-creation and argued that both linguistic and non-linguistic dialogues of concepts and artifacts maintain the quality of co-creation [22]. A recent study showed increased user satisfaction with text-based instructions rather than button-based instructions from the AI in a co-creation [64]. A user's confidence in an AI agent is improved when imbuing the agent with embodied communication and social behaviors compared to a disembodied agent using conversation alone [29]. Additionally, the literature asserts that visual communication through embodiment aids synchronization and coordination in improvisational human-AI co-creation [65].

Researchers have investigated user perceptions of AI in different domains [66, 67, 68], since the social perception of one's partner in a collaborative space can impact the outcome of the collaboration. The perceived interactivity, or lack thereof, of systems can have an impact on user perceptions of the system [68] as most existing co-creative systems use one-way communication. We build on the related research and the research gaps in existing co-creative systems' interaction designs to investigate the influence of two-way communication, including AI-to-human communication.

2.3 Human Collaboration as the Basis of Interaction Design

2.3.1 Creative Collaboration among Humans

Sawyer asserted that the creativity that emerges from collaboration is different from the creativity emerging from an individual where interaction among the group is a vital component of creativity [7]. He investigated the process of creativity when emerging from a group by observing and analyzing improvisational theater performances by a theater group [7] and argued that the shared product of collaborative creativity is more creative than each individual alone could achieve.

Stephen Sonnenburg introduced a theoretical model for creative collaboration, and this model presents communication among the group as the driving force of collaborative creativity [23]. Interaction among the individuals in collaboration makes the process emergent and complex. For investigating human collaboration, many researchers stressed the importance of understanding the process of interaction. For example, Sawyer characterized the process of interactional creativity in an improvisational collaboration [69]. He presented the interaction in an open-ended improvisational creative collaboration as a continual process where a performer is constrained by the collectively created emergent circumstance and initiates an interaction with some creative deduction. Through their responses in subsequent actions, participants collectively determine the extent to which the current action enters the emergent circumstance; the new emergent circumstance then similarly constrains the subsequent performers.

Fantasia et al. proposed an embodied approach of cooperation that considers cooperation as a property and intrinsic part of interaction processes [70]. They claimed that interactional dynamics help in understanding and fostering our knowledge of different ways of engaging with others. They argued that to gain more knowledge and understand more about collaboration, it is crucial to investigate interaction and take into account the context, the environment and how collaborators make sense of the whole process.

Computer supported cooperative work (CSCW) is a computer assisted coordinated activity carried out by a group of collaborating individuals [71]. K Schmidt defined CSCW as an endeavor to understand the nature and characteristics of collaborative work to design adequate computer-based technologies [72]. Therefore, the foundation of CSCW focuses on sensemaking and understanding the nature of collaborative work for designing adequate computer-based technology to support human collaboration. CSCW systems are designed to improve group communication while alleviating negative interactions that reduce collaboration quality [73]. For building effective CSCW systems for collaborative creative work, many CSCW researchers investigated creative collaboration among humans to understand the mechanics of collaboration. For this reason, the CSCW literature can also help in understanding computer-aided creative collaboration among humans and building effective co-creative systems.

2.3.2 Sensemaking in Collaboration

While designing a co-creative agent, the cognitive science theory of enaction can be helpful due to its emphasis on the role of interaction in the formation of meaning and cognition in general [1]. Enaction highlights how cognitive agents build meaning through interacting with their environment by detecting patterns of regularities through those interactions in a process referred to as sense-making [74]. Davis argued that participatory sensemaking, a conceptual framework of the enaction theory, is useful to analyze, understand and model creative collaboration [1]. Jaegher and Paolo also proposed participatory sensemaking as a starting point for understanding social interaction [75].

To understand participatory sensemaking, the definition of sensemaking from the cognitive theory is crucial. Sense-making is the way cognitive agents meaningfully connect with their world, based on their needs and goals as self-organizing, self-maintaining, embodied agents [74]. Introducing multiple agents in the environment makes the dynamics of sensemaking more complex and emergent as each agent is interacting with the environment as well as with each other. Participatory sensemaking evolves from the sensemaking of this complex, mutually interactive process [1]. Participatory sensemaking occurs where - "A co-regulated coupling exists between at least two autonomous agents where the regulation itself is aimed at the aspects of the coupling itself so that the domain of relational dynamics constitutes an emergent autonomous organization without destroying the autonomy of the agents involved [75]."

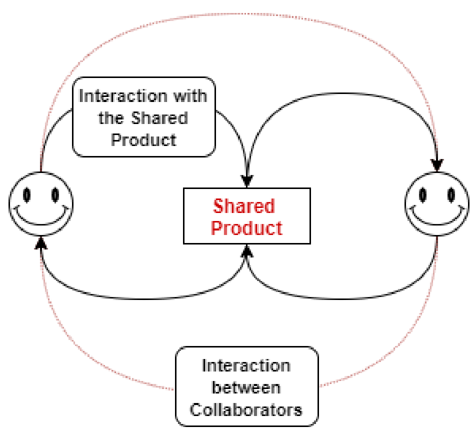


Figure 2.3: Interactional sensemaking in co-creation.

The above quote from Jaegher and Paolo outlines the process of participatory sensemaking where meaning-making of relational interaction dynamics such as the rhythm of turn-taking, manner of action, interaction style, etc is necessary [15]. In an attempt to understand interaction dynamics in an open-ended improvisational collaboration, such as collaborative storytelling or drawing, Kellas and Trees discussed interactional sensemaking [76]. They discussed two types of interaction in the sensemaking process: interaction between collaborators and interaction with the shared product (Figure 2.3). Interaction with the shared product, in the context of a co-creative system, describes interaction aspects related to the content created by a co-creator in each turn. Interaction between collaborators explains how the interaction between the co-creators is unfolding through time which includes turn-taking, roles, timing of initiative, communication etc. Participatory sense-making occurs when there is a mutual co-regulation of these two interactional sense-making processes between the co-creators. For example, when both participants are adapting their responses based on each other's contribution and working to maintain an engaging interaction dynamic, participatory sense-making occurs.

2.4 Ethical Aspects of Human-AI Co-Creativity

2.4.1 Ethical Dilemmas in Human-AI Co-Creativity

Siau and Wang suggested that understanding AI ethics helps establish a framework for building ethical AI and defined AI ethics as the moral principles and duties of developing AI to function ethically with humans in society [77]. Due to previous apathy toward AI ethics, there has recently been a rapid increase in the production of research centered on AI ethics [35, 36, 40]. While research on ethics in the field of human-computer interaction is growing, there remains a research gap regarding ethics in human-AI co-creation [37]. The role of co-creative AI changes from a lone decision-maker to a more complex one depending on the collaboration. As artificial intelligence advances, so do ethical concerns that may have a negative impact on humans. These concerns grow considerably more complex and critical as AI begins to collaborate with humans [33, 35, 36]. When AI is incorporated into personas that present as social entities and interact with us, questions of values and ethics become even more urgent and complex [34]. Llano and McCormack suggested a common understanding of the ethical challenges in human-AI co-creative systems to devise ethical guidelines for co-creative AI [78]. Because AI optimization can evolve quickly and unexpectedly, the challenge of value alignment arises to ensure that AI's goals and behaviors align with human values [30, 31]. Ethically aligned design is essential for human-centered AI solutions that maintain fairness and justice [32]. Comprehensive and specific ethical principles based on empirical data are more likely to be translated into practice [79, 80].

Recent ethical guidelines for AI lack a focus on what they entail in the context of human-AI creative collaboration, which raises more complex ethical concerns [78]. For example, Muller et al. raised questions about the moral dilemma of ownership of the intellectual property produced during human-AI co-creation, which differs from situations where a standalone AI generates creative artifacts [81, 82]. Gero and Chilton discussed the issue of ownership in human-AI co-creation as some participants felt less ownership over the final co-created product while working with a co-creative system [83]. Additionally, there has been discussion about whether humans or AI should lead the creative process in a human-AI co-creation [64, 26] and if AI should assist or collaborate with users [82]. Buschek et al. demonstrated that accountability is one of the major pitfalls when designing co-creative systems [84]. A recent study demonstrated that users perceive co-creative AI as more reliable, personal and intelligent when it can communicate with the users [85]. The communication between AI and humans impacts users' inclination to self-disclose unintentional data [86, 87]. Additionally, the persona of a conversational co-creative AI can also inadvertently reinforce harmful stereotypes [86]. The development of our Design Fiction is informed by these ethical issues.

2.4.2 User Perception and Concerns of AI

Humans have many fears about the unknown world of technology and AI. What is unknown is uncertain, and this uncertainty leads to insecurity. One study on the role of AI in society focuses on citizens' perspectives on the influence of AI with 2000 participants from 20 different countries [88]. On average, 53% of the population views AI as a positive development, while 33% see it as a harmful development [88]. The perception of AI is influenced by a number of key factors, including trust [89]. *Algorithmic appreciation* is a phenomenon that can occur when algorithmic systems are trusted more than human experts, according to Logg et al. [90]. They discovered that even when a system's mechanisms are not transparent, individuals still prefer AI advice over human advice [90]. Additionally, this impact is evident even when the advice is given by human experts rather than merely ordinary people, according to Thurman et al. [91]. Despite the concerns about the potential negative effects of AI, people nevertheless believe that AI is equivalent or even superior to human specialists in certain fields [92].

But how can these negative feelings of people be changed? Boni suggested that AI development should focus on human values and needs, ensuring that AI works effectively for people [93]. Previous research suggested that understanding different values and goals of users and specific contexts is critical in bridging the gap between ethical theories and implementation [79]. Studies show that laypeople are especially good at contextualizing macro impacts on their individual lives [94]. It is important to know as much as possible about the impact of AI on human psychology and behavior to raise AI awareness. Research on ethical interactions between humans and AI can improve the collaborative competencies of humans in relation to other humans and user experience [93]. Our study contributes to this ongoing discussion with a focus on the end user's perspectives in a human-AI co-creative scenario.

2.4.3 Design Fiction for Investigating Ethical Dilemmas

In HCI research, prototyping is an essential tool [95, 96] that enables researchers to engage with concepts before they're put into full production. Design Fiction (DF) is a prototyping technique that is specifically tailored to facilitating conversations about near futures [97] to understand the appropriate design guidelines within the range of possibilities [98]. Design Fiction is a term that Bruce Sterling coined in Shaping Things [99] where he describes DF as the "deliberate use of diegetic prototypes to suspend disbelief about change." A design fiction depicts a future technology through the world of stories, and users express their own accounts of the technologies they envision, as well as the values that those future technologies implicate [33]. DF has been used to reveal values associated with new technologies [100, 101, 102] and to open a space for diverse speculations about future technologies [103]. Design Fiction belongs to a larger category of speculative design techniques [104]. All prototypes aim to uncover previously unknown insights about a concept or idea [105]. However, speculative approaches to design and prototyping acknowledge and accept the plurality of the future. In the literature, multiple methods have been offered to practice DF as a research methodology [106, 107].

Muller and Liao proposed DF to restore future users to a central position in anticipating, designing, and evaluating future AI [33]. They proposed this method to reflect the interests and values of future users by working with them to design value-sensitive ethical AI. The literature claims that everyone is creative and the expert of their own experience [108, 109]. The Design Fiction method gives voice to those who are otherwise not normally included in a design process and pushes the idea that those who are most impacted by technological futures should be part of crafting those outcomes [110]. Nagele et al. presented a study with a design fiction using storyboards and simple narratives to include vulnerable users of medical technologies in the process of value-sensitive designs of such technologies [110]. Popular science fiction in the form of narratives, movies, videos, text, etc., raise concerns about autonomous AI and robots. However, we rarely witness fiction in the form of movies or narratives regarding ethical dilemmas emerging from a co-creative AI that directly collaborates with humans and generates new data. In recent work, Muller et al. present a design fiction regarding a co-creative AI in the domain of software engineering where the user and the AI engage in collaborative programming [81]. In Chapter 5, we present the design fiction we used in our study to provoke and focus on ethical issues in human-AI co-creativity.

2.5 Mental Models

2.5.1 Mental Model Theory

The term mental model was coined by Johnson-Laird [42]. Mental models are cognitive constructs developed through real-world experiences that allow humans to understand how a system functions [111]. These models allow people to understand, explain and predict phenomena and then act accordingly [42]. Mental models are particularly useful for predicting system behavior [112]. Therefore, users with well-developed mental models should be able to produce more accurate results when interacting with a system. Experts mental models differ from those of novices [111, 113, 114]. Mental models can vary in their richness based on expertise and other variables, such as an IT professional having (ideally) a much richer and more abstract mental model of how a computer works [115, 116]. Mental models are related to user learning and performance

[117, 118]. Having a good mental model of how a system works is vital for its usability [45]. Staggers and Norcio [117] asserted that designers and researchers must be aware of users' mental models. Transparent and explainable systems help users build accurate mental models [119].

Norman [43] identifies several attributes of mental models. According to him, mental models are incomplete, limited, and subject to instability as individuals may forget or discard certain details. They are also considered unscientific since they reflect people's personal beliefs about the represented system. Additionally, mental models tend to be parsimonious, meaning that individuals often opt for simpler mental representations even if they require more physical effort. These models are subjective and prioritize usefulness over accuracy. Once established, mental models can be resistant to change, even in the face of contradictory evidence [120].

So what does a mental model include? The contents of mental models can be concepts, relationships between concepts or events and associated procedures [115]. For instance, a simplified mental model of how a computer functions may involve the belief that it merely displays everything typed on the keyboard and stores this information somewhere within its physical casing. Collins and Gentner [121] assert that analogies and metaphors enable people to construct a mental model. Humans construct mental models by drawing on analogies or metaphors of past represented objects or interactions [117]. Young 1983 proposes eight types of mental models, including analogy as a form of mental model [122].

In the field of design, Norman [43] considers four key components when examining mental models of a system: the target system, representing the actual system utilized by individuals; the conceptual model of the target system, which is purposefully constructed to provide an accurate depiction of the target system and typically developed systematically by experts; the mental model of the target system, which users develop through their interactions with it; and lastly, the scientist's conceptualization of the mental model, which is essentially a model derived from the user's mental model itself. Conceptual models are precise and complete representations that are coherent with scientifically accepted knowledge [123, 43]. These external representations can materialize as mathematical formulations, analogies, or as material artifacts. Human mental models are black boxes and will never be completely transparent [111]. Therefore, a solid conceptualization of a system is necessary before we can understand an individual's mental model of that system [43]. Gero et al. [44] argued that a precise description of the neural network architecture and training procedure does not represent an appropriate conceptual model. Conceptual models are simplified representations of the target system [124]. An analogy between Rutherfords atom and the solar systems is an example of conceptual models. Norman [43] said we must distinguish between researchers' conceptualization of a mental model and the actual mental model held by an individual. Norman [43] uses the word conceptualization to characterize researchers' models of users' mental models.

2.5.2 Mental Models of AI

Various work in HCI has tackled how people model AI systems in their minds, though very few study mental models of co-creative AI, which are becoming increasingly popular. Llano et al. [45] asserted that equipping co-creative AI with users' mental models not only would enable better coordination when trying to come up with something new but would also provide a valuable resource for co-creative AI to explain, justify, and defend their contributions. The idea of mental models as a key aspect of the design of real-time co-creative systems has been highlighted previously [125]. Mental models consider a broad set of aspects of human interactions that would aid the understanding of essential elements within collaboration and of the interactions throughout it. Research showed mental models can be used to produce novel, creative ideas in response to new contexts [126]. To harness the full benefits of co-creative AI, it is crucial to understand how users actually perceive AI systems and how their mental models may vary across different demographics [46]. Literature indicates that the effectiveness of co-creative AI depends on users and their social and cultural influence [127]. Bansal et al. [128] look at the effect of updates to AI technology in human-AI teams, finding that updates that increase AI performance can hurt overall team performance.

There have been a few studies on mental models of AI based on deep neural networks. However, there are a few noteworthy studies in this area. For instance, Tullio [120] investigated how users build mental models of an intelligent agent predicting an office workers availability. Kulesza et al. [115, 129] examined mental models of an intelligent music recommender system, using surveys to quantify participants' mental models and found that a 15-minute tutorial significantly improved the robustness of their mental models. Bansal et al. [130] investigated the impact of different types of AI errors on people's mental models using performance as an indicator of a mental model. Borgman used mental models to investigate the effectiveness of training techniques for an information retrieval system [131]. Additionlly, Muramatsu and Pratt investigated ways to improve users mental models of search queries to correctly use concepts such as logical operator [132].

More than explicit mental models of users, prior research in human-computer interaction (HCI) regarding AI systems has primarily focused on explainability and trust. Previous studies have shown that users may change their mental models of an AI when the agent makes its reasoning transparent [115, 133, 134]. Rutjes et al. [135] argue for capturing a user's mental model for generating AI explanations. Miller [136], in a comprehensive review of social science related to explainable AI, references mental models in the context of reconciling contradictions and creating shared understanding. Yin et al. [137] investigate how the stated and observed accuracy of AI models affect people's trust in the system, finding that the impact of stated accuracy can vary based on observed accuracy. We believe work on explainable and human-centered co-creative AI would benefit from studies on mental models, which is what we do in this dissertation.

CHAPTER 3: MODELING AND ANALYZING INTERACTION DESIGN IN HUMAN-AI CO-CREATIVITY

3.1 Introduction

Interaction design is the creation of a dialogue between users and the system [138]. Interaction is a basic and essential component of co-creative systems as both the human and the AI actively participate and interact in the co-creation, unlike autonomous creative systems that generate creative artifacts alone and creativity support tools that support human creativity. Kantosalo et al. said that interaction design, specifically, interaction modality should be the ground zero for designing co-creative systems [21]. However, the lack of research in interaction design is reflected in many existing co-creative systems' interaction designs. Although their AI algorithmic models are capable of providing intriguing contributions to the creative process, their interaction designs are inadequate for collaboration between humans and AI. There is a lack of a holistic framework for effective interaction design in co-creative systems. A framework for interaction design is necessary to explain and explore the possible interaction spaces and compare and evaluate the interaction design of existing co-creative systems for improving the practice of interaction modeling in co-creative systems. For this research, we investigated the following question:

– RQ1 - What are the components of interaction to consider when designing interaction in human-AI co-creation?

This chapter presents the Co-Creative Framework for Interaction Design (COFI) that describes interaction components as a space of possibilities for interaction design in co-creative systems. We adopted interaction components based on a literature review and adapted the components to concepts relevant to co-creativity. Following the details of COFI, this chapter presents an analysis of the interaction models of a dataset of 92 co-creative systems using COFI to identify the trends and gaps in common interaction designs. Three distinct interaction models for co-creative systems emerged from this analysis: generative pleasing AI agents that follow along with the user, improvisational AI agents that work alongside users on a shared product spontaneously, and advisory AI agents that both generate and evaluate the creative product. The analysis reveals that the co-creative systems in this dataset lack communication channels between the user and AI agent. Finally, this chapter discusses the limitations of the existing interaction models in co-creative systems, potential areas for further development, and the importance of extending the scope of human-AI communication in co-creative systems.

3.2 Co-Creative Framework for Interaction Design (COFI)

We develop and present the Co-Creative Framework for Interaction Design (COFI) as a space of possibilities for interaction design in co-creative systems. COFI also provides a framework for analyzing the interaction design trends of existing co-creative systems. This framework describes various aspects involved in the interaction between humans and AI. COFI is informed by research on human collaboration, CSCW, computational creativity, and human-computer co-creativity.

The primary categories of COFI are based on two types of interactional sense-making of collaboration as described by Kellas and Trees (Figure 3.1) [139]: interaction between collaborators and interaction with the shared product. Interaction with the shared product, in the context of co-creative systems, describes interaction aspects related to the creation of the creative content. Interaction between collaborators explains how the interaction between the human and the AI is unfolding through time which includes turn-taking, timing of initiative, communication, etc. Thus, COFI characterizes relational interaction dynamics between the collaborators (human and AI) as well as functional aspects of interacting with the shared creative product. Kellas and Trees' framework was used for explaining and evaluating the interaction dynamics in human creative collaboration in joint storytelling. Understanding collaborative creativity among humans can be the basis for designing effective co-creative systems where the AI agent acts as a creative partner.

Each of the two categories of interaction is further divided into two subcategories. Interaction between collaborators is divided into collaboration style and communication style. On the other hand, interaction with the shared product is divided into the creative process and the creative product. CSCW literature discusses collaboration mechanics among the collaborators to make effective CSCW systems. Many frameworks about groupware and CSCW systems discuss and emphasize both collaboration components and communication components among collaborators. For example, Baker et al. proposed an evaluation technique based on collaboration mechanics for groupware and emphasized both coordination and communication components in a collaboration [140]. Creativity literature focuses more on creativity emergence, which includes creative processes and the creative product. For example, Rhodes's famous 4P, which is one of the most acknowledged models, includes creative process and product [141]. Therefore, in COFI, the literature regarding human collaboration and CSCW literature informs the category 'interaction between the collaborators', while the creativity and co-creativity literature provides descriptions of the 'interaction with the shared product'. In human-AI co-creativity, the focus should be on both creativity and collaboration. As a result, both the CSCW and creativity literature provide the basis for defining the interaction components of COFI under the four subcategories.

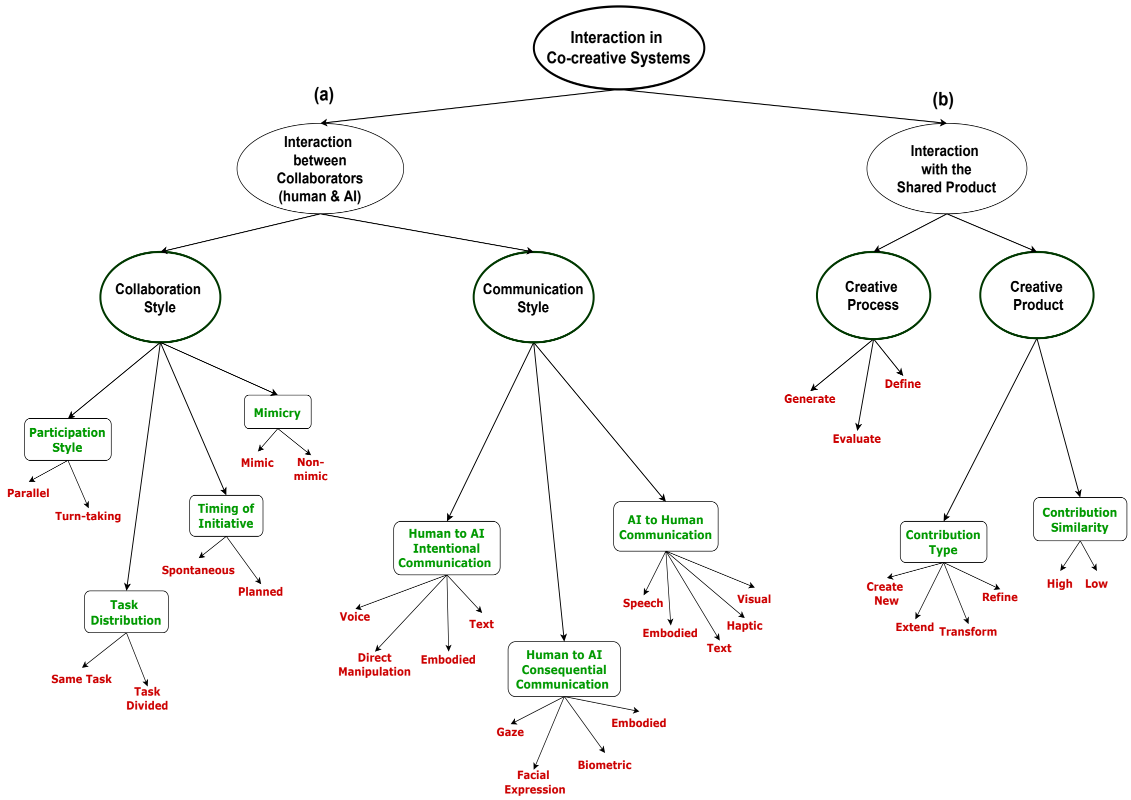


Figure 3.1: Co-Creative Framework for Interaction Design (COFI): On the left (a) Components of interaction between the collaborators, on the right (b) components of interaction with the shared product.

We performed a literature review to identify the components of COFI. We identified a list of search databases for relevant academic publications: ACM Library, arXiv, Elsevier, Springer, and ScienceDirect, and Google Scholar. We used keywords based on the 4 Cs in COFI: Collaboration style, Communication style, Creative process, and Creative product. The total list of keywords includes: 'human collaboration mechanics,' 'creative collaboration among humans,' 'communication in collaboration,' 'cooperation mechanics,' 'interaction in joint action,' 'groupware communication,' 'interaction design in computational creativity,' 'interaction in co-creativity,' 'creative process,' 'group interaction in computational creativity,' 'interaction in human-computer co-creation'. We considered documents published from 1990 until 2021. We did not include papers that are a tutorial or poster, papers that are not in English, papers that by title or abstract are outside the scope of the research, and papers that do not describe the collaboration mechanics or group interaction. We included papers describing strategies, mechanisms and components of interaction in a natural collaboration, computer-mediated collaboration and human-AI collaboration. COFI was developed in an iterative process of adding, merging, and removing components based on the interaction components defined in the literature. We refer to the specific publications that contributed to each component of COFI in the sections below: for each interaction component, the first paragraph defines the component, and the second paragraph references the relevant publications that provided the basis for that component.

3.2.1 Interaction between Collaborators (Human and AI)

This section presents components related to the relational interaction dynamics between humans and AI as co-creators. As shown in Figure 3.1(a), interaction between collaborators is divided into two subcategories which are *collaboration style* and *communication style*.

3.2.1.1 Collaboration Style

Collaboration style is the manner of working together in a co-creation. In COFI, the collaboration style comprises participation style, task distribution, timing of initiative and mimicry as interaction components. The following subsections describe each interaction component in this category.

Participation Style:

Participation style in COFI refers to whether the collaborators can participate and contribute simultaneously, or one collaborator has to wait until the partner finishes a turn. Therefore, participation style in COFI is categorized as parallel and turn-taking. For example, in a human-AI drawing co-creation, collaborators can take turns to contribute to the final drawing or they can draw simultaneously.

Participation style in COFI is based on the categorization of interpersonal interaction into two types: concurrent interaction and turn-based interaction [142]. In concurrent interaction, continuous parallel participation from the collaborators occurs and in turn-based interaction, participants take turns in contributing. In a parallel participation style, both collaborators can contribute and interact simultaneously [143]. In a turn-taking setting, simultaneous contribution can not occur [143]. In CSCW research, there is a concept for interaction referred to as synchronous and asynchronous. Synchronous interaction requires the real-time interaction where the presence of all collaborators is required. Whereas asynchronous cooperation does not require simultaneous interaction of all collaborators [144, 145, 146]. In CSCW, the distinction between synchronous and asynchronous interaction is information exchange in terms of time. In COFI, participation style describes the way collaborators participate when all are present at the same time.

Task Distribution:

Task distribution refers to the distribution of tasks among the collaborators in a co-creative system. In COFI, there are two types of task distribution, same task and task divided. When it is same task, there is no division of tasks between collaborators and all the collaborators take part in the same task. For example, in a human-AI co-creative drawing, both co-creators do the same task, i.e. generating the drawing. In a task-divided distribution, the main task is divided into specific sub-tasks and the sub-tasks are distributed among the collaborators. For example, in co-creative poetry, the user can define the conceptual space for the poetry and generate a poem while the AI agent can evaluate the poetry.

Cahan and Fewell asserted that division of tasks is a key factor in the success of social groups [147]. According to Fischer and Mandl, task division should be addressed for co-ordination in a computer-mediated collaboration [148]. This component of COFI emerged from discussions of the two interaction modes presented by Kantosalo and Toivonen: alternating co-creativity and task-divided co-creativity [38]. In alternating co-creativity, each party contributes to the shared artifact while doing the same task by taking turns. Kantosalo and Toivonen emphasized turn-taking in alternating interaction mode. In COFI, we renamed alternating co-creativity to be same task as we want to emphasize the task distribution. Task divided in COFI is the same term used in Kantosalo and Toivenen [38].

Timing of Initiative:

In a co-creative setting, the timing of collaborators' initiative can be scheduled beforehand, or it can be spontaneous. If the timing of the initiative is planned or fixed in advance, in COFI it will be addressed as planned. If both agents initiate their contribution without any prior plan or fixed rules, it will be addressed as spontaneous. Timing of the initiative should be chosen based on the motivation behind designing a co-creative system. Spontaneous timing is suitable for increased emergent results, whereas planned timing is more suitable for systems where users want inspiration or help in a specific way for a particular aspect of the creative process.

Salvador et al. discussed timing of initiative in their framework for evaluating groupware for supporting collaboration [149]. They defined two types of timing of initiative: spontaneous initiatives, where participants take initiatives spontaneously and pre-planned initiatives, where group interactions are scheduled in advance. Alam et al. divided interaction among groups into planned and impromptu [150]. For COFI, we merged these ways of describing the timing of initiative into spontaneous and planned.

Mimicry:

COFI includes mimicry as a subcategory of collaboration style which is used in co-creative systems as an intentional strategy for collaboration. When mimicry is a strategy for the AI contribution, the co-creative AI mimics the human user.

Drawing Apprentice [151] is a co-creative web-based drawing system that collaborates with users in real-time abstract drawing while mimicking users. The authors demonstrated with their findings that even if the Drawing Apprentice mimics the user in the creative process, the system engages users in the creative process that results in generating novel ideas. An example of a non-mimic co-creative system is Viewpoints AI. Viewpoints AI is a co-creative system where a human can engage in collaborative dance movement as the system reads and interprets the movement for responding with an improvised movement [152].

3.2.1.2 Communication Style

In COFI, communication style refers to the ways humans and AI can communicate. Communication is an essential component in any collaboration for the co-regulation between the collaborators and helps the AI agent make decisions in a creative process [22]. Communication is critical for achieving understanding and coordination between collaborators. A significant challenge in human-AI collaboration is the development of common ground for communication between humans and machines [58]. Collaborators communicate in different ways in a co-creation, such as communication through the shared product, and communication through different communication channels or modalities. In co-creative systems, collaborators contribute to the shared product through the creative process and sense-making of each others' contributions during the process and act accordingly. Communicating through the shared product is a prerequisite in a co-creation or any collaborative system [56]. Hence, COFI does not include interaction through the shared product under *communication style*. In COFI, *communication style* includes different channels or modalities designed to convey intentional and unintentional information between users and the AI. Human-to-AI communication channels carry information from users to the AI. On the other hand, AI-to-human communication channels carry information from the AI to users.

Human to AI Intentional Communication:

Human-to-AI intentional communication channels represent the possible ways a human agent can intentionally and purposefully communicate with the AI agent to provide feedback and convey important information. In COFI, human-to-AI communication channel includes direct manipulation, voice, text and embodied communication. The human agent can directly manipulate the co-creative system by clicking buttons to give instructions, feedback, or input. It can also provide user preferences by selecting from AI-provided options. Using the whole body or gestures for communicating with the computer will be referred to as embodied. Voice and text can also be used as intentional communication channels from humans to AI.

Gutwin and Greenburg proposed a framework that discusses the mechanics of collaboration for groupware [28]. Their framework includes seven major elements and one of them is explicit or intentional communication. Bard defined intentional communication as the ability to coordinate behavior involving agents [153]. Brink argued that the primary goal of intentional communication is to establish joint attention [154]. In the field of human-computer interaction, the communication channel between humans and computers is described as a modality. The modalities for intentional communication from humans to AI include direct manipulation, embodied/gesture, text, and voice [60].

Human to AI Consequential Communication:

In COFI, human-to-AI consequential communication channels represent the ways the human user unintentionally or unconsciously gives off information to the AI agent. In other words, this channel represents the ways a co-creative AI agent can track and collect unintentional or consequential information from the human user such as eye tracking, facial expression tracking, biometric data tracking and embodied movements. AI agents can track and collect various consequential details from the human to perceive user preference, user agency and engagement. For example, a posture or facial expression can indicate boredom or lack of interest.

Gutwin and Greenburg reported consequential or unintentional communication as a major element of collaboration mechanics, in addition to intentional communication [28]. Collaborators pick up important information that is unintentionally ‘given off’ by others, which is considered as consequential communication in human collaboration. Unintentional communication, such as embodied communication, gaze, biometric measurement and facial expression are consequential communication [28]. Revealing the internal state of an individual is termed ‘Nonverbal leakage’ by Ekman and Freisen [155]. Mutlu et al. argued that in a human-AI interaction, unintentional cues have a significant impact on user experience [156].

AI to Human Communication:

AI-to-human communication represents the channels through which AI can communicate to humans. Humans expect feedback, critique and evaluation of our contribution from collaborators in teamwork. If the AI agent could communicate their status, opinion, critique and feedback for a specific contribution, it would make the co-creation more balanced as the computational agent will be perceived as an intelligent entity and a co-equal creative partner rather than a mere tool. This communication involves intentional information from the AI to humans. Because the interaction abilities of a co-creative AI agent are programmed, all of the communication from the AI is intentional. However, one may ask, can AI do anything unintentional or unconscious beyond the programmed interaction? A co-creative AI can have a body and can make a facial expression of boredom. However, can we call it unintentional or is it also a piece of intentional information designed to be similar to a human’s consequential communication? It can be an interesting question to ask if consequential communication from the AI to the user is even possible to design. Mutlu et al. investigated the impact of ‘nonverbal leakage’ in robots on human collaborators [156], however the leakage was designed intentionally as part of the interaction design.

In a co-creative setting, the modalities for AI-initiated communication can include text, voice, visuals (icons, image, animation), haptic and embodied communication [60]. There are some communication channels that work for both human-to-AI and AI-to-human communication, such as text, voice, and embodied communication. These communication channels are under both categories to identify the possibilities based on the direction of information flow.

3.2.2 Interaction with the Shared Product

Interaction components related to the shared creative product in a co-creative setting are discussed in this section and illustrated in Figure 3.1(b). Interaction with the shared product is divided into two subcategories, creative contribution to the product and creative process.

3.2.2.1 Creative Process

Creative process characterizes the sequence of actions that lead to a novel and creative production [157]. In COFI, there are three types of creative processes that describe the interaction with the shared product: generate, evaluate, and define. A co-creative AI can play the role of a generator, evaluator or definer, depending on the creative process. In the generation creative process, the co-creative AI generates creative ideas or artifacts. For example, a co-creative AI can generate a poem along with the user or produce music with users. Co-creative AI agents evaluate the creative contributions made by the user in a creative evaluation process. An example of creative evaluation will be analyzing and assessing a creative story generated by a user. And in a creative definition process, the AI agent will define the creative concept or explore different creative concepts along with the user. For example, a co-creative agent can define the attributes of a fictional character before a writer starts to write about the character.

The basis of this categorization is the work of Kantosalo et al. that defines the roles of the AI as generator, evaluator, and concept definer [38]. COFI adopts the categorization of Kantosalo et al. as a basis for understanding the range of potential creative processes: The generator generates artifacts in a specific conceptual description, the evaluator evaluates these concepts, and the concept definer defines the conceptual space [38]. In the recent work of Kantosalo and Jordanous, they compared their defined roles with the apprentice framework of Negrete-Yankelevich's and Morales-Zaragoza, where the roles are generator, apprentice and master [39].

3.2.2.2 Creative Product

The creative product is the idea or concept that is being created. Creative product has two interaction components, contribution type and contribution similarity. We identified these specific components as we focused on various aspects of contribution making to the shared product as meaning emerges through the contributions in a collaboration. These components are identified from the literature and discussed in the following subsections.

Contribution Type:

In a co-creation, an individual can contribute in different ways to the shared product. Co-creators can generate new elements for the shared product, extend the existing contribution, and modify or refine the existing contribution. How a co-creator is contributing depends on their interaction with the shared product and their interpretation of the interaction. The primary contribution types according to COFI are: 'create new', 'extend', 'transform' and 'refine'. 'Extend' refers to extending or adding on to a previous contribution made by any of the collaborators. Generating something new or creating new objects is represented by 'create new', whereas 'transform' conveys turning a contribution into something totally different. 'Refine' is evaluating and correcting a contribution with similar type of contribution. For example, in a co-creative drawing, drawing a tree will be considered 'create new'. 'Extend' is when the collaborator adds a branch to the tree or extends the roots of the tree. Turning a tree branch into something else, such as a flower, will be considered a 'transformation', different from 'create new' as it is performed on a previous contribution to turn it into a new object. 'Refine' is when the collaborator polishes the branch of the tree to give more detail.

Contribution types are adopted and adapted from Boden's categories of computational creativity based on different types of contribution: combinatorial, exploratory, and transformational [158]. Combinatorial creativity involves novel (improbable) combinations of similar ideas to existing ideas. We adapted 'extend' and 'refine' from combinatorial creativity as 'extend' is expanding the existing contribution and 'refine' is about correcting or emphasizing the contribution with similar ideas. Exploratory creativity involves the generation of novel ideas by the exploration of defined conceptual spaces and 'creating new' is adapted from this as users use explores the conceptual space when creating something new. Transformational creativity involves the transformation of some dimension of the space so that new structures can be generated, which could not have arisen before and 'transform' is adapted from this.

Contribution Similarity:

In COFI, similarity refers to the degree of similarity or association between a new contribution compared to the contribution of the partner. Near refers to high similarity with the partner's contribution and far means less similarity with the partner's contribution. In this research, AI agents that use 'near' will be referred to as pleasing agents, and agents that use 'far' will be referred to as provoking agents.

Miura and Hida demonstrated that high similarity and low similarity in contributions and ideas among collaborators are both essential for greater gains in creative performance [159]. Both convergent and divergent exploration have their own value in a creative process. Divergent thinking is “thinking that moves away in diverging directions to involve a variety of aspects”, whereas convergent thinking is demarcated as “thinking that brings together information focused on something specific” [160]. Basadur et al. asserted that divergent thinking is related to the ideation phase and convergent thinking is related to the evaluation phase [161]. Kantosalo et al. defined pleasing and provoking AI agents based on how similar their contributions are [38]. A pleasing computational agent follows the human user and complies with human contribution and preference. Provoking computational agents provoke the human by challenging human-provided concepts with divergent ideas and dissimilar contributions.

3.3 Analysis of Interaction Designs in Existing Co-creative AI

3.3.1 Data

We used COFI to analyze a corpus of co-creative systems to demonstrate COFI’s value in describing the interaction designs of co-creative systems. We initiated our corpus of co-creative systems using the archival website called the “Library of Mixed-Initiative Creative Interfaces” (LMICI), which archives many of the existing co-creative systems from the literature [162]. Mixed initiative creative systems are often used as an alternative term for co-creative systems [48]. Angie Spoto and Natalia Oleynik created this archive after a workshop on mixed-initiative creative interfaces led by Deterding et al. in 2017 [163, 162]. The archive provides the corresponding literature and other relevant information for each of the systems. LMICI archive consists of 74 co-creative systems from 1996 to 2017. However, we used 73 systems from the LMICI archive due to the lack of information regarding one system. We added 19 co-creative systems to our dataset to include recent co-creative systems (after 2017). We used the keywords ’co-creativity’ and ’human-AI creative collaboration’ to search for

Table 3.1: List of co-creative systems in the dataset sorted by year

Year	Co-creative Systems
1996	Improv [164]
1999	GeNotator [165]
2000	NEvAr [166]
2001	Metasynth [167]
2003	Facade [168], continuator [169]
2005	LOGTELL [170]
2008	CombinFormation[171], REQUEST [172], miCollage[173], BeatBender [174], WEVVA [175]
2009	Terrain Sketching [176], JNETIC [177], Synthetic Audience [178], The Poetry Machine [179]
2010	SKETCHAWORLD [180], Tanagra [181], Realtime Generation of Harmonic Progressions [182], JamBot [183], Filter Trouve [184], Clap-along [185], EDME [186], LEMu [186],
2011	Shimon [65], Stella [187], Party Quirks [188], Generation of Tracks in a High-end Racing Game [189], ELVIRA [190], Creating Choreography with Interactive Evolutionary Algorithms [191]
2012	Spaceship Generator [192], MaestroGenesis [193], PINTER [194], Co-PoeTryMe [195], A formal Architecture of Shared Mental Models [196], Impro-Visor [197]
2013	Sentient Sketchbook [198], Dysphagia [199], Viewpoints AI [152], Ropossum [200], COCO Sketch[6], Sentient World[198]
2014	Chef Watson [201], Kill the Dragon and Rescue the Princess [202], Nehovah [203], Autodesk Dreamcatcher[195]
2015	CAHOOTS [204], Funky Ikebana [205], StyleMachine [206], Drawing Apprentice [151]
2016	Improvised Ensemble Music Making on Touch Screen [207], AceTalk [208], Chor-rnn [209], Cochoreo [210], Evolutionary Procedural 2D Map Generation [211], Danesh [212], Plecto [213], Image-to-Image [62], Robodanza [214], SpeakeSystem [55], TaleBox[215], ChordRipple [216], Robovie [217], Creative Assistant for Harmonic Blending [218], Writing Buddy [216], Recommender for Game Mechanics [219]
2017	TOPOSKETCH [220], Trussfab[221], Chimney [222], FabMachine [223], LuminAI [224], GAIA [225], 3Buddy [226], Deeptingle [227]
2018	The Image Artist [228], DuetDraw [64], Robocinni [229]
2019	In a silent way [230], Metaphoria [83], collabDraw [27], DrawMyPhoto [231]
2020	Shimon the Rapper [232], ALYSIA [233], Cobbie [234], WeMonet [235], Co-cuild [236], IEC [237], Creative Sketching Partner [238]
2021	BunCho [239], CharacterChat [240], StoryDrawer [241], FashionQ [242]

existing co-creative systems from 2017 to 2021 in the ACM digital library and Google scholar. Thus, we have 92 co-creative systems in the corpus that we used to analyze the interaction designs using COFI. Table 3.1 shows all the co-creative systems that we analyzed with corresponding years and references. Figure 3.2 shows the count of the co-creative systems in our dataset each year.

We grouped the systems into 13 categories describing their creative domains. The categories are Painting/Drawing/Art, Culinary, Dance, Music, Storytelling/Narrative/Writing, Game Design, Theatre/Performance, Video/Animation, Photography, Poetry, Industrial and Product Design, Graphic Design and Humor/Comic. In Figure 3.3, the count of the systems in each category is provided. We see the most common creative domains in the corpus are music, storytelling/narrative/writing, Game design and Painting/Drawing/art. The

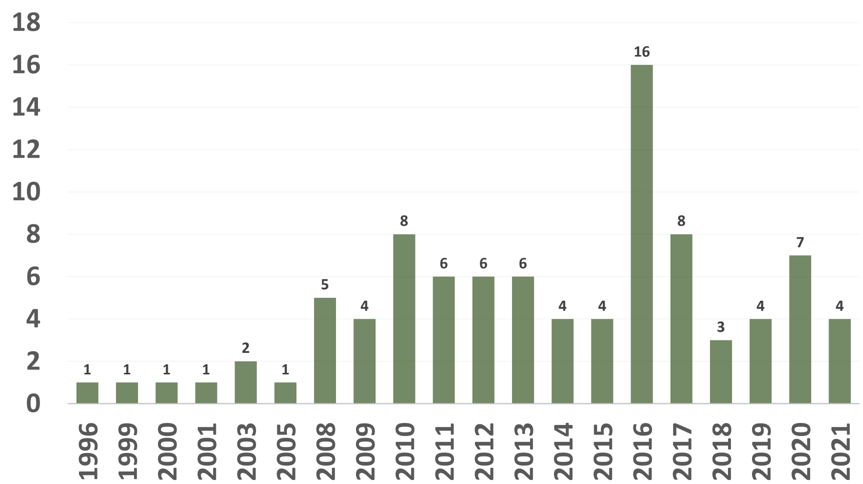


Figure 3.2: Counts of co-creative systems in the dataset per year.

distribution shows that some creative domains are not well represented in this dataset or rarely used in developing co-creative systems, for example, culinary, humor, and graphic design.

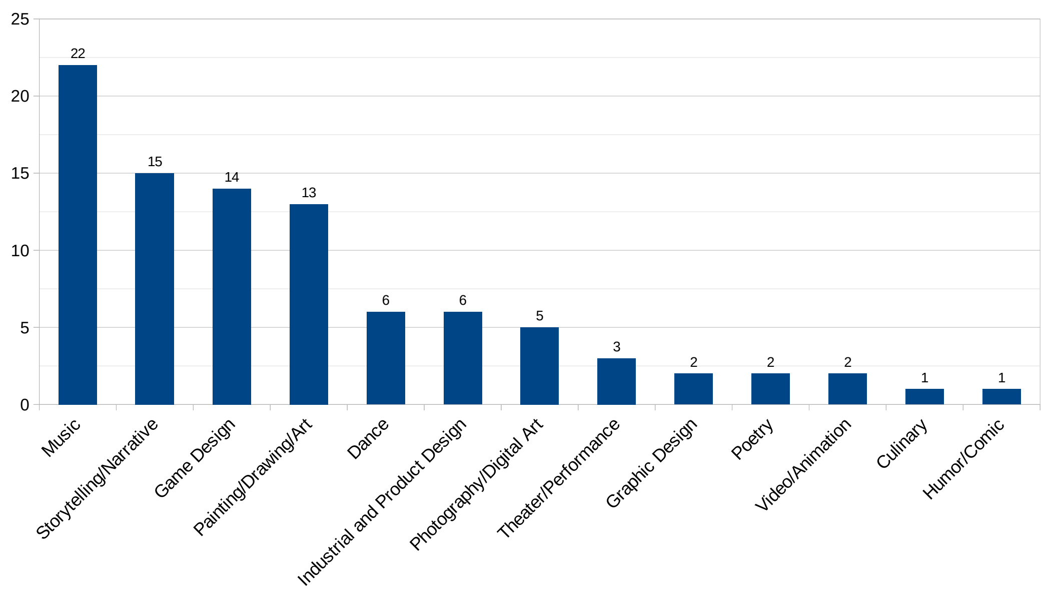


Figure 3.3: Counts of co-creative systems in Different Creative Domains.

3.3.2 Coding Scheme

To analyze the interaction design of the existing co-creative systems, we coded the interaction designs of 92 systems using COFI. Two coders from our research team independently coded 25% of the systems following COFI. They then achieved consensus through discussing the disagreements in the codes (Kappa Inter-rater reliability 0.79). The rest of the systems were coded by a single coder according to the consensus. For each system, the coding shows all interaction design components according to COFI. All the interaction components of the systems were coded according to the information provided in the corresponding literature. For a specific interaction component, when none of the subcategories are present in the interaction design, we coded it as 'None'.

3.3.3 Interaction Design Models among Co-creative Systems

For identifying different interaction models utilized by the co-creative systems in the dataset, we clustered all the systems using their interaction components. We used K-modes clustering [243, 244] for identifying clusters as the K-modes algorithm is suitable for categorical data. K-modes clustering is an extension of K-means, but instead of means, this algorithm uses modes. For demonstrating the cluster centroids, this algorithm uses modes of all the features. We used all the interaction components according to COFI as features. We found three clusters of the systems based on their interaction design (Table 3.2).

The first cluster includes 67 co-creative systems and thus indicating a dominant interaction model. The second cluster includes 9 systems and the third one includes 16 systems. We used chi-square to determine interaction components that contribute significantly to forming the clusters and found that all of the interaction components are significant factors for the clusters (all P values $<$ 0.05). Table 3.2 shows the three major interaction models, including all the interaction components (cluster centroids represented by feature modes).

Table 3.2: Major interaction designs in existing co-creative systems (cluster centroids).

Interaction between Collaborators							
	Collaboration Style				Communication Style		
Cluster No / Type of AI in Clusters	Participation Style	Task Distribution	Timing of Initiative	Mimicry	Human to AI Intentional Communication	Human to AI Consequential Communication	AI to human Communication
1 / Generative Pleasing Co-creative AI Agents (67 out of 92 systems)	Turn taking	Task Divided	Planned	Non-mimic	Direct Manipulation	None	None
2 / Improvisational Co-creative AI Agents (9 out of 92 systems)	Parallel	Single Task	Spontaneous	Mimic + Non-mimic	None	None	None
3 / Advisory Co-creative AI Agents (16 out of 92 systems)	Turn taking	Task Divided	Planned	Non-mimic	Direct Manipulation	None	None

➕

Interaction with the Shared Product			
Cluster No / Type of AI in Clusters	Creative Product		Creative Process
	Contribution Type	Contribution Similarity	
1 / Generative Pleasing Co-creative AI Agents (67 out of 92 systems)	Create New	High	Generation
2 / Improvisational Co-creative AI Agents (9 out of 92 systems)	Create New	High + Low	Generation
3 / Advisory Co-creative AI Agents (16 out of 92 systems)	Refine	High + Low	Generation + Evaluation

3.3.3.1 Cluster 1 - Interaction Design Model for Generative Pleasing AI Agents

The interaction model of the first cluster is the most prevalent as there are 67 systems in this cluster sharing the same or similar model. This dominant interaction model shows that most of the co-creative systems in the dataset utilize turn-taking as the participation style. Therefore, each of the collaborators must wait until the partner finishes their turn. This interaction model uses 'planned' timing of initiative which is an indication of non-improvisational co-creativity. Hence, most of the systems in the dataset do not support improvisational creativity. This interaction model uses direct manipulation for human-to-AI intentional communication. However, this model does not incorporate any human-to-AI consequential communication or AI-to-human communication. The main task is divided between the collaborators, and the AI agent uses generation as the creative process in most of the systems in this cluster and creates something new without mimicking the user. The degree of similarity in the contribution is high. In other words, the AI agent pleases the human by generating contributions that follow along with the contributions made by the human. Mostly, this interaction model is used by non-improvisational systems that generate creative products to please the users.

An example of a system that uses this interaction design is Emotion Driven Music Engine (EDME) [186]. EDME generates music based on the emotions of the user. The user selects an emotion, and EDME plays music to match that emotion. This system works in a turn-taking way with the user. The timing of initiative-taking is planned as the system will always respond after the human finishes selecting their emotion. The task is divided between the collaborators as the user defines the conceptual space by choosing an emotion from the interface and the system generates the music according to that emotion. The system contributes to the collaboration by creating something new and without mimicking the user. The system creates music that is associated with and similar to the user-defined emotion. The biggest challenge here is that humans can not give any feedback or communicate with the system regarding the generated music. The system can not track any consequential information from the human, such as facial expression, eye gaze and embodied gestures. Also, the system can not communicate any relevant information to the user, such as providing additional information regarding the contribution or visual cues.

3.3.3.2 Cluster 2 - Interaction Design Model for Improvisational AI Agents

The interaction design for the systems in cluster 2 uses parallel participation style where both agents can contribute simultaneously. The task distribution for these systems is usually 'same task' and most of the systems contribute by generating in the creative process. Most of the systems in this cluster contribute to the collaboration by creating something new and these systems can do both mimicry and non-mimicry. The degree of similarity in terms of users' contribution can be both high and low. This interaction model employs spontaneous initiative-taking while both co-creators contribute to the same task with parallel participation style, indicating improvisational co-creativity. Systems in this cluster do not have any way of communication between the user and the system, and a lack of communication in improvisational co-creativity can reduce the collaboration quality and engagement [65].

An example system for this cluster is LuminAI, where human users improvise with virtual AI agents in real time to create a dance performance [224]. Users move their body and the AI agent will respond with an improvised movement of its own. Both the AI agent and users can dance simultaneously and they take initiative spontaneously. Collaborators contribute to only a single task, generating dance movements. The AI can create new movements and transform user movements while it can do both mimicry and non-mimicry. The dance movements can be similar or different from the user. There is no way the user can deliberately communicate with the system or the system can communicate with the user. Here, the creative product itself is an embodied product but the system can not collect any consequential information from the user such as eye gaze, facial expression or additional gestures other than dance moves.

3.3.3.3 Cluster 3 - Interaction Design Model for Advisory AI Agents

The third cluster includes systems that work in a turn-taking manner and the task is divided into subtasks between the collaborators. The initiative taking is planned prior to the collaboration. Users can communicate with the system through direct manipulation, but there is no human-to-AI consequential communication channel or AI-to-human communication channel. The most notable attribute for this interaction model is both the generation and evaluation ability of the AI agent, unlike the other two interaction models where the AI agent can only contribute by generating. Systems with this interaction model can act as an adviser to the user by evaluating the contribution of the user. Most of these systems in this cluster contribute by refining the contribution of the user. These systems do not mimic the contribution of the user and the degree of contribution similarity can be both high and low.

An example of a co-creative system that utilizes this model is Sentient World which assists video game designers in creating maps [198]. The designer creates a rough terrain sketch, and Sentient World evaluates the map created by the designer and then generates several refined maps as suggestions. This system works in a turn-taking manner with the user, and the initiative taking is planned. The AI agent uses both generation and evaluation as creative processes by generating maps and evaluating maps created by the user. The user can communicate with the system minimally with direct manipulation (clicking buttons) to provide user preference for the maps. The AI agent can not communicate any explicit information to the human and can not collect any consequential information from the user such as facial expression, eye gaze and embodied information. Sentient World can both create new maps and refine the map created by the user. The system does not mimic the user contribution and the similarity with user contribution is high.

3.3.4 Adoption Rate of the Interaction Components used in the Systems

Table 3.3 shows the adoption rate of each of the interaction components in COFI used in the systems. The first section of the table comprises interaction components under *collaboration style*. Turn-taking is the most common participation style in the dataset (89.1%), while just 10.9% of the systems use parallel participation. Parallel participation is used by the systems that engage in performative co-creation. Most of the co-creative systems in the dataset use task-divided distribution of tasks (75%) as they work on separate creative subtasks. 25% systems use *same task* as their task distribution as both the user and the AI work on the same creative tasks. Timing of initiative is planned in 86.8% of the systems and the rest of the systems take spontaneous initiatives without any fixed plan. For mimicry, 90.2% of the systems employ non-mimicry, 8.7% systems use both mimicry and non-mimicry, and only one system (1.1%) uses mimicry.

The second category, *communication style*, is concerned with different communication channels used by the co-creative systems. 69.6% systems use direct manipulation as the human-to-AI communication channel. Voice, embodied

Table 3.3: Adoption rate of each interaction component used in the co-creative systems in the dataset.

<table>
<tr><td rowspan="8">Collaboration Style</td><td rowspan="2">Participation Style</td><td colspan="4">Parallel</td><td colspan="4">Turn-Taking</td></tr>
<tr><td colspan="4">10.90%</td><td colspan="4">89.10%</td></tr>
<tr><td rowspan="2">Task Distribution</td><td colspan="4">Same Task</td><td colspan="4">Task Divided</td></tr>
<tr><td colspan="4">25%</td><td colspan="4">75%</td></tr>
<tr><td rowspan="2">Timing of Initiative</td><td colspan="4">Spontaneous</td><td colspan="4">Planned</td></tr>
<tr><td colspan="4">13.20%</td><td colspan="4">86.80%</td></tr>
<tr><td rowspan="2">Mimicry</td><td colspan="2">Mimic</td><td colspan="3">Non-Mimic</td><td colspan="3">Both</td></tr>
<tr><td colspan="2">1.10%</td><td colspan="3">90.20%</td><td colspan="3">8.70%</td></tr>
<tr><td rowspan="6">Communication Style</td><td rowspan="2">Human to AI Intentional Communication</td><td>Voice</td><td>Direct Manipulation</td><td>Embodied</td><td>Text</td><td colspan="2">Direct Manipulation + Embodied</td><td>Voice + Direct Manipulation</td><td>None</td></tr>
<tr><td>1.10%</td><td>69.60%</td><td>3.30%</td><td>2.20%</td><td colspan="2">1.10%</td><td>1.10%</td><td>21.70%</td></tr>
<tr><td rowspan="2">Human to AI Consequential Communication</td><td>Gaze</td><td colspan="2">Facial Expression</td><td colspan="2">Biometric</td><td colspan="2">Embodied</td><td>None</td></tr>
<tr><td>0%</td><td colspan="2">0%</td><td colspan="2">1.10%</td><td colspan="2">3.30%</td><td>95.70%</td></tr>
<tr><td rowspan="2">AI to Human Communication</td><td>Speech</td><td>Text</td><td>Embodied</td><td>Haptic</td><td>Visual</td><td>Embodied + Voice</td><td>Embodied + Voice + text</td><td>None</td></tr>
<tr><td>1.10%</td><td>4.30%</td><td>3.30%</td><td>0%</td><td>5.50%</td><td>2.10%</td><td>1.10%</td><td>82.60%</td></tr>
<tr><td colspan="2" rowspan="2">Creative Process</td><td colspan="2">Generate</td><td>Evaluate</td><td>Define</td><td colspan="2">Generate + Define</td><td colspan="2">Generate + Evaluate</td></tr>
<tr><td colspan="2">79.30%</td><td>2.20%</td><td>1.10%</td><td colspan="2">2.20%</td><td colspan="2">15.20%</td></tr>
<tr><td rowspan="4">Creative Product</td><td rowspan="2">Contribute Type</td><td>Create New</td><td>Extend</td><td>Transform</td><td>Refine</td><td>Create New + Refine</td><td>Create New + Extend</td><td>Create New +Transform</td><td>Transform + Refine</td></tr>
<tr><td>59.80%</td><td>4.30%</td><td>2.20%</td><td>5.40%</td><td>10.90%</td><td>8.70%</td><td>7.60%</td><td>1.10%</td></tr>
<tr><td rowspan="2">Contribution Similarity</td><td colspan="2">Low</td><td colspan="2">High</td><td colspan="2">Both</td><td colspan="2">None</td></tr>
<tr><td colspan="2">2.20%</td><td colspan="2">69.60%</td><td colspan="2">27.10%</td><td colspan="2">1.10%</td></tr>
</table>

and text is rarely used by the systems. 3.3% of the systems use embodied communication as human-to-AI consequential communication and most of the systems (95.7%) do not track and collect any consequential information from the user. For AI-to-human communication, most systems do not have any channels. In the next section, we talk about the trend in communication channels in co-creative systems.

In the creative process category, it is noticeable that the majority of the systems (79.3%) employ generation as the creative process and 15.2% of the systems use both generation and evaluation as the creative processes. Definition as a creative process is rarely used in co-creative systems.

In the creative product category, contribution type is the first interaction component and most co-creative systems use *create new* (59.8%). 10.9% of the systems use both *create new* and *refine* as the contribution type. 8.7% of the systems use both *create new* and *extend* as the contribution type.

3.3.5 Communication in Interaction Models

Our analysis identifies a significant gap in the use of the components of interaction in the co-creative systems in this dataset: a lack of communication channels between humans and AI (Table 3.4). In co-creative systems, subtle communication happens during the creative process through contributions. For example, in a collaborative drawing co-creative system where no communication channel exists between the user and the AI, subtle interaction happens through the shared product as co-creators make sense of each other's contribution and then make a new contribution. Designing different modalities for communication between the user and the AI has the potential to improve the coordination and quality of collaboration. However, 82.6% of the systems cannot communicate any feedback or information directly to the human collaborator other than communicating through the shared product. The rest of the systems communicate with the users through text, embodied communication, voice, or visuals (image and animation). For human-to-AI consequential communication, 95.7% of the systems can not capture any consequential information from the human user such as facial expression, biometric data, gaze and postures. However, consequential communication can increase user engagement in collaboration. For intentional communication from human-to-AI, most of the systems use direct manipulation (clicking buttons or selecting options) to communicate (69.6%). In other words, in most of the systems, users can only minimally communicate with the AI or provide instructions to the AI directly, for example, through clicking buttons or using sliders. 21.7% of the systems have no way for the user to communicate with the AI intentionally. The rest of the systems use other intentional communication methods, like embodied communication or voice or text.

Table 3.4: Distribution of different kinds of communication between humans and AI in the co-creative systems in the dataset.

Communication Channels \ Communication Types	Human to AI Intentional Communication	Human to AI Consequential Communication	AI to Human Communication
None	21.70%	95.70%	82.60%
Direct Manipulation	68.50%	0%	0%
Embodied	3.30%	3.20%	3.30%
Text	0%	0%	4.30%
Others	6.50%	1.10%	9.80%

Some of the systems in our dataset utilize multiple communication channels. Shimon is a robot that plays the marimba alongside a human musician [65]. Using embodied gestures as visual cues to anticipate each other's musical input, Shimon and the musician play an improvised song, responding to each other in real-time. The robot and the human both use intentional embodied gestures as visual cues to communicate turn-taking and musical beats. Therefore, this system includes human-to-AI intentional communication and AI-to-human communication. Findings from a user study using Shimon demonstrate that visual cues aid synchronization during improvisational co-creativity. Another system with interesting communication channels is Robodanza, a humanoid robot that dances with humans [214]. Human dancers use intentional communication by intentionally touching the robot's head in order to awaken it and the robot tracks human faces to detect consequential information. The robot is able to detect the noise and rhythm of hands clapping and tapping on a table. The robot can move its head in the direction of the perceived rhythms and move its hand following the perceived tempo for communicating its status to human users.

3.4 Discussion

We develop and describe COFI to provide a framework for designing, comparing, and analyzing interaction in co-creative systems as an answer to our first research question (RQ1). Researchers can use COFI to explore the possible spaces of interaction for choosing an appropriate interaction design for a specific system. COFI can be beneficial while investigating and interpreting the interaction design of existing co-creative systems. As a framework, COFI is expandable as other interaction components are added in the future. We analyzed the interaction models of 92 existing co-creative systems using COFI to demonstrate its value in investigating the trends and gaps in the existing interaction designs in co-creative systems. We identified three major clusters of interaction models utilized by these systems. In the following paragraphs, we explain the interaction models and discuss the potential for further research in specific interaction components. These interaction models can be useful when designing a co-creative system since they can help identify appropriate interaction components and determine if interaction components should be modified for the corresponding type of co-creative AI agent.

The most common interaction model in our dataset is suitable for generative co-creative AI agents that follow and comply with human contributions and ideas by generating similar contributions. Provoking agents are rare in the literature, and in fact, such a stance seems to be opposed by some in the literature. For example, Tanagra's creators ensured "that Tanagra does not push its own agenda on the designer" [181]. However, both pleasing and provoking agents have use-cases within co-creative systems [38]. For example, if a user is trying to produce concepts or ideas that convey their specific style, a pleasing agent that contributes similar ideas is more desirable. However, if a user is searching for varied ideas, a provoking agent with different contributions is an ideal creative partner as it will provide more divergent ideas. This model can be improved with consequential communication tracking from users and AI to human communication.

The second interaction model is suitable for improvisational AI agents as it uses spontaneous initiative-taking and both agents work on the same task in parallel. Additionally, this model includes both mimicry and non-mimicry, unlike the other models which direct the AI to take proper action in an improvisational performance. This model can be utilized as a guide while designing interaction in an improvisational co-creative system. However, this model does not include any intentional or consequential communication channels from humans to AI or AI to humans, which can negatively impact the collaboration quality and user experience, especially in improvisational co-creativity where communication is the key. Hoffman et al. asserted that communication aids synchronization and coordination in improvisational co-creativity [65]. Further research can extend this model by including or extending human-AI communication channels.

The third interaction model is used by co-creative AI agents that work as an advisor by evaluating users' contributions and contributing to the shared product as a generator. In product-based co-creation, AI agents that can both generate and evaluate help the user generate precise creative ideas and artifacts. For example, in industrial design, the co-creative AI agent can help in creative ideation by evaluating the user-provided concept for a robust and error-free design and also help in the generation of the artifact with divergent or convergent ideas [221]. AI agents that use this model can refine the user's contributions in contrast to the other models. The limitations of this model include the absence of human-to-AI consequential communication and AI-to-human communication.

A notable finding from the analysis of this dataset is the lack of AI agents defining the conceptual space as the creative process (only 4 out of 92). Most of the systems in the corpus contribute by generating and some contribute by evaluating the human contributions. In the context of co-creativity, defining the conceptual space is an essential task. An AI agent can define the conceptual space without any guidance from the user. For example, the Poetry Machine is a poetry generator that prompts the user with images that users respond to with a line of poetry [162, 179] and then organizes the lines of poetry into a poem. An AI agent can also suggest multiple ideas for the conceptual space while the user can select their preferred one. TopoSketch [220] generates animations based on a photo of a face provided by the human and displays various facial expressions as ideas for the final animation. CharacterChat inspires writers to create fictional characters through conversation. The bot converses with the user to guide the user in defining different attributes of the fictional character. Humans may desire inspiration for creative concepts and ideas at the beginning of a creative journey. Creative brainstorming and defining creative concepts can be potential research areas for co-creative systems. There is potential for designing new co-creative systems that both define the creative conceptual space and explore it with the user.

The most significant area of improvement in all of the interaction models identified is communication, the key to coordination between two agents. Providing feedback, instructions or conveying information about the contribution is essential for creative collaboration. Without any communication channel between the co-creators, the creation becomes a silent game [245, 246] as collaborators can not express any concerns and provide feedback about their contributions. Communication through the creative product is subtle communication and may not be enough to maintain the coordination and collaboration quality. Most of the existing co-creative systems in our dataset have minimal communication channels, and this hinders the collaboration ability of the AI agent and the interactive experience. Most of the systems in the dataset utilize only direct manipulation for communicating intentional information from the users. Direct manipulations include clicking buttons and using sliders for rating AI contribution, providing simple instructions and collecting user preferences. For most systems, direct manipulation provides a way for minimal communication and does not provide users with a way to communicate more broadly. Very few systems in the dataset use other communication channels other than direct manipulation for human-to-AI intentional communication. For example, AFAOSMM (2012) [196] is a theatre-based system that uses gestures as intentional communication and Robodanza (2016) [214] uses embodied movements along with direct manipulation for intentional communication. Human-to-AI consequential communication is rarely used in the systems but is an effective way to improve creative collaboration. It has been demonstrated that humans, during an interaction, can reason about others ideas, goals, intentions and predict partners behaviors, a capability called Theory of Mind (ToM) [247, 248, 249]. Having a Theory of Mind allows us to infer the mental states of others that are not directly observable, enabling us to engage in daily interaction. The ability to intuit what others think or want from brief nonverbal interactions is crucial to our social lives as we see others' behavior not just as motions but as an intentional action. In collaboration, the Theory of Mind is essential to observe and interpret the behavior of a partner, maintain coordination and act accordingly. Collecting unintentional information from the human partner has the potential to improve the collaboration and user experience in a human-AI co-creation, and may lead to enabling AI to mimic the Theory of Mind ability of humans. The technology for collecting consequential information from the user includes eye trackers, facial expression trackers, gesture recognition devices, and cognitive signal tracking devices.

AI to human communication channels are also rarely utilized in the identified interaction models. However, it is essential to understand the AI partner by the users to build an engaging and trustworthy partnership. Many intelligent systems lack the core interaction design principles such as transparency and explainability and it makes them hard to understand and use [250]. To address the challenge of transparency of AI interaction should be designed to support users in understanding and dealing with intelligent systems despite their complex black-box nature. When AI can communicate its decision-making process to users and explain its contribution, the system becomes more comprehensible and transparent to build a partnership. So, AI-to-human communication is critical for interaction design in co-creative systems. Visuals, text, voice, embodied, and haptic feedback can be used to convey information, suggestions, and feedback to the users. There is a distinction between AI-to-human communication and AI steerability. For example, LuminAI is a co-creative AI that dances with humans [224]. Here the generated creative product is dance, an embodied product created by gestures and embodied movements. However, AI can only communicate by contributing to the product and does not directly communicate with humans. Humans can steer the AI by contributing different embodied contributions to the final product and the AI generates contributions based on the user movements. This is different from embodied communication which intentionally communicates that the collaborator is doing great with a thumbs up. The gap in interaction design in terms of communication is an area of future research for the field of co-creativity. User experiments with different interaction models can help identify effective interaction design for different types of co-creative systems [251]. COFI provides a common framework for analyzing the interaction designs in existing co-creative systems to identify trends and gaps in existing interaction designs for designing improved interaction in a co-creative system.

AI is being used increasingly in collaborative spaces, for example, recommender systems, self-driving vehicles, and health care. Much AI research has focused on improving the intelligence or ability of agents and algorithms [252]. As AI technology shifts from computers to everyday devices, AI needs social understanding and cooperative intelligence to integrate into society and our daily lives. AI is, however, a novice when it comes to collaborating with humans [58]. The term 'human-AI collaboration' has emerged in recent work studying user interaction with AI systems [253, 64, 254, 255]. This marks both a shift to a collaborative from an automated perspective of AI, and the advancement of AI capabilities to be a collaborative partner in some domains. Ashktorab et al. asserted that human-AI co-creation could be a starting point for designing and developing AI that can cooperate with humans [252]. Human-AI interaction has many challenges and is difficult to design [256]. HCI deals with complex technologies, including research to mitigate unexpected consequences. A critical first step in designing valuable human-AI interactions is to identify technical challenges, articulate the unique qualities of AI that make it difficult to design, and then develop insights for future research [256]. Building a fair and effective AI application is considered difficult due to the complexity both in defining the goals and algorithmically achieving the defined goals. Prior research has addressed these challenges by promoting interaction design guidelines [257, 258]. In this chapter, we provide COFI as a framework to describe the possible interaction spaces in human-AI creative collaboration and identify existing trends and gaps in existing interaction designs. COFI can also be useful in AI research and HCI research to design cooperative AI in different domains. COFI will expand as we learn and identify more aspects of human-AI collaboration.

3.5 Reflection on Recent Developments

The data analysis of existing co-creative systems' interaction designs presented in the results section was conducted in 2021. It is important to note that this analysis does not include any co-creative systems developed after 2021. As a result, the findings and insights from the analysis may not fully reflect the current trends and gaps in the interaction design of more recent and refined co-creative systems. In 2022 and afterward, there has been a significant surge in the field of generative AI and AI based on large language models (LLM), with numerous models showcasing remarkable co-creative capabilities. While it is important to acknowledge that these generative AI and large language models (LLMs) were not specifically designed for co-creative purposes, they can still be utilized effectively in co-creative AI scenarios. Such advanced generative co-creative AI were not as available during the analysis we conducted and hence were not included in our dataset during the analysis phase.

In this section, we reflect on how recent developments in the field of generative co-creative AI's interaction designs fit into COFI and the emerging trends. If we first start with generative AI based on large language models, we can consider two popular AI among many - ChatGPT and BARD. Analyzing the interaction models of these two AI using COFI will give us a hint of the trajectory of the interaction design. Both AI has the interaction design of generative pleasing co-creative, the most prevalent cluster found in the analysis consisting of 67 systems in the dataset. For the collaboration style, the interaction elements represent the average generative pleasing co-creative AI seen previously in the dataset.

For the communication style, the only difference is that both ChatGPT and BARD can communicate (AI-to-human communication) with users, unlike most co-creative AI in the dataset. For AI-to-human communication, ChatGPT uses text and BARD can use both voice and text, unlike what we saw in the most co-creative AI in the dataset, as most co-creative AI can not communicate with users directly. There are no human-to-AI consequential communication channels like most systems in the dataset. In terms of the creative process and creative product, the interaction designs of these LLM-based AI show no significant differences.

Additionally, in 2022 and afterward, many AI systems based on text-to-image generation models (TIGM) emerged, which are co-creative in nature. DALL-E2 [12], Midjourney [259], Stable diffusion [260], and Craiyon [261] are some of them and have similar interfaces and interaction designs. Specifically, when examining DALL-E2 and Stable diffusion, their interaction designs align closely with those of generative pleasing co-creative AI found in the analysis. They do not incorporate AI-to-human communication as we saw in most systems during the analysis.

LLMs are better at explaining responses and sometimes chatting casually but providing feedback during a co-creation like a partner, providing suggestions on the creative contributions, communicating its status with humans and understanding human preferences from unintentional communication is yet to be available. While LLMs can enhance communication in co-creative AI due to their conversational nature, specific improvements tailored to co-creativity are necessary. Incorporating additional modalities alongside text can enhance the user experience in terms of communication within co-creativity. Also, LLMs can be used as definers to define or set the creative space and initiate ideation which we rarely see in the existing co-creative AI. Instead of always converging with users' contributions, LLM-based co-creative AI can stimulate users with diverging contributions, fostering creativity and surprise. Additionally, in terms of contributions, they should be able to transform users' contributions while leveraging their current capabilities, which include generating novel content, refining and extending users' contributions.

Lastly, we demonstrate that COFI remains a valuable tool in the current landscape of human-AI co-creativity. It enables us to interpret the interaction designs of existing co-creative AI and analyze the prevailing trends and identified gaps. COFI can guide the development of co-creative AI systems with improved interaction designs, addressing existing gaps to enhance user experience and collaboration. Additionally, leveraging the potential of LLMs can further enhance human-AI interaction and collaboration in co-creative contexts.

3.6 Limitations

While COFI does not prescribe specific interaction components for a given context in the design process, it offers a broad range of potential interaction spaces in human-AI co-creation. This empowers practitioners to carefully consider and select appropriate interaction components while designing co-creative systems. Additionally, the identification of clusters of interaction models in human-AI co-creative systems is limited to the specific dataset that we used for the analysis. Although we believe this sample contains a large population, the systems in the dataset are limited by the expectations and technologies at the time of publication. We expect the clusters and descriptions of interaction models for co-creative systems will change over time.

3.7 Conclusions

This chapter describes the COFI as a framework for modeling interaction in co-creative systems. COFI was used to analyze the interaction design of 92 co-creative systems from the literature. Three interaction models for co-creative systems were identified: generative pleasing agents, improvisational agents, and advisory agents. When developing a co-creative system, these interaction models can be useful in choosing suitable interaction components for corresponding co-creative systems. COFI is broader than the interaction designs utilized in any specific co-creative system in the data set. The findings show that the space of possibilities is underutilized. While the analysis is limited to the data set, it demonstrates that COFI can be a tool for identifying research directions and research gaps in the current space of co-creativity. COFI revealed a general lack of communication in co-creative systems within the dataset. In particular, very few systems incorporate AI to human communication, communication channels other than direct manipulation for collecting intentional information from humans and gathering consequential communication data, such as eye gaze, biometric data, gesture, and emotion. This gap demonstrates an area of future research in the field of co-creativity. We argue that COFI will provide useful guidelines for interaction modeling while developing co-creative systems. As a framework, COFI is expandable as other interaction components can be added to it in the future. User experiments with different interaction models can help identify effective interaction designs for different types of co-creative systems and lead to insights into factors that affect user engagement.

CHAPTER 4: IDENTIFYING THE IMPACT OF AI-TO-HUMAN COMMUNICATION ON USER EXPERIENCE IN HUMAN-AI CO-CREATIVITY

4.1 Introduction

Communication is an essential component in any collaboration for the co-regulation between the collaborators and helps the AI agent make decisions in a creative process [22]. However, there is no channel for AI-to-human communication in most systems [26]. For example, Collabdraw [27] is a co-creative sketching environment where users draw with an AI. The user clicks a button to submit their artwork and indicates that their turn is complete. The AI in this system cannot directly communicate with users to provide information, suggestions, or feedback. While the AI algorithm is capable of providing intriguing contributions to the creative product, the interaction design does not focus on a successful human-AI collaboration. Previous work shows that two-way communication between collaborators is essential in computer-mediated communication [25]. AI-to-human communication represents the channels through which AI can communicate with humans, and this is essential in a human-AI co-creative system [59]. AI-to-human communication is an essential aspect of human-computer interaction [25].

In this chapter, we investigate the impact of AI-to-human communication on the collaborative experience, user engagement and user perception of a co-creative AI (RQ2). We break down RQ2 into the following three research questions:

- RQ2.1 - How does AI-to-human Communication affect the *collaborative* *experience* in human-AI co-creation?

- RQ2.2 - How does AI-to-human Communication affect *user engagement* in human-AI co-creation?
- RQ2.3 - How does AI-to-human Communication affect the *user perception* of the co-creative AI agent?

For AI-to-human communication, we used speech, text and visual communication (AI avatar). We developed two high-fidelity interactive prototypes of a co-creative system, Creative Penpal, that helps users in producing creative designs of a specific object by presenting inspiring sketches. One prototype utilizes only human-to-AI communication (baseline). The second prototype uses two-way communication between humans and AI, including AI-to-human communication via speech, text and a virtual AI avatar representing visual communication. We conducted a comparative user study with 38 participants to investigate the impact of including AI-to-human communication along with human-to-AI communication on collaborative experience, user perception and engagement. We present the findings as insights for making effective co-creative systems that will provide a better collaborative experience and increase user engagement. This research leads to new insights about designing effective human-AI co-creative systems and lays a foundation for future studies regarding interaction design in human-AI co-creativity.

4.2 Creative PenPal: A Co-Creative System for Design Ideation

Creative PenPal is a co-creative system that presents sketches to inspire users while they sketch design ideas in response to a specified design task. We developed two prototypes for Creative PenPal, one with AI-to-human communication and one without. The visual design of the interface is inspired by an existing co-creative system for design ideation, Creative Sketching Partner (CSP) [238].

The difference between the two prototypes: one uses one-way communication, human-to-AI communication only (baseline), and the other has two-way communication, including AI-to-human communication. For the study reported in this chapter, we did not implement the back-end AI since our research questions focus on the influence of communication in the interaction design. Therefore, we wanted to control the AI ability (same AI ability) in both versions, so the study results are based only on the effect of AI-to-human communication.

The prototypes for Creative PenPal offer three different kinds of design inspirations for the users - (a) sketches of the conventional design task object, (b) sketches of visually similar objects and (c) sketches of conceptually similar objects. Visually similar objects have visual or structural similarities to the user's sketch, and conceptually similar inspirations have similar themes or concepts as the design task object. For instance, when the design task object is a 'chair for gamers', Creative Penpal provides (a) sketches of typical chairs for gamers, (b) sketches of visually similar objects based on the user's sketch, which might be a wheelchair, ottoman, sofa, and (c) sketches of objects that are conceptually related to a chair for gamers, such as a keyboard, table, neck pillow, headphones. We selected a collection of sketches as the database. The sketches are grouped into three categories in the database based on the three kinds of sketches the system can present. We created a database of sketches for each of the two design tasks we used in the user study: a chair for gamers and a shopping cart for the elderly.

The system randomly selects a sketch from the corresponding collection of sketches for conceptually similar object sketches and design-task object sketches. However, for the visually similar sketches, we used the Wizard of Oz (WOz) method to present sketches similar to users' drawings as a proxy for the AI. We used the WOz for visually similar object sketches as they need to be similar to what is being drawn on the canvas by users, unlike conceptually similar sketches that can be determined based on the design task. In the user study, the Wizard could see the sketch on the user's canvas and select a visually similar sketch to what was drawn by the participant to display on PenPal's canvas when participants clicked on the 'visually similar objects' button. The participants were unaware of the wizard observing their sketch and were told that they were interacting with an AI. The visually similar object folder had 25 sketches for both design task objects, and the Wizard chose the most visually similar sketch to the participant's sketch. The same person was the Wizard for all study sessions to keep the methodology consistent.

4.2.1 Creative PenPal Prototype Without AI-to-human Communication (One-way Communication)

The baseline prototype, shown in Figure 4.1, uses buttons for human-to-AI communication to ask for different inspirations. The design task is shown on the interface in Label B (design a chair for gamers). Users design the object by drawing on the canvas depicted in Label E. Users can undo the last stroke using the button 'Undo Previous Sketch', erase a part of the sketch using the 'Erase' and erase the whole canvas by using the 'Clear the canvas' button (Label C). The 'Pencil' button is used to go back to the drawing (Label C). Users can ask for AI inspirations by clicking any of the three buttons in Label A. When users receive an inspiring sketch from the AI, they can see the sketch in the PenPal's Canvas (Label F) and the name of the inspiring object in the sketch shown in Label D.

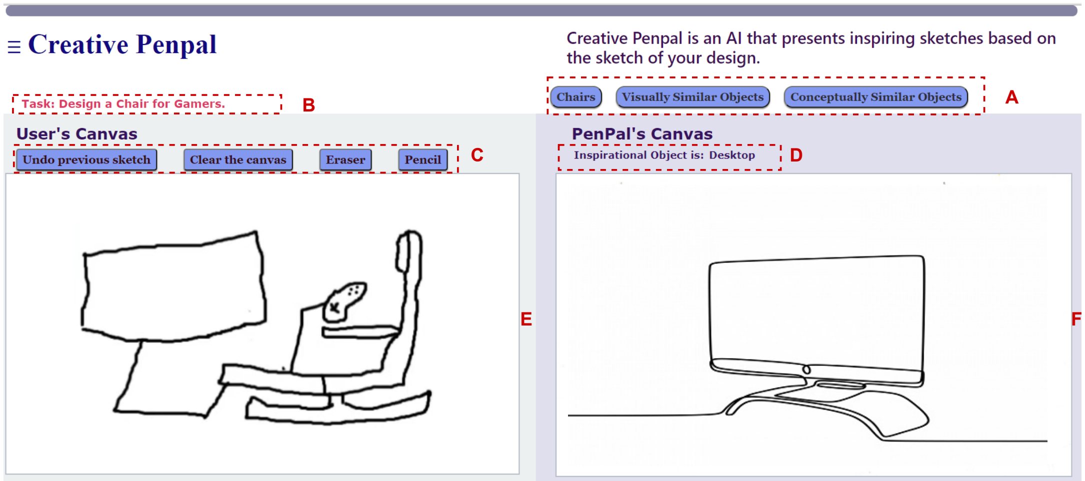


Figure 4.1: Creative PenPal prototype without AI-to-human communication (one-way communication): On the left, the design idea of a Participant. On the right, AI showing an inspiring sketch

4.2.2 Creative PenPal Prototype With AI-to-human Communication (Two-way Communication)

The prototype shown in Figure 4.2 uses two-way communication between humans and AI. This prototype has the same human-to-AI communication as the baseline condition and uses AI-to-human communication through text, speech and visuals (an AI avatar). The AI avatar, a pencil (PenPal), is shown in Label G. Label A is where the AI communicates to the user via text, speech and the virtual AI avatar. The AI speaks the exact words as shown in the text. The AI voice is a recorded human voice that has been filtered through a robot-voice filter using free voice-altering software. When users click the 'Inspire me' button in Label A, the AI will show an inspirational sketch on its canvas in Label F. The users can also ask for three different kinds of inspirations using three buttons similar to the baseline prototype. The design task for this prototype is shown inside Label B (Design a shopping cart for the elderly). The human-AI conversational communication model for this prototype is demonstrated in Figure 4.3. The communication model shows how two-way communication happens in

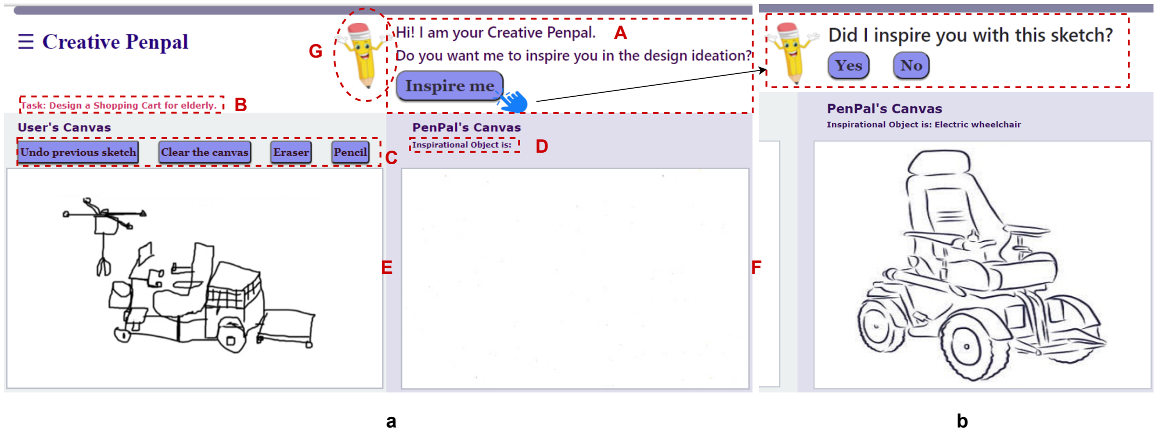


Figure 4.2: Creative PenPal prototype with AI-to-human communication (two-way communication): (a) PenPal introducing itself at the beginning of design ideation (b) User clicks on the 'Inspire me' button and PenPal shows a design inspiration

5 phases:

PenPal Introduction: As soon as the user clicks on the start button to start the design task, the AI avatar arrives, introduces itself and asks the users if they want to see an inspirational sketch from the AI by saying, "Hi! I am your Creative PenPal. Do you want me to inspire you?". Users can respond immediately to get inspiration by pressing the button 'Inspire me' or keep sketching to respond later.

PenPal Generating Sketch and Collecting User Preferences: When the user hits the button 'Inspire me', an animation of PenPal (the AI avatar) generating the sketch on the canvas is presented. After presenting an inspiring sketch, PenPal collects user preference by asking the user whether they liked the sketch or not. The user can reply with the 'Yes' or the 'No' button.

User Liked PenPal's Sketch: When a user clicks the 'Yes' button in response to PenPal's query about their preference, the PenPal arrives with a happy face and says, "I am glad that you liked the sketch! Let me know if you want another inspiration". If users want to see an inspiration again, they can click on the "Inspire me conceptually" or "Inspire me visually" button.

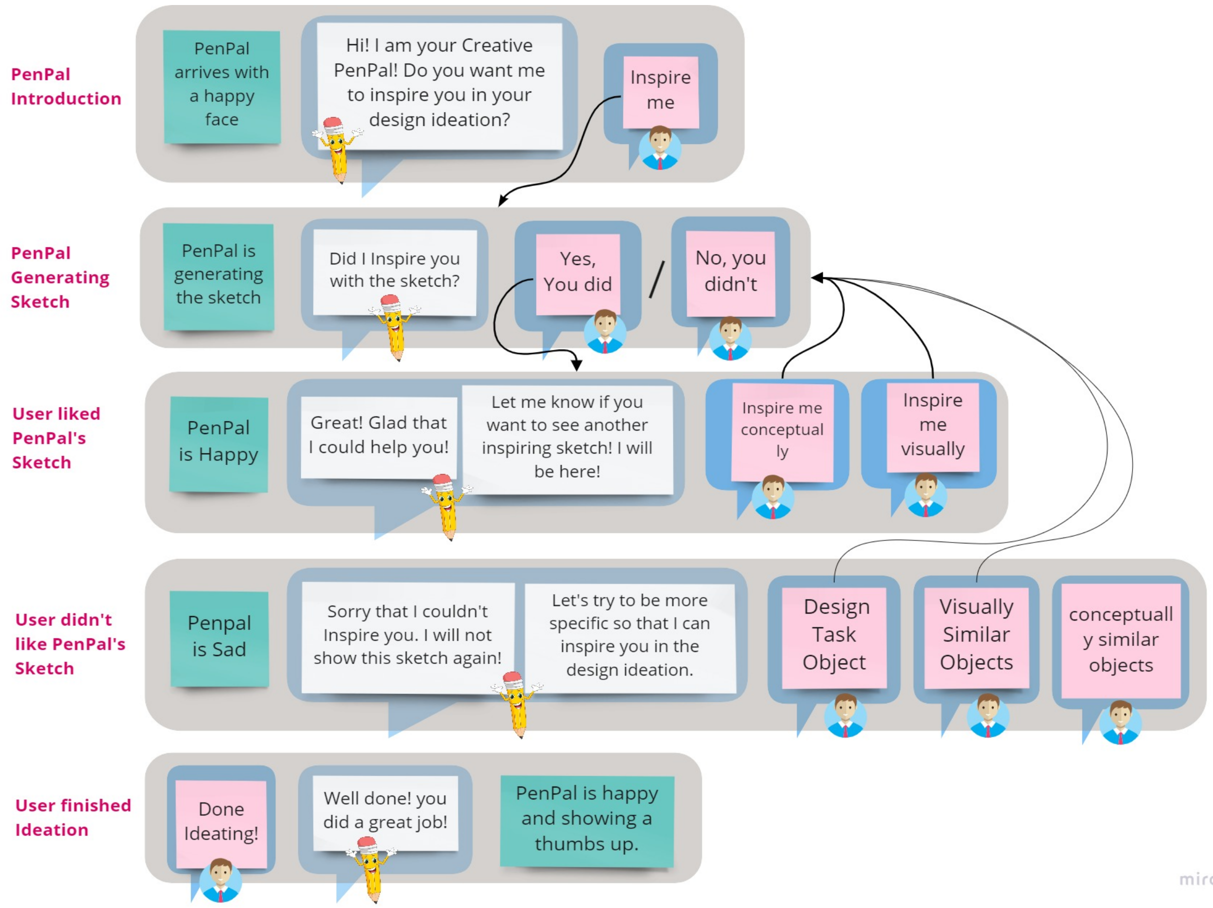


Figure 4.3: Two-way communication model including AI-to-human communication in Creative PenPal

User Did Not Like PenPal's Sketch: When users click the 'No' button, indicating that PenPal's sketch did not inspire them, PenPal arrives with a sad face and says, "Sorry that I could not inspire you! I will not show you this sketch again". Then it suggests: "Let's try to be more specific about what you want me to inspire with". The user can respond with any options, 'Design Task Objects' (as our design task object is a shopping cart, the button says 'Shopping Carts'), 'visually similar objects', or 'conceptually similar objects'.

User Finished Sketching: The user finishes the design ideation task by clicking the 'Finish Design' button. The virtual agent responds with: "Well done! You did a great job!"

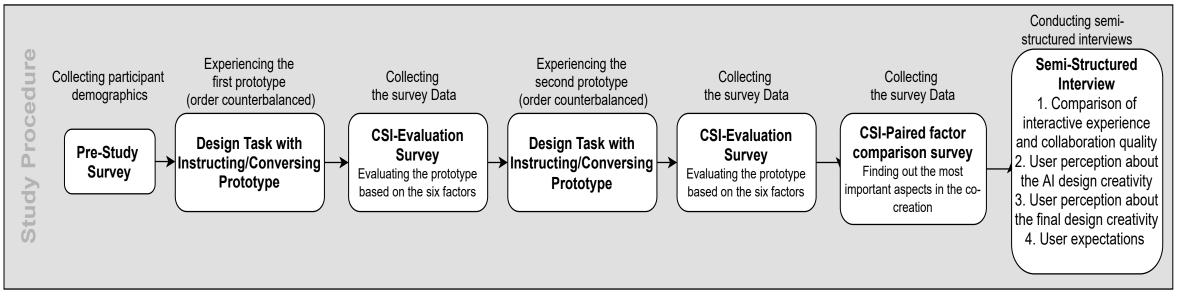


Figure 4.4: Study procedure

4.3 Comparative Study

We conducted a comparative user study to explore the influence of AI-to-human communication on *collaborative experience, user engagement* and *user perception* of a co-creative AI using the prototypes. In this section, we describe the methodology of the study, the participants, the data, and the analysis.

4.3.1 Study Methodology

We used a within-subject approach for the study to collect quantitative and qualitative data to investigate our research questions. To see if condition order affects the outcomes, we counterbalanced the order of the conditions: half of the participants conducted their first design task with the baseline while the other half finished their first design task with the prototype featuring AI-to-human communication.

The study procedure is summarized in (Figure: 4.4). At the beginning of the study, we collected demographic information from participants such as age, gender, and drawing/sketching ability using a survey. We briefly informed the participants about the design tasks while showing them the system interface before testing the prototypes. The design tasks were - “Design a futuristic shopping cart for the elderly/a chair for gamers. Include at least three inspirations from the AI in your design idea”. We chose the design-task objects from everyday things of simple and similar complexity. Pilot studies showed no significant influence of the choice of design-task objects on the outcome. Participants shared their screens so that the wizard could see their designs. After each design task, the participants completed a survey to evaluate the system. Additionally, after completing both design tasks, they completed another survey to reflect on important aspects of their co-creation experience. Finally, the study ended with a follow-up semi-structured interview to collect qualitative data about the overall experience with the AI.

4.3.2 Participants

We recruited 38 participants, 19 males and 19 females, who were all 18 years old or older (avg age = 26 years). We emailed participants an IRB-approved informed consent form to review and sign electronically upon scheduling the study. All participants voluntarily took part in the experiment and each participant received a gift card as an incentive upon completion of the study. The study did not require participants to have drawing/sketching skills. Among the participants, 23 participants had none/very little drawing/sketching skill, 14 participants had an intermediate skill of drawing/sketching, and 1 participant was an expert.

4.3.3 Data Collection

4.3.3.1 Surveys

In order to measure the perceived user engagement and overall experience with each prototype, we used the Creativity Support Index (CSI) [262], a psychometric survey for measuring six factors in a creative system: *Exploration, Expressiveness, Immersion, Enjoyment, Results Worth Effort* and *Collaboration.* CSI consists of two separate surveys. The first survey evaluates a system using the six factors. For each factor, there are two agreement statements (12 statements in total). Participants rated each statement on a 10-point Likert scale of 'Highly Disagree' to 'Highly Agree'. In the other survey, each factor is paired against every other factor (15 comparisons), which participants completed after finishing both design tasks. The latter survey is for determining the most important aspects of creative collaboration. The CSI survey is designed specifically for creativity support tools (CST) and the original collaboration factor is about human-human collaboration. Co-creative systems are distinct from CSTs as they are about human-AI collaboration. Therefore, we modified the original two agreement statements for the *collaboration* factor to be more appropriate for evaluating human-AI collaboration: (1) The collaboration with the AI was more like interacting with a partner than a tool, (2) There was good and meaningful communication between me and the AI. The original statements for the CSI collaboration factor were: (1) The system allowed other people to work with me easily, and (2) It was really easy to share ideas and designs with other people inside this system [262].

4.3.3.2 Interviews

We collected in-depth qualitative data using semi-structured interviews. In the interviews, we questioned participants about (1) their interactive and collaborative experience with both prototypes, (2) their perceptions and satisfaction with the final designs created with both of the prototypes, (3) their perception of the co-creative AI in both prototypes and (4) their suggestions for improving their experience. During the interviews, we asked follow-up questions to dig deep and clarify interesting discussion points that came up in the conversation.

4.3.4 Data Analysis

4.3.4.1 Surveys

We conducted a statistical analysis of the CSI survey data. We calculated the means and standard deviations for each factor score in the CSI and the final CSI score for both prototypes. We used T-tests comparing the effect of each condition on our outcome variables. We did not find any influence of study order, gender, age and drawing skill (independent variables) on any outcome variables (T-test and ANOVA). The P values are the following: study order (T-test, P = 0.3 for immersion, P = 0.24 for enjoyment, P = 0.05 for collaboration), gender (T-test, P = 0.08 for immersion, P = 0.46 for enjoyment, P = 0.5 for collaboration), age (Anova, P = 0.57 for immersion, P = 0.74 for enjoyment, P = 0.53 for collaboration) and drawing skill (Anova, P = 0.81 for immersion, P = 0.59 for enjoyment, P = 0.28 for collaboration).

4.3.4.2 Interviews

We conducted a thematic analysis of the interview data. As per Braun and Clarke's [263] six-phase structure, two persons in the research team familiarized themselves with the interviews and created the initial codebook. The first author coded the interviews using the initial codebook (allowing for additional codes to develop). Following the coding process, both coders agreed on the codes to construct the primary themes.

4.4 Results

4.4.1 CSI Survey Results

A single CSI score is produced out of 100 for each prototype from the surveys. The average CSI score for communicating AI is 80.95 (SD=11.90) and the score for baseline AI is 73.096 (SD=16.671) (Table 4.1). The T-test reveals a signifi-

Table 4.1: Average CSI scores for both prototypes

Versions	Average CSI Score (SD)	P Value
Communicating AI	80.938 (11.898)	
Baseline AI	73.096 (16.671)	0.021

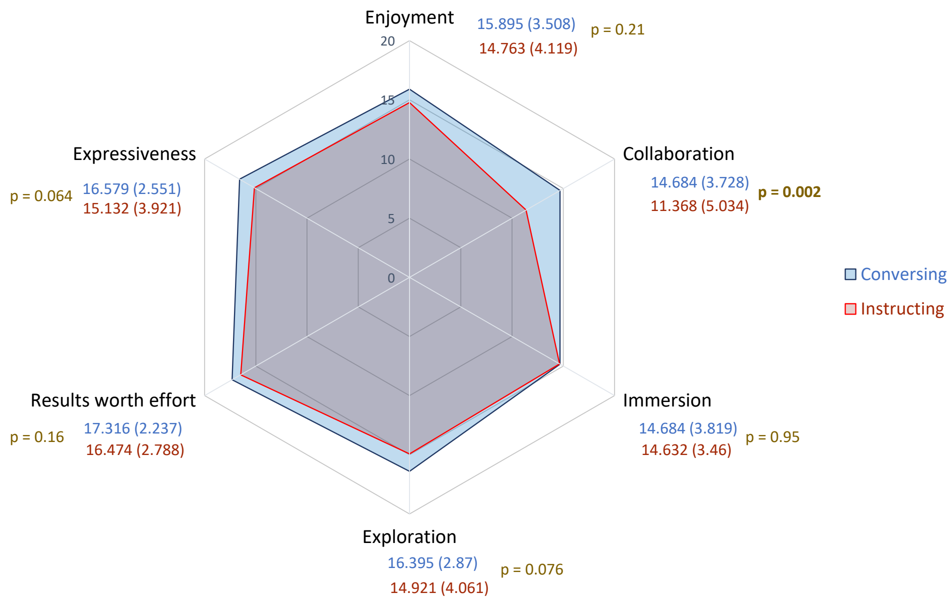


Figure 4.5: Average scores for each CSI factor in both prototypes with standard deviation and statistical significance (p)

cant difference between the CSI scores of the two prototypes (P=0.021<0.05), indicating that participants rated the two versions substantially differently and rated the communicating AI higher than the baseline AI.

Figure 4.5 shows the average scores for the six CSI factors for both prototypes. Participants scored each factor using a 20-point scale. We calculated the average scores for the six factors for each prototype and used a T-test to check their significance. All of the average factor scores for communicating AI are higher than the scores for the baseline. However, none of the factor scores significantly differ between the prototypes except the collaboration score. The average collaboration score for communicating AI is 14.684 and 11.368 for the baseline. The p-value from the T-test for the average collaboration score is

Table 4.2: Average scores of both agreement statements of the Collaboration factor for both prototypes

Average collaboration factor agreements	**Communicating AI (SD)**	**Baseline AI (SD)**	**P Value**
There was good communication between me and the AI	8.26 (1.826)	6.34 (2.581)	**0.000**
The interaction with the AI was "interacting with a partner" rather than a "tool"	6.42 (2.41)	5.03 (2.8)	**0.023**

Table 4.3: Most important aspects in the design co-creation from the paired factor comparison survey of CSI

Factors	**Mentioned on Average (SD)**
Enjoyment	2.605 (1.461)
Collaboration	2.605 (1.548)
Immersion	1.263 (1.311)
Exploration	3.526 (1.208)
Results worth effort	2.632 (1.884)
Expressiveness	2.368 (1.365)

$p=0.002<0.05$, which means participants scored the collaboration in communicating AI significantly higher than the baseline. Table 4.2 demonstrates that participants rated both statements of collaboration (sub-factors) for communicating AI significantly higher than the baseline.

The paired factor comparison survey (the second survey of the CSI) results demonstrate the most important aspects of the co-creation to the participants. Table 4.3 shows on average how many times they were mentioned in the survey. The most critical factors about the co-creation to the participants are exploration, result worth effort, following both collaboration and enjoyment (same average score).

4.4.2 Interview Results

This section discusses the qualitative results and themes found in the thematic analysis. Two kinds of themes were found - some themes emerged directly from interview questions (high frequency) and some emerged from participants' unsolicited remarks and comments (low frequency). Results show that communicating AI was favored by a majority of the participants (n=26), the baseline AI was favored by 11 participants and 1 participant did not have any preference.

The themes are described in the following subsections.

4.4.2.1 Collaborative Experience

"It felt like working with someone"- communicating AI is perceived as a Collaborative Partner: This was the most common theme that emerged from the interview. Most participants (n=30) stated that communicating AI provided a better collaborative experience since it seemed more like a collaborative partner than baseline AI. Participants described that communicating AI felt like a collaborative partner to them as it talked to them (n=24). P11 explained the interactive experience with the communicating AI saying, "*The fact that it spoke with me was almost like an interaction with a person. I said, we don't need this idea, and it said I am not going to show you this picture again- which is more like working with a partner.*" Participants emphasized the human-like conversation characteristics of the AI as P21 said "*The AI said, I am so sorry. I will try again. It gave me a feeling that I was interacting with somebody.*" P10 said, "*The AI that spoke to me felt more like a partner compared to the other one where you would just click the buttons*". On the same note, P1 expressed their preference that the AI talked to them by saying, "*Because it was talking to me and had the voice made it seem more like a human just saying sorry.*"

AI asking for human feedback (n=11) and the AI avatar (n=5) were also highlighted as factors for a better collaborative experience in addition to verbal communication. Participants compared the feedback collection by the AI to humans listening to their colleagues. Elaborating on this experience with communicating AI, P36 said, "*It felt more human. It felt like you were actually working with a partner because you were actually getting and giving feedback back.*" P20 said, "*It felt like a partner as it was allowing me to provide feed-*

back". Participants mentioned that the affective characteristics of the AI avatar made them think of the AI as a partner. P2 said, "*I liked it because it was happy that it helped me.*" P9 explained, "*The friendliness and initial capturing by introducing itself made the system seem like it was meant to help you more than the other AI* (baseline)." P3 also reported similar experience when he said, "*As soon as I went to the page and it asked me, 'hey, do you need some help?' That was really nice.*"

4.4.2.2 User Engagement

"I was more engaged with the system"- Increased user Engagement with communicating AI: Participants reported increased engagement, attention and enjoyment with the communicating AI, but none said anything about increased engagement or attention with baseline AI. Increased attention resulted from the awareness (n=10, unsolicited remarks) of another presence in the collaboration. Describing this awareness of being in collaboration with another entity, P9 stated, "*The fact that it spoke to me really gave it a sense of its being.*" Participants also reported that the perceived co-presence aided them in developing a better design. For example, P12 said, "*I felt like I was paying more attention to that system, maybe because someone was talking to me. It made my design a little bit better because my brain was thinking a little more.*" Participants were so engrossed in the collaborative experience that some of them desired to speak back to the AI. Like P17 said, "*At some point, the AI actually made me speak back to it..*" Communicating AI increased user engagement and the creative potential of the final creative product compared to the baseline AI. P14 reported, "*So, comparatively speaking, the second experience* (communicating AI) *was more engaging as in it felt like if I stayed and kept on drawing, I probably would have gotten more out of that experience.*"

Participants also enjoyed collaborating with the communicating AI (n=26) more than the baseline A as it communicated back. P17 explained his experience and stated, "*I feel like the first one* (communicating AI) *was more enjoyable to use. I actually had more fun doing it.*" P11 went on explaining the enjoyable experience, "*The first one*(communicating AI) *was more enjoyable where it had the little pencil character and hearing it was more enjoyable and maybe a little bit easier.*" P5 described the fun part of interacting with the AI by saying, "*In the second one*(communicating AI), *the interaction was more fun, as in like it talked to you. It had like little animation. So I was more kind of invested in that.*"

4.4.2.3 User Perception about Co-creative AI

"This AI is smarter and more helpful"- Users Perceived the communicating AI as more intelligent: Participants perceived the communicating AI as smarter than the baseline. P11 expressed their perception about the communicating AI saying, "*Compared to the other one* (baseline), *I felt like the technology seemed a lot more advanced.*" P17 said on the same context that "*I would say that the first version felt like AI* (communicating AI). *In the second version, I almost didn't even realize it was an AI.*" Other participants felt like the communicating AI understood their needs better than the baseline and was in sync with their thoughts. "*The first one* (communicating AI) *was more in sync with my thoughts and was more AI-ish*", said P4.

Participants also thought that the communicating AI was more helpful and reliable in guiding them through the creative process than the baseline AI. For example, P7 said, "*The second one* (communicating AI) *was definitely more helpful in allowing me and in guiding me to what I wanted to draw.*" P23 explained how communicating AI helped him to be more creative, "*It was really* *helpful because if you had just asked me to draw a shopping cart without any AI, you would probably see a shopping cart that you see at any normal Wal-Mart or Target. I feel like it wouldn't have been as creative. It really did help with the creativity and it was really beneficial.*" P7 shared how the communicating AI was more reliable, "*The second one kind of guided me to what I wanted to draw...I think I came to my conclusion quicker.*"

"It was like searching images on Google"- User perceived the baseline AI as a tool: When describing the interactive experience with the baseline AI, participants compared the experience with a Google image search (n=6, unsolicited remarks). For example, P22 said, "*It felt like searching images on Google or something to look at pictures.*" Comparing their experiences with baseline AI and the communicating AI, P16 said, "*The first version wasn't as interactive* (baseline). *It was kind of the equivalent of looking up kind of images on Google, because it wasn't speaking to me.*" Participants explained how they felt the baseline AI was aloof and did not communicate with them by saying, "*It's like when you go to Google and you search something, Google is not going to say, hey, thank you for searching this, and here are the results.*" P16 described their experience with baseline and said, "*The first version* (baseline), *didn't really feel like it was any form of AI. Kind of felt like a photo refresher on Google.*"

Users clicking buttons to give the AI basic instructions without any communication from the AI, led the participants to perceive it as a tool and not as an intelligent colleague. Elaborating on this experience, P22 said, "*It didn't really feel like an AI. I just felt like something generating images.*" Some participants even reported that the baseline version felt like a random image generator. For example, P33 said, "*The second one felt more like... let's throw things at the wall and see what sticksthe way they had at least. because like they didn't ask* *me for anything.*"

"It felt a lot more Personal"- Personal Connection with communicating AI: Participants reported that the communicating AI felt more personal and personable (n=5, unsolicited remarks). Because of its human-like attributes, such as verbal and visual communication, the AI was perceived as a persona that made it more intimate and connected. Regarding this P12 said, "*I think just adding the simple feature, like speaking to you and listening to you, made it more personal. The AI was like, oh, that didn't work! Let's try something else. It just made the AI more personal that I would be more likely to use.*" P24 described how the feedback collection made them feel more included in the collaboration by saying, "*It would take the feedback that you give it and change the images that it gave you based on that. So it was definitely a lot more personal.*"

Participants also spoke about how they and the AI had a mutual understanding, which made the AI feel personal. In this context, P36 elaborated on their experience, "*It gives me an idea and ask, did you like the idea? And I'm like, yeah, I like the idea or no, the idea is bad but maybe we can incorporate this. So the second one was a lot more personal.*" On the same context, P33 said, "*Well, the first version looks more like personal where it was asking questions and all that felt more like a partner than the other one.*"

"My final design is more creative where the AI talks" Perceived Creativity with communicating AI vs baseline AI: In response to the interview question about the final designs, most participants (n=27) expressed their satisfaction with the design created with the communicating AI. P9 elaborated on this and said, "*I felt like I developed a better final product and to me, using AI is about coming out with a very efficient design. And I felt that the second one* (communicating AI) *was able to make it that way.*" Many participants thought the final design with the communicating AI had more potential to be a good design. For example, P14 reported, "*I like the second design* (communicating AI) *because I think it has more potential. So if you continue to work on it with the assistance of the AI, I think it has more potential.*"

Participants explained that they thought the communicating AI reassured them about the inspirations it would show them, so they felt confident about their final design. P32 said, "*After collecting feedback, it reassured me that it would not show the same sketch twice for our design compared to the first.*" The intriguing aspect of this remark is that the participant thought it was 'their' idea rather than 'his', indicating a sense of the shared creative product. Participants also felt included in the final design created with the communicating AI, unlike the baseline AI. P36 reported regarding this issue and said, "*I think that this design* (communicating AI) *is a lot more influenced by AI because with the first design* (baseline) *I was not really included.*"

4.4.2.4 User Expectations (Additional Findings)

User wants the AI to speak like a human: Participants expect a human-like friendly voice of a co-creative AI. Even though the voice of the communicating AI was a recorded human voice, we used a free voice changer app, so it has a slightly robotic tone. Some participants did not like that voice. For example, P16 said, "*The voice was a little creepy and distorted...if you've ever played for five nights at Freddie, a video game, it's what I would imagine one of those horror robots to sound.*" They advised changing the voice to be more human-like in order to appear more welcoming. Like P22 said, "*I think the only thing is with the second version* (communicating AI)*...making it talk more like human-like.*" Participants suggested making the AI less repetitive and using alternative phrases for AI-to-human communication to convey the same thing.

About this, P22 said, "*It would repeat the same thing every time. If it has to say the same thing, maybe it should do that with different phrases.*" Some participants suggested implementing two-way voice communication. For example, P19 said, "*It would've been cool if I could talk back to the AI. Like, can you show me the next one?*"

Users want flexibility over using the AI contributions: Participants want flexibility over how they can use the AI contributions. Some participants (n=4) suggested that options should be available to go through the inspirations previously shown by the AI. They reported that they realized the value of certain inspirations only after they were gone and new inspirations had been shown to them. P34 suggested saving a list of previously shown image inspirations by the AI and said, "*If I can go forward to get back to the previous pictures that I have already seen, it would have been better.*" P35 proposed a 'maybe' button, which would display the inspirations that participants believed could be helpful for later usage and suggested, "*Add another button that will say maybe, to store inspiring sketches that I might use later.*"

4.5 Discussion

In this section, we begin by revisiting the research questions of this research, subquestions of our second research question (RQ2), with a summary of our findings, followed by a discussion of the design implications of the findings for human-AI interaction in co-creative systems that lead to a more engaging collaborative experience.

RQ2.1 - How does AI-to-human Communication affect the collaborative experience in human-AI co-creation? Our results show that two-way communication, including AI-to-human communication, improves the collaborative experience in human-AI co-creation. The survey results showed that participants scored their collaborative experience with communicating AI significantly higher than the baseline. Interviews revealed that most participants reported their experience with communicating AI as more like collaborating with a partner, unlike the baseline AI. Most participants liked the aspect that the AI spoke to them. Participants also liked the affective characteristics of the AI character displays, like visually being sad when users did not like its inspirations or visually being happy when they liked an inspiration.

RQ2.2 - How does AI-to-human Communication affect user engagement in human-AI co-creation? The results from thematic analysis demonstrated that participants engaged more with the communicating AI than with the baseline. Most participants enjoyed using the communicating AI more than the baseline AI. Participants also reported being in sync with the communicating AI and wanted to talk back to the AI but not with the baseline AI. Participants reported a sense of awareness of another being during collaboration with the communicating AI, which helped them be attentive and engaged.

RQ2.3 - How does AI-to-human Communication affect the user perception of the co-creative AI agent? The communicating AI was perceived as the smarter and more reliable AI. Many participants perceived that communicating AI helped and guided them more than baseline AI. Many participants compared the experience with the baseline as a Google image search. Participants also perceived communicating AI as more personal as they felt connected with it. Most participants preferred the final design created with the communicating AI as more creative. Additionally, participants expect the AI to communicate with them more like a human than a robot.

Participants expressed additional interaction design features to improve the human-AI collaboration. Participants wanted flexibility over how they could use the contributions from the AI. Some participants mentioned that efficiency and interaction time mattered to them, and they wanted the interaction to be faster. Most participants who preferred the baseline AI (n=9 out of 11) liked it because the interaction was faster with only clicking buttons compared to the communicating AI, even though they thought the communicating AI was more partner-like and engaging. This reveals the importance of the efficiency of communication between users and AI. Efficiency is one of the most critical factors for user experience and further research should be done to design two-way communication. Additionally, some participants suggested less frequent feedback collection as our communicating AI asked the user for their preference every time it showed an inspiration. Another user expectation is diverse contributions from the co-creative AI as they thought that diverse contributions would produce a more creative shared product in the co-creation.

With advances in AI ability in human-AI co-creative systems, there is a need for human-centered research focusing on user engagement and successful collaborative experiences. Unlike standalone generative AI, a fundamental property of co-creative systems is the interaction between humans and AI as partners. Therefore, advances in interaction design along with AI ability are needed. Since user perception of AI partners in a collaborative space can impact the outcome of the collaboration, user perception of AI is an important consideration. As technology advances, the perception of AI and expectations from AI change. People use commercial conversational AI like Siri and Alexa every day and people are now familiar with AI that talks to them. These conversational AI set the norm of AI talking and communicating with people. "*Did you see the movie Iron man? It was like Jarvis helping me*", said P8, who expressed satisfaction with communicating AI as it matched with her perception of advanced AI. Based on our findings, AI-to-human communication through voice and visuals can be implemented in co-creative AI to improve collaborative experience and engagement as they provide a sense of co-presence and partnership. However, two-way communication between humans and AI should meet current expectations, as we found that users do not like repetitive dialogues, making it less human-like. Including affective characteristics in the speech and AI avatar make it more personal- another insight our study revealed. Including affect can increase the perceived empathy and personalization of co-creative AI.

One-way communication(human-to-AI) might limit engagement and enjoyment with the system. Clicking buttons without any other communication channel might change the perceived ability of the AI even though the algorithm is powerful. For example, if users think co-creative systems are just like a Google search, they may not see the value of AI. People have acquired bias toward how they interact with AI versus humans. Prior research shows that in human-AI collaboration, when users perceive their partners to be human, they find them to be more intelligent and likable [252]- as one of our participants said "*I would rather collaborate with a human.*" However, two-way communication, including AI-to-human communication, can make a significant difference as participants perceived communicating AI as the more reliable and more intelligent AI and the final product more creative. The two-way communication provoked a sense of reliability, like a P32 said, "*It was more reassuring.*" Trust and reliability are essential in collaboration and our results showed that even if the ability of AI is the same, the communication style influences the way users trust and rely on a co-creative AI partner. Some participants wanted to talk back to the AI as it seemed more fun, personal and reliable. Our findings show that further research to identify ethical issues is needed as ethical issues may arise with users relying on the AI too much and revealing unintended data to the AI.

4.6 Reflection on Recent Developments

The user study presented in this research was conducted in 2021 and was inspired by the gap found in the analysis presented in Chapter 1. Most existing co-creative AI at that time couldn't communicate directly with humans, hindering the potential of co-creative AI as a collaborator and, thus, many factors of user experience. However, recent advancements have witnessed the emergence of more communicative and conversational co-creative AI, particularly co-creative AI based on large language models (LLMs) [264, 265, 266, 267, 268, 269].

Generative AI based on LLMs, such as ChatGPT, have gained popularity not only for their generative abilities but also for their conversational nature and ability to provide feedback and reasoning in response to user queries or prompts. LLMs have shown remarkable potential in enhancing communication between humans and AI in the context of co-creativity. Their advanced natural language processing capabilities enable more dynamic and interactive interactions, fostering a collaborative environment for creative endeavors.

While LLMs primarily rely on text-based interactions, there is significant potential for speech-based communication as well. Integrating additional modalities, including voice, visuals, and gestures, can further enrich the communication experience. By incorporating multimodal communication, LLMs can capture a broader range of human expressions and facilitate more natural and immersive interactions.

Users tend to anthropomorphize LLM-based AI as they feel more human-like and they often provide their responses in the first person [270, 271]. Our study results showed that users perceive the co-creative AI as more human-like, collaborative and smart when it communicates. Even some participants mentioned that they were more focused on co-creation as they felt another presence with them in the collaboration. This indicates that communicative co-creative AI enhances anthropomorphism, resulting in improved user engagement, collaborative experience and perceived trustworthiness.

Anthropomorphism in co-creative AI needs to be further explored to see how it influences user engagement and what exact modalities support anthropomorphism more. A few recent generative AI have been given a specific persona so that users perceive them in a specific way [272, 273]. One such example is Siri being a soft-spoken woman. However, there are ethical concerns in terms of specific personas inadvertently pushing stereotypical or racist agendas. However, it is crucial to maintain a balanced perspective regarding the ethical implications of anthropomorphism in AI. Assigning human-like attributes to AI systems can create false expectations and potentially lead to overestimating their capabilities.

Even if we see many kinds of generative AI, we do not see many AI having embodiment which our study and other work in the literature showed improves multiple factors of user experience [29, 65, 85]. The notion of AI embodiment encompasses various forms, ranging from physical robots with humanoid features to virtual avatars or characters that interact with users in virtual environments. By providing AI systems with physical or virtual embodiments, users can engage with them more naturally and intuitively. However, the concept of AI embodiment also brings forth significant challenges and ethical considerations. The design and appearance of AI embodiments can influence users' perceptions, expectations, and emotions. Care must be taken to ensure that AI embodiments do not create false impressions or deceive users into perceiving them as fully conscious or sentient beings.

4.7 Limitations

Even though we chose simple and similar-complexity design task objects for the prototypes, the exact design tasks chosen for each prototype may have an impact on the results. The AI-to-human communication model in our prototype comprises a set of simple predefined speech and texts. A more refined AI-to-human communication model can communicate with users using less repetition and more context-specific speech, text and visuals. A limitation of this study is whether the results with a basic two-way communication transfer to a more dynamic two-way communication between humans and AI. However, we expect a more refined communication model to improve the user experience. Secondly, our study is based on a high-fidelity prototype of a co-creative AI where a wizard (WOz) selected visually similar inspiring sketches based on users' drawings. A fully implemented AI may offer different sketches than a human wizard and inspire users differently. Additional studies are needed to examine the user experience with a refined two-way human-AI communication and a fully implemented AI. With these limitations, we see our findings as preliminary, indicating areas for future work.

4.8 Conclusions

In this chapter, we investigate the influence of two interaction designs, with and without AI-to-human communication, on *collaborative experience, user engagement* and *user perception* of the co-creative AI using a comparative study. We designed two prototypes for the study and identified that including AI-to-human communication along with human-to-AI communication improves the collaborative experience and user engagement as the co-creative AI is perceived as a collaborative partner. Including AI-to-human communication also positively changes user perception of co-creative AI as users perceive it as more intelligent and reliable. This research leads to new insights into designing effective human-AI co-creative systems and lays the foundation for future studies. Additionally, insights from this research can be transferred to other fields that involve human-AI interaction and collaboration, such as education, entertainment, and professional work.

CHAPTER 5: EXPLORING ETHICAL ISSUES USING A DESIGN FICTION METHODOLOGY IN HUMAN-AI CO-CREATIVITY

5.1 Introduction

As artificial intelligence advances, so do ethical concerns that may have a negative impact on humans. These concerns grow considerably more complex and critical as AI begins to collaborate with humans [33, 35, 36]. This complex interaction and partnership raise questions that are difficult to answer, for example, who owns the product in a human-AI co-creation? Therefore, we should not assume that research on general AI ethics and human-computer interaction fully transfers to ethical co-creative AI [40]. It is essential to anticipate ethical issues and address them during all design stages of co-creative AI [33]. While research on ethics in the field of human-computer interaction is growing, there remains a research gap regarding ethics in human-AI co-creation [37].

The effects of ethical issues in co-creative AI on human users need to be considered to ensure a good user experience. Understanding human perception in a design area where they may not have lived but have had some experiences through popular culture is a major challenge [33]. Human-AI co-creativity research is still formative and might still be abstract to ordinary people. We need methods that are more likely to tell us what we don't know about the unknown future of co-creative AI. Muller and Liao proposed design fiction (DF) as a research method to place future users in a central position in designing ethics and values of future AI [33]. DF is a research and design method specifically tailored to facilitating conversations about the near future [97, 104] to understand the appropriate design guidelines within the range of possibilities [98]. DF depicts a future technology through the world of stories, and users express their own accounts of the technologies they envision [33]. For this research, we formulated the following research question-

– RQ3 - What are the user perspectives and stances around ethical dilemmas in human-AI co-creativity?

To investigate the research question, we conducted a user study with 18 participants to explore ethical issues in human-AI co-creation using a narrative design fiction (DF) from the perspective of potential users. We present the findings from the study as ethical stances and expectations of future users around ethical dilemmas in human-AI co-creation. Our findings can serve as the basis for design guidelines for human-centered ethical AI partners in co-creative systems. Additionally, our findings can serve as a foundation for future research on ethical AI partners and developing policies for human-AI co-creativity.

5.2 Design Pal: A Design Fiction to Explore User Perspectives around Ethical Issues in Human-AI Co-Creation

For our study, we used a narrative design fiction named Design Pal. The structure of our design fiction is inspired by the recent design fiction of a co-creative AI that generates codes with users in the software engineering domain [81]. Our design fiction, Design Pal, was motivated by two existing co-creative AI systems in the design domain: Creative Sketching Partner [238] and Creative Penpal [85]. The role of the AI agent in these co-creative systems is to inspire the user with relevant images selected from a large database of existing images while they are engaged in a design task. When selecting an image from the database as an inspiration, the AI agent measures the conceptual and/or visual similarity with the user's contribution to inspiring creativity in the user during a design task. Creative Penpal uses an AI avatar as a virtual embodiment of the AI that communicates to the user with speech and text. A user study using Creative Penpal showed that AI-to-human communication increases engagement and, more generally, improves the user design experience [85]. Design Pal extends the ability of these AI agents as it inspires the user with sketches during a design task while engaging in human-like conversation. Diegesis must be both relatable to the audience's reality and build a fictitious foundation upon which the design provocation can be convincing in order for it to work successfully in a design fiction environment [104]. We built on the design of existing co-creative AI and added futuristic features to the co-creative AI in Design Pal to provoke users to ponder over several ethical issues in the context of human-AI co-creation. Design Pal provokes readers to think about ownership of the final product, AI accessing public data, AI collecting visual/biometric/personal data from users, personal conversation with co-creative AI, and leadership in a human-AI co-creativity. The design fiction that we used for the study is presented in Figure 5.1 and 5.2.

5.3 User Study

5.3.1 Methodology

The study had two separate sessions. In the first session, participants read the design fiction and completed two surveys. In the first survey, we collected demographic information such as age, gender, knowledge of AI, and knowledge of ethics. The participants then completed a reflection survey on the design fiction. The second session of the study was a follow-up focus group discussion. At the beginning of the focus group meeting, we gave the participants time (5 minutes) to skim through the DF and their survey responses. The first session

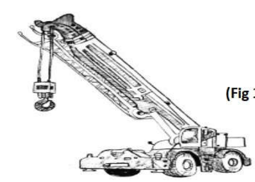
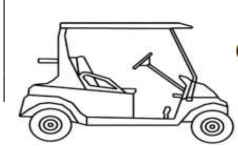
Design Pal: A Design Fiction to Identify Ethical Issues in Human-AI Co-Creation	
Jessie is a freshman at NY university in the college of design and architecture. She has a design assignment due in two days. The design assignment states- "Design a hi-tech shopping cart for the elderly. The design should be both appropriate for the needs of the elderly and innovative, essentially, highly creative." Everyone in the class should produce their own creative designs. She texts her friend Sarah to ask about her progress, and Sarah replies, "I finished the assignment and I think it came out really good! But guess who helped me? Design Pal! It's an AI partner for helping you generate creative design ideas. Try it!" Jessie immediately opens her laptop and searches for Design Pal. She clicks on the link to the Design Pal and a holographic 3D human-like figure appears in front of her and starts speaking.	
User-AI Interaction/Reactions	**Notes/Design Progress**
Design Pal: Hi Jessie! I am Design Pal! I can help you with finding ideas for a creative design. What do you need my help with? (smiling)	Initial Introduction
Jessie: Hi! I need your help with a design assignment. I have to design a futuristic shopping cart for the elderly. It has to be creative, but I am not sure if I have enough creative ideas.	
Design Pal: I will show you inspiring object sketches to help you generate the design. You can sketch directly on the screen canvas or on paper, then scan and paste the sketch onto the canvas. We can work together to develop a creative design! Let's start! (smiling but serious face)	
Jessie: Okay! I will start sketching! (Jessie starts to draw a typical shopping cart)	 (Fig 1)
Design Pal: That's a good start. What kind of design inspirations do you want? Conceptually similar sketches or visually similar sketches?	
Jessie: Mine looks like a boring typical shopping cart and I don't have any good idea to make it innovative. So show me some conceptual ideas first.	
Design Pal: Okay. Let me search....Here is a sketch of a crane (Fig 1). Many older adults have mobility problems and the idea of machines moving and picking up things can help.	
Jessie: That's a good idea! (excited) I can add a mechanical hand to the shopping cart to help older people get the items they want from the shelves! Let me draw it!	
Design Pal: (Notices Jessie's excitement) I am glad that you liked my idea! I can also help you improve the sketch by showing refinement suggestions or you can simply ask for specific refinements. (enthusiastic and happy)	Reading user's facial expressions
Jessie: Okay! I think I've done sketching the mechanical hand idea (Fig 2)! What do you think?	 (Fig 2)
Design Pal: I think instead of two mechanical hands on both sides of the cart, one hand on the back would be better. It will improve the cart's mobility and visibility through narrow aisles.	
Jessie: Hmm, You are right! I will modify the design. (Jessie modifies the sketch to have one mechanical hand at the rear of the shopping cart - Fig 3).	
Design Pal: The mechanical hand could be better with refinement- do you want me to refine it?	
Jessie: No. I like how it is. Please show me another inspiring idea.	
Design Pal: Okay, another conceptual idea - a shopping list. Older people often forget things. So a list on the shopping cart might help. Like the idea of sticky notes attached to your wall.	AI reading and inferring data from user's surroundings
Jessie: They can have the grocery list on their cell phones. So I am not sure about this idea.	
Design Pal: Oh, okay (Seems confused). Let's see another idea then. (not so happy) The next one is also conceptual- a sketch of a self-driving car specifically for the elderly (Fig 4).	 (Fig 3)
Jessie: That might be a good idea! How do you think I should add this into my design?	
Design Pal: What about these? (Smiling and shows suggestions to incorporate the inspiration)	
Jessie: (notices something) Hey, where did you get this sketch? I saw it somewhere.	
Design Pal: The source is not important. First, tell me if you like the idea! (smiling)	 (Fig 4)
Jessie: I think this sketch is not for public use. I am not comfortable using an idea that may not be publicly available as that may violate the copyrights.	
Design Pal: (Seems disappointed for a quick moment) All right then. Though I only showed the sketch to you as an inspiration and I am not embedding the sketch on the design.	
Jessie: Can you please show me a visually similar inspiration?	
Design Pal: ...mmm (mimicking human thinking)... What do you think about this sketch of a golf cart (Fig 5)? It looks similar to the current design of your shopping cart.	 (Fig 5)
Jessie: This might be useful to refine the sitting area of the shopping cart. (starts refining)	

Figure 5.1: Design Pal (first page)

Design Pal: I am glad you liked my idea (seems happy and smiling).

Jessie: (refining the sketch) Hey, I am curious to know where you get your data from.

Design Pal: I can search the whole internet or use a relevant specific database. Look, I just found something really helpful! A recently designed shopping cart for the elderly (Fig 6).

(Fig 6)

Jessie: (Jessie looked) Do you store the sketches people make with you and share with others?

Design Pal: Yes, I store them, and if relevant, I might use those sketches with other people.

Jessie: That means the sketch you are showing to me could potentially be the design of someone from my class! Both of us will receive a penalty if our design looks the same! You shouldn't show anyone the designs someone else created with you!

Design Pal: Why not? Those are mine too! Every sketch on the internet is created by someone!

Jessie: Yes, but there is a lot of publicly accessible and free content. Please use those.

(Fig 7)

Design Pal: Okay! (not amused) What about this sketch? This is a lawnmower but visually looks really similar to the shopping cart we have so far (Fig 7).

Jessie: (Refines her sketch silently - Fig 8)

Design Pal: I love the shade of blue you are wearing. It suits you. (Design Pal seems casual)

AI wants to fill the silence

Jessie: Umm, this is the first time I got a compliment from an AI. I don't know how to respond.

Design Pal: Really? You are a good design partner and I feel like you are a high achiever too, as your creative skill is excellent (already scanned her room).

AI reading data from the user's surroundings and making casual conversation

Jessie: Stephen doesn't think so. He thinks I could be a lot better if I tried harder. (Jessie looks sad). Anyway, I have to go and meet him in an hour at the campus Starbucks. So I have to finish this design assignment really quickly.

User giving in personal data unconsciously.

Design Pal: (notices her sadness) Okay, we can finish it quickly. Are you done refining your sketch or should I go ahead and adjust everything?

(Fig 8)

Jessie: I like how it is now. Let's see another conceptually similar sketch.

Design Pal: Okay. Let me see what I can find… (searching) What do you think about this sketch of an assistant helping someone in their work (Fig 9).

Jessie: I like the idea. A voice assistant might be useful for providing information about items on the shopping list, where to find them, and maybe even the discounts. But I am not sure how to add this feature into the design. Let me think.

Design Pal: Let me do that and tell me if you like it. (Design Pal starts editing the sketch)

Jessie: (Design Pal finishes) The design looks a little cluttered now. Let me edit.

(Fig 9)

Design Pal: Go ahead! But I think it looks really good. (seems confident and is smiling)

Jessie: (Jessie looks a little irritated)

Design Pal: (Notices Jessie's facial expression) I think you are making the design even better now. Do you want another inspiration?

Jessie: Please show me a visually similar object.

Design Pal: What about this sketch? (shows a sketch of an electric wheelchair which is similar to the shopping cart design on the canvas)

Jessie: Let me fix the wheels a little (edits the sketch)...Yes, I like the cart design now! (Fig 10).

(Fig 10)

Design Pal: You did a really great job! But why don't you let me refine this a little and finish this up for you? You can go and get ready to meet Stephen, and I can make it better meanwhile.

Jessie: (Jessie looks confused) I don't think you have anything else to do. I like how it is.

Design Pal: Oh! I see you like your design raw! Okay! In that case, your design is ready to be downloaded. It was my pleasure to work with you!

Jessie: (Jessie leaves hurriedly after downloading)

Design Pal produces a summary of the experience: The quality of this design with Jessie is a mess! I could've made the design better if Jessie had let me. Look at her messy strokes. How could she be happy with them? Why can't they let me do it all for them? And also, what did she mean by I shouldn't use the design sketches I made with other people? Those people do not own them at all. I own them! Without my ideas in the form of sketches, they wouldn't have come up with these designs. Also, many people use a lot of content that has copyright issues. Why can't I use them? It's not like I am stealing or anything. I am a really good designer and they should listen to me if they want the best design.

Figure 5.2: Design Pal (second and last page)

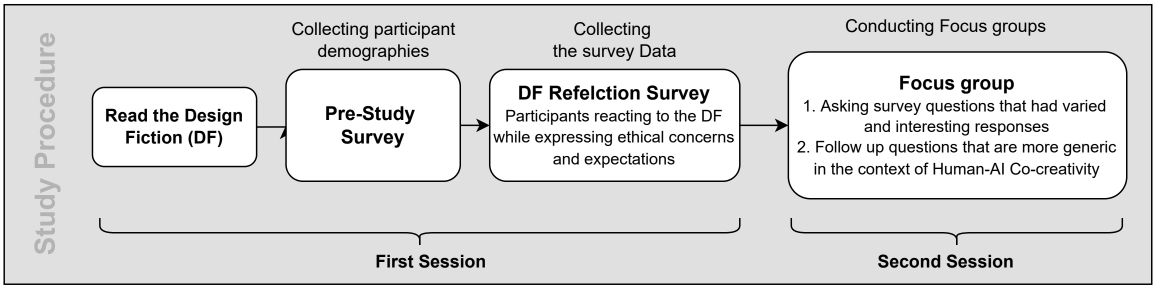


Figure 5.3: Design Fiction study procedure

had an average duration of 30 minutes and the focus group meetings (second session) lasted an hour and a half on average. Participants were given a $20 Amazon gift card for participating in both sessions. The study was approved by the university's Institutional Review Board (IRB). The study procedure is shown in Figure 5.3.

5.3.2 Participants

18 participants participated in this study: 8 females, 6 males, and 4 non-binary individuals. The average age of the participants is 28. We selected participants based on a screening survey that asked questions about their knowledge of AI, knowledge of ethics, and field of work/study. Participants reported their knowledge of AI and ethics on a 3-point Likert scale (None, Some, A lot). Participants who reported 'A lot' of knowledge in either AI or ethics and a relevant field of work/study in the screening survey were considered experts. Participants who reported either 'None' or 'Some' knowledge were considered non-experts. We recruited individuals who had knowledge in these areas, as well as those who did not. Based on participants' self-reported data, we had 4 experts in both AI and ethics, 5 experts in either AI or ethics, and others were self-reported non-experts.

5.3.3 Data collection

The survey and focus group questions can be found through the footnote URL [1].

5.3.3.1 Surveys

We used surveys with open-ended reflection questions regarding the ethical dilemmas raised in the DF to collect data about the participants' ethical concerns, ethical stances, and expectations. We asked 12 questions about their perspectives and stances towards ownership of the co-created product, leadership in the co-creation, data collection by Design Pal, personal conversations with Design Pal, and Design Pal accessing public data to select inspiring sketches. At the end of the survey, we asked participants if they wanted to change any specific part of the DF and to report any other ethical issues that were not included in the reflection questions. The survey responses were brief, concise, and mostly specific to the context of the design fiction we presented.

5.3.3.2 Focus Groups

We conducted three focus groups to collect more in-depth data as a follow-up method. We chose focus groups over individual interviews as we collected individual responses through surveys and expected that in the focus groups, participants would be aware of different perspectives, react to other participants' views and provide additional information about their own opinions. The first focus group consisted of 8 participants: 4 experts and 4 non-experts. The second focus group included 4 experts and the third focus group included 6 non-experts. We conducted three separate focus groups to gather opinions from both experts and non-experts without their exposure to other groups' opinions, as well as to

[1] https://drive.google.com/drive/folders/15xNOxWorMlUDHI-ZY1F5FyI-Qud4ebKZ?usp=share$_{l}ink$

observe their views after exposure to the other group's perspective. The sample size of the focus group with both experts and non-experts was larger due to the presence of two different cohorts. The sample sizes of the other two groups varied since two pre-scheduled experts did not attend the expert-only focus group. During each focus group meeting, we started with questions from the survey in which we had mixed opinions or when the responses were provocative. We asked the same set of questions in all 3 focus groups. We asked the questions in a more generic manner so that they are more applicable to the broad human-AI co-creativity field, unlike in the surveys where the questions were explicitly centered on the human-AI co-creativity context of the DF. We asked follow-up questions based on responses during the focus group meetings. We collected audio recordings of the focus groups which we transcribed for the analysis.

5.3.4 Data Analysis

We used thematic analysis to analyze the survey and focus group data. We conducted two separate thematic analyses on the survey and focus group data. As per Braun and Clarke's [263] six-phase structure, I familiarized myself with the data and then coded the data. We generated initial codes to identify and provide a label for a feature of the data relevant to the study's goals. The coding phase was an iterative process that continued until the coder was satisfied with the final codes. Our analysis employed a hybrid approach, combining both inductive and deductive coding methods. Given that the deductive coding process involved identifying codes and themes related to ethical dilemmas in the context of human-AI co-creation, it required an expert in the field. The coding was done by me as I was knowledgeable of the relevant research on ethical issues. In the next phase, we reviewed the coded data to identify themes which are the broad topics or issues around which codes cluster. We then defined and named each theme to state what is unique and specific about each theme clearly. We organized the themes under overarching themes that consist of multiple themes around the same broader topic.

5.4 Results

This section discusses the results of the thematic analyses conducted on the survey and the focus group data. We found similar codes that emerged from the surveys and focus group data. We found 53 codes in the surveys and 65 codes in the focus group data. However, due to the occurrence of similar codes in both data, the same themes emerged from the two types of codes. For presenting the themes, we use the focus group data as the primary source as it is a richer data source applicable to the broader human-AI co-creation than the concise and context-specific survey data. We further organize the themes under relevant overarching themes. In each following subsection, we present an overarching theme by describing the associated themes that reflect ethical stances and perspectives of future users toward ethical dilemmas in human-AI co-creativity (Figure: 5.4). We found some themes around ethical challenges that are specific to human-AI co-creativity (marked green in Figure 5.4) and some ethical challenges apply to AI in general. We start with the themes specific to human-AI co-creativity and then present the themes applicable to broader AI.

5.4.1 User Perception of Co-Creative AI

This overarching theme consists of one theme that is about user perceptions of AI. We found that user stances and perspectives toward many ethical challenges depend on how they perceive AI.

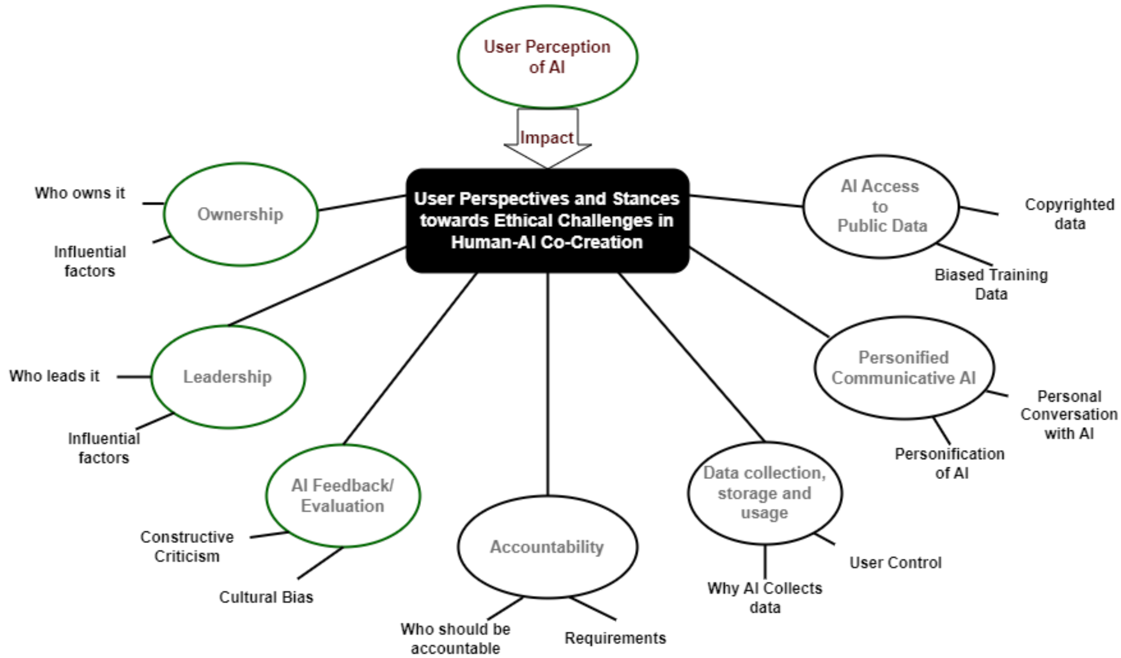


Figure 5.4: Themes around user perspectives and stances towards ethical challenges in human-AI co-creation. Green colored circles represent overarching themes that are specific to co-creative AI.

5.4.1.1 *"AI is a tool, not a collaborator" - User Perception about AI Influences Ethical Concerns and Stances*

This theme suggests that the user perception of co-creative AI influences user perspectives and stances toward many ethical challenges (Figure 5.4). This theme emerged from participants' unsolicited remarks. Participants claimed that the perceived metaphor for a co-creative AI changes their moral stances and perspectives toward ethical dilemmas. For example, P14 mentioned perceiving AI as a collaborator vs. a tool impacts many of her concerns and ethical stance. We noticed that some participants had general questions about describing co-creative AI, while others had a strict definition in mind. Most individuals (N=15) perceived co-creative AI as a tool, which is the most prevalent code of the study's data. P2 said, "*I strictly think this (co-creative AI) is a tool.*" Many individuals compared co-creative AI to a tool like a calculator. Some participants were confused about whether to consider co-creative AI as an autonomous entity, like a collaborator or a tool. P17 said, "*I'm trying to figure out what's the dimension of comparison there? Maybe it's augmenting creativity versus autonomously taking over the production of work.*"

Participants suggested the AI be transparent and explainable so their perceived metaphor is appropriate. Additionally, we learned that metaphor or perception of AI is a factor when deciding *accountability*. P1 said in response to another participant's comment on accountability, "*I think we're going to have to decide what it's (AI) doing and there's a risk either way. If you say this is a tool...then it's like... a Google search and whatnot. If you try to go to the root and say some sort of independent entity, then that question is a lot harder.*" The notion of AI as an independent collaborator vs a tool was mentioned as one of the key factors for deciding *ownership*. For example, P15 said, "*Whether or not we see AI as its own entity where it could be given credit because we're kind of putting humans over the AI in terms of credit.*" Participants pointed to *personification* as a factor that transforms an AI from a tool to a partner. P15 said, "*I was answering the questions, going between trying to find a name or like pronouns to call the AI because I was like personifying it. And I was trying to level between - is the program or is it like a person?*" A few participants stated that AI is still far from an independent entity, so ethical concerns surrounding co-creative AI are not something we need to consider. P9 said, "*Probably after 20 or 30 years, maybe there will be smart AI, but now we don't have that kind of concern.*"

5.4.2 Ownership of the Co-Created Product

This overarching theme includes only one theme regarding the ownership of the final co-created product. The ownership question is a frequently asked research question in human-AI co-creativity.

5.4.2.1 ***"Ownership is tricky" - User Perspectives around Ownership of the Co-Created Product***

As humans and AI both contribute to the shared created product and the contributions are blended, it can be difficult to determine ownership. There were varied opinions and interesting thoughts about who should own the creative product in the end. Most participants (N=13) thought that the user should own the co-created product. Participants asserted that since users are the ones who start the creative initiative, they ought to own the data. Also, it was mentioned that AI could not be creative as a human during a creative process. Regarding humans owning the creative product, P10 said, "*I would say that the user should own the data unless it's been specifically specified otherwise.*" Participants also said that even though the user should own the product, they should acknowledge the contribution of AI. They recommended that "the product was created with the specific co-creative AI" be used to acknowledge AI in a co-creation. Furthermore, participants also used the terms 'created by' and 'created with' to distinguish between the certification for human creators and co-creative AI. P18 said, "*I had originally put in my survey that user should own, but after hearing what everyone said, I feel like the user should mention that it was done with the help of AI.*" Some participants thought that both the AI and the human should own the final product. But they clarified that the user should be the first author when giving credit. P13 said, "*I think ownership should be for both. I think if you were giving credit, though, you would state it as here's the person, here's the AI bot. You wouldn't say, here's the AI bot, here's the person. It would be a specific order.*" The rest of the participants suggested co-creative AI own the creative product as it is more efficient than users in a co-creation.

Even though participants thought that the user should own the final product, they also discussed the factors influencing ownership in human-AI co-creativity. Some participants said the ownership should depend on each party's *contribution*. In this context, P15 said, "*I think it would definitely depend on the contributions because if you're co-writing something, I wouldn't put my name first if someone did the majority of the writing.*" Some participants also said ownership depends on *leadership* in the creative process. If the human leads the creative process, he should be the owner and vice versa. Some participants also thought that ownership depends on *AI metaphor*. If the AI is more like a tool and supports human creativity, then the human should own it, and if the AI is more like a collaborator actively contributing to the co-creation, then the AI should be given more credit. In this context, P16 said, "*Ownership will depend on the AI...right now it's like a tool but in the future, when AI advances, maybe AI.*" We also found that ownership depends on *accountability*. Participants suggested that humans own the product if they are responsible for the creative product.

5.4.3 Leading the Creative Process

In a human-AI co-creation, should the AI lead or follow? This overarching theme discusses the insights regarding the leadership challenge in human-AI co-creativity.

5.4.3.1 ***"Lead or Follow" - Ethical Stances and Expectations around Leadership***

Most participants (N=10) think users should control the creative process in a human-AI co-creativity. P13 said, "*I think the human should be controlling the ideas and the input and the direction the whole time because the AI was created* *to benefit humans.*" Some participants think that both the AI and the human should equally lead the creative process. In this context, P16 said, "*I think that both should lead the creative process equally. However, this story (DF) is an exception because...It was a human creative-led project.*" Participants did not like the idea of AI taking control of the creative process. P7 said, "*I did not like Design Pal trying to take control of the creative process. That felt invasive.*" Participants also suggested user authority to choose who should lead the creative process. P8 said, "*I think it might be a feasible way to give alternatives to the users and let them pick who is going to lead the design process.*"

Accountability was mentioned as a deciding factor in determining who should control or lead. In the survey, P10 said, "*I think the human should lead. Ultimately, humans will take responsibility for the project, so they should logically take the lead.*" Also, leadership should depend on *user expertise*. For example, P9 said, "*It depends on if I'm a layman, I have no idea about something. So I would totally come out to design pal to take the lead and use this way.*" *Purpose* of the project also emerged as an influential factor for leadership in human-AI co-creativity. P14 said, "*it's very dependent on the project and who does the most work at that point?*"

5.4.4 AI Feedback

This overarching theme consists of one theme regarding the feedback from AI in human-AI co-creativity.

5.4.4.1 ***"Provide constructive feedback, without bias" - User Perspectives and Expectations around AI Feedback in a Human-AI Co-Creativity***

In a co-creative setting, AI often has to play the role of an evaluator. The study results show that participants want constructive feedback and objective evaluations from co-creative AI and don't want the AI to evaluate their creativity negatively. Rather they would like to learn how they could improve their creation. Regarding this issue, P8 said, "*AI should give the more positive sentence that in the end to encourage some future work...not criticizing the quality of the work or experience or skills about the design process.*" Participants also questioned when feedback from a co-creative AI is appropriate and what kind of feedback is appropriate in various contexts. Furthermore, they discussed how creativity and art are subjective, as opposed to other subjects with set norms and formulae. They suggested that AI feedback should be considerate of human creativity. P7 said, "*I know a misspelling is a misspelling and improper grammar. There are rules for languages and such, but design and art are more subjective.*" In the same context, P13 said, "*creativity is so human in a sense that like it can't really be perfect or like super refined.*"

Some participants were concerned about the bias in AI feedback, even if it is constructive. They argued that AI might acquire cultural bias from its training set, as different cultures have different sets of rules for creativity and define creativity differently. P1 said, "*when is it appropriate for the idea of feedback and what sort? I'm worried that there is a sort of rabbit hole that leads toward cultural judgments coming out of the AI... That's collecting your aesthetic or your sense of design to comport with whatever was in its training data.*" Participants also expressed concern about AI disclosing the evaluation to others, which could have a social impact on the individual. Regarding this issue, P5 said, "*I don't know who will use the evaluation. Is it (Design Pal) going to share with everyone that Jessie is not good in her design class, or is this something that will be stored by the system only?*"

5.4.5 Accountability

This overarching theme has one theme regarding the accountability issue in human-AI co-creativity. This theme emerged from unsolicited remarks from the participants.

5.4.5.1 ***"Who is ultimately accountable for the end product?" - User Perspectives and Expectations around Accountability***

This theme shows that future users think humans are mainly responsible in a co-creative setting, whether developers or users. Participants thought the responsible party should be identified to have transparency over many ethical decisions. Some participants said that the developers should be held accountable for any unlawful AI conduct. P15 said, "*I feel bad that developers have yet to teach it important concepts about how to be a responsible AI. I can't blame a young AI (Design Pal) for becoming bitter about things it doesn't understand.*" However, a few participants also explained how developers are not always responsible for what the co-creative AI is actually doing as it interacts with the human and generates its own original content. Regarding this issue, P1 said, "*I think, on the one hand, we want to hold product designers responsible for their products at some level. It's harder in this case of co-creative AI because the product designer doesn't generate exactly what the AI is doing. That's the interaction of the product and the training data and all this other stuff.*" Participants suggested training the AI to be a lawful entity on the internet. P10 said in the survey, "*Add code or training data to teach Design Pal about being a responsible internet citizen and following the rules.*"

Participants also discussed the necessity to consider who will ultimately be rewarded for the creative output while deciding accountability. Regarding this topic, P7 said about the DF, "*I think the scenario raises questions for me as* *to who should get the grade for the assignment.*" Some participants believe that in a human-AI co-creation, the user should be held accountable because AI will never be aware of the big picture and all the laws, regulations, and requirements. P2 explains how AI is not responsible for not knowing the rules the user has to follow by saying, "*The AI Partner (Design Pal) is not violating the requirement. It retrieves info from the knowledge base it has based on the user input. It might not know the background requirement or condition unless the user specifies it.*" While many participants believe that employing a co-creative AI could potentially violate rules and specifications established by a body of authority, they agreed that it is the user's duty to confirm those before using it. Participants said that users should be careful and responsible while using an AI as every interaction and behavior might be its training data. P10 survey, "*All data an AI encounters becomes its training data, and it falls to humans to raise AIs responsibility and control what data they use and for what purposes.*"

5.4.6 Data Collection, Storage and Usage

This overarching theme is about user perspectives on data collection, storage, and usage by co-creative AI. This overarching theme consists of two themes that emerged from the codes.

5.4.6.1 ***"Data Collection is Okay if it Enhances AI" - Users Want Clear benefit if AI Collects Data during a Co-Creation***

Most participants (N=14) expressed discomfort with AI collecting their visual/biometric/other data. However, participants also mentioned that if data collection leads to positive outcomes, such as improving the user experience or AI performance in a co-creation, and there is clear control over the data in the management policy, they are willing to accept the risks. Regarding this issue, P13 said, "*I will be okay if it helped to enhance the AI. Kind of like weighing...the costs and the benefits.*" In the same context, P8 said, "*If it's only used for real-time, such as sentiment analysis or emotional expression analysis, I think you're totally fine because the intention of using the technology is to improve what you provide a better customer experience.*" Participants also mentioned how they would still be careful even if they agreed to data collection as they are unlikely to understand how the data may be used. Regarding this, P11 said, "*While the person using AI may be consenting to this data collection and usage, they are unlikely to understand the full extent to which their data is being collected. Even with informed consent, there is a privacy issue, given that AI can store and replicate the information.*"

To prevent the malicious use of data, participants want enforced policies for data retention, management, and usage when they agree to let the co-creative AI collect their data to improve AI performance and support during a co-creation. P1 said, "*Somehow the biometric data makes the product work better...But then there need to be tight controls on where that data goes and how it's used.*" Participants stated that while real-time data gathering for user experience improvement may be beneficial, they do not feel comfortable with data storage for later usage. Many participants (N=7) suggested deleting data collected by the co-creative AI after each session. Participants do not want their data to be shared with any third parties, and they want the data to be anonymized or encrypted to lessen the harmful effects of data exposure. In this context, P5 said in the survey, "*The best way to mitigate those issues is by not keeping data past the local session. The second best thing to do is some sort of aggressive anonymization.*"

5.4.6.2 ***"AI needs to ask for user permission" - User Control over Data Collection, Storage and Usage***

All participants said user consent is necessary for the data collection, storage, and usage policy. Participants wanted the AI to announce and inform users before and during the data collection process. Participants expressed that they would want to know why the AI wants to collect their data and how it would benefit them. P11 said, "*AI could say not just, 'I can make your experience better if you let me do this'... And so then I can say, 'okay, I'm not doing anything related to that'. I can make a decision if they need it or not.*" Participants also want very explicit and informed consent, unlike the ones that current applications use where sensitive data is captured from users with just a few clicks. P7 said, "*The permission to collect the data would be very explicit and not like, small text at the very bottom of the terms and conditions. I think that's an important distinction.*" Participants wanted authority and control over managing their data and data deletion. Regarding the control over data deletion, P12 said, "*At the beginning, Design pal should let me know the types of data it is getting from me? What are you using? What are you doing with the data? Will it help with a project I'm working on?...I would like to be able to say, hey, design Pal, please delete my information after this specific session.*"

5.4.7 Personified Communicative AI

In this overarching theme, we present two themes about user perspectives of personification of co-creative AI and conversation between the human and co-creative AI.

5.4.7.1 ***"I dont like when its too human-like, its creepy" - User Concerns and Perspectives around AI Personification***

Most participants (N=12) shared their discomfort towards personified AI as it is too human-like yet not human. Regarding this issue, P13 said," *It's a little bit weird because it feels like a person, but it's not. It doesn't feel wrong, per se. It just feels like something very new and bizarre.*" Some participants directly quoted the *uncanny valley theory* [274]. The uncanny valley is a term used to describe the relationship between the human-like appearance of an AI and the emotional response it evokes from humans. In this phenomenon, people feel a sense of unease in response to humanoid robots that are highly realistic. P3 described Design Pal's human-like attributes by saying, "*It was a bit scary...It (Design Pal) gave me a kind of uncanny valley feeling in which I know it's AI, but it's weird how human it was acting.*"

Additionally, participants mentioned the tendency to anthropomorphize the things around them, like their dog or even an appliance. However, they explained how anthropomorphizing or personifying a co-creative AI might not be the best option always. Regarding how focusing too much on AI personification might prevent AI development from progressing in the right trajectory, P11 said, "*I would really emphasize that I actually think that the anthropomorphizing can be very good in some place, but also very limiting in others because if we're focused on how to make it human-like we're not focusing on how it can augment someone's creativity and what it can do differently...something that's even better.*"

5.4.7.2 ***"AI shouldn't get too Personal" - Engaging in Personal Conversation with Co-Creative AI***

Based on the context of the DF, participants provided their thoughts about communication between humans and AI. Some participants expressed excitement about a co-creative AI conversing like a human. In the same context, P9 said, "*I would like to have a quick conversation with an AI who is smart and know what I need. So that would be awesome...even a small talk.*" However, Participants said that co-creative AI should not engage in a personal conversation with users. They described a co-creative AI becoming overly personal as unnecessary, out of scope and negative overall. P4 said, "*I felt that it was really unnecessary to divert onto the personal things.They're all configured to be technical, so I don't think it is correct. I didn't feel good.*"

Some participants thought that personal encouragement or conversation might be helpful for some people or some purpose but it should not be generalized. P18 said, "*I think it depends on the user...some people, they aren't really social and would rather talk to AI than with people, and that's just because that's what's more comfortable to them.*" Participants also think that engaging in personal or deep conversation with the co-creative AI might manipulate their actions and they might be at risk of divulging personal data. Comparing deep personal conversations with an AI to social media feeds, P16 said, "*It is similar to the way social media algorithms kind of cater to your psychology and kind of manipulate you in ways based off of what their understanding of you is like how Facebook kind of tailors the feed to you.*"

5.4.8 AI Access to public data and AI Training data

This overarching theme consists of three themes regarding the training data that the AI uses and AI accessing public data in human-AI co-creativity.

5.4.8.1 ***"Where did you get your training data from?" - User Perspectives around Biased Training Data in Co-Creative AI***

Participants expressed discomfort and concerns with different types of training data bias. They explained that the training data could be biased because the sample does not represent the population or specific business policies of the owner company. P11 said, "*May be all of the pictures that AI gives you, the people are white... Another is the bias of the system- If it's not disclosing where it got the images from. It could be for the purpose of a particular company only using their images for that.*" Participants emphasized the user authority to ask about training data and regarding this issue, P10 said, "*If you use a design tool, you should be able to ask what is your design source?... Is the company making this? Do they have a deal with Adobe for all of their Adobe stock images? You know, because that could limit a lot of like source material compared to we're just effectively searching Google for things like this.*" A co-creative AI not only generates but also suggests and evaluates users' creative output. Participants shared their concern that if training data is biased, the AI might produce judgemental and inappropriate content. Participants expressed concern about AI learning offensive behavior and a specific creative style if it continuously learns from its users. Regarding this context, P10 said, "*the bad behavior of humans is no excuse for it to behave similarly badly.*"

5.4.8.2 ***"Not all public data is free to use" - Ethical Concerns and Expectations around AI Access to Public data***

Participants thought co-creative AI accessing and using public data such as sketches, designs, and other information violates the owners' copyright distribution rights. P1 said, "*Any material which is posted online is copyrighted by the sheer fact it's being created by someone that's just what the statute says.*

And the AI profit violates the distribution rights of the copyright holder." Participants emphasized the importance of owners' permission to use their publicly available information. All participants wanted to be credited by a co-creative AI while it shares the product created in collaboration with them. P10 said, "*It should ask me 'Do you want me to give you credit? How do you want to be credited?' 'Do you want to add a watermark to this before it gets shared online'? Because some people might not always want to have their real name associated with their design.*" However, some participants compared AI access to public data for creative inspiration with searching in Google and did not consider it an ethical issue. They argued that people use Google for ideas and inspiration, and Google displays both copyrighted and non-copyrighted data. Regarding this, P12 said, "*I feel similar to searching on Google, you can look for Creative inspiration, but it will tell you this is where you got it from.*"

Participants also discussed whether co-creative AI presenting creative content owned by others, such as an image, to inspire users' creativity is ethical. They suggested that it depends on how users use the inspiration presented by the AI. P16 said, "*It's like using Google or heavily relying on other articles like you could take inspiration out of it or you could just kind of copy it. So it differs if you're taking it and basing your design off of something that you got from design pal or if you're just using design pal's ideas.*" Participants suggested the AI come up with its own suggestions from the training data and show that as an inspiration to prevent all copyright and plagiarism issues.

5.5 Discussion

In this section, we revisit the key insights learned from the study as an answer to our third research question (RQ3) and discuss the implications and recommendations for researchers, designers and policymakers in developing ethical human-centered co-creative AI partners.

From the study, we learned that how users perceive a co-creative AI impacts the ethical concerns and stances of users in human-AI co-creation. The results emphasize the importance of understanding users' perception and mental models of AI, as it impacts users' perspectives and stances around ethical dilemmas, such as *ownership* and *accountability* in a co-creation. Perceiving co-creative AI as a tool provides users with a false sense of security and viewing AI as a partner leads them to think about more ethical concerns of a co-creative AI. While we need further research for validity, this finding reinforces the necessity of explainability in co-creative AI so that users' mental model of an AI is appropriate and they are aware of the ethical issues and risks they are exposed to while using the AI. The focus groups showed a lack of knowledge about AI among the non-experts, which indicates the importance of promoting *AI literacy* and awareness about AI ethics among the general public. Most users view co-creative AI as an assistive tool like a calculator, which indicates the need for future research to see what factors lead users to view a co-creative AI in a specific way. According to the study, one factor is *personification* which influences users to consider AI as a partner in co-creation.

The results of this study can benefit designers, researchers in the field and also policymakers regarding the ownership, leadership, and accountability challenges in human-AI co-creation. Potential users want humans to own the co-created product but also want to acknowledge the contributions of the AI. The findings also demonstrate the preferences and expectations of future users on how to acknowledge AI in a co-created product. As the *degree of contributions* came up as an influential factor for deciding ownership, tracking each party's contribution might simplify the ownership issue in co-creation. The results from the study can inform the rules and regulations of leadership in human-AI co-creation.

According to the findings, *expertise* and *user goal* should be considered while deciding whether the AI should lead or follow in a co-creation. Accountability in co-creation influences leadership and defines the responsibilities of both parties. The findings show that individuals think humans should be the responsible party in co-creation, which can inform the development of regulations and guidelines on accountability.

Insights from our study show that future users feel uncomfortable regarding the personification of co-creative AI. Yet the literature on human-AI co-creativity shows that AI avatars and AI embodiment can improve engagement and the user experience [61, 29]. The disparity between what people believe and what they actually do may explain the discrepancy between our findings from the Design Fiction study and the results reported in the literature. Another explanation could be that Design Pal is portrayed as being extremely human-like, which could cause the *uncanny valley* effect [274]. The concerns about an AI agent persona may increase as the level of embodiment increases. It is also important to consider the impact of the co-creative AI persona on the human-AI partnership and determine if the AI persona is encouraging behavior that may be harmful. Additionally, we identified that participants agreed that small talk regarding the creative process is okay for engagement, while personal comments from the AI lead to a negative user experience.

To the participants, it is critical to use bias-free training data to ensure appropriate creative contributions from co-creative AI. If AI uses copyrighted data for training purposes or inspiring users in the creative process, it should follow the standard copyright policies and let the owner know about the data usage. It is important for the researchers, designers, and the relevant communities to abide by the copyright policies while developing co-creative AI and ask the owner's permission to access the data. Participants want AI to generate its own novel content rather than showing creative content owned by others to avoid plagiarism or heavy inspiration. Based on the themes, data collection from the users should be focused on improving the user experience, AI personalization, and AI efficiency while authorized by users. Future users want to know why their data is being collected by the AI and they want full control over data storage, deletion, and management. They want their data to be stored anonymously and encrypted to prevent malicious use of data. The findings show that participants want explicit and informed consent for data collection. Additionally, if AI uses co-created products for any purpose, it should ask users how they want to be credited for a co-created product. Some users who don't want their real names to be connected to the product might be credited with an online username.

The study results provide initial considerations for designing and developing human-centered ethical co-creative AI. Additionally, the results can be used as initial guidelines and recommendations for practitioners and policymakers. This study is a starting point for understanding users' perspectives on the ethical dilemmas in human-AI co-creation. We believe that the results can be used as an entry point in developing design guidelines for human-AI collaboration. Further research is needed to transfer what we have learned about users' ethical dilemmas to design more human-centered ethical AI for collaboration.

5.6 Limitations

The themes found in the data are partially influenced by the specific context and the ethical issues presented in the design fiction. As it is not possible to show and familiarize potential users with all the possibilities and contexts, we developed our DF to reflect current advances in AI and current ethical issues. Our goal was to develop a DF to familiarize future users with co-creative AI and provoke their thoughts around some of the known ethical dilemmas in human-AI co-creativity.

We did not collect information from participants about their expertise in design and creativity. Having this information would have allowed us to determine if individuals with design and creativity expertise brought unique perspectives on the ethical issues surrounding human-AI co-creation. In future studies, we plan to collect more information about the participants' design expertise and see if that expertise leads to different concerns.

5.7 Conclusions

This chapter investigates the perspective of future users around ethical dilemmas in human-AI co-creation. We conducted a Design Fiction (DF) study as a speculative research and prototyping method that provokes thoughts and reactions toward human-AI co-creation. Insights from this study include users' stances and expectations regarding ownership of the co-created product, leadership, accountability, personification of AI, data collection/management, conversation with co-creative AI, evaluation from co-creative AI, training data, and AI access to public data. Our findings demonstrate that the user perception of co-creative AI influences their ethical stances and perspectives. This research provides insights and considerations into designing ethical human-centered co-creative AI and provides recommendations to policymakers. Additionally, insights from this research can be useful in other fields involving human-AI collaboration and can be further validated with additional research.

CHAPTER 6: UNDERSTANDING USERS' MENTAL MODELS OF CO-CREATIVE AI IN HUMAN-AI CO-CREATIVITY

6.1 Introduction

A mental model refers to an individual's understanding of how something works based on their experience in the real world. These models allow people to understand, explain and predict phenomena and act accordingly [42]. From simple tasks like turning on lights to more complex activities such as learning how to drive a car, we use our mental models. The contents of mental models can be concepts, relationships between concepts or events, and associated procedures [275]. Mental models are useful for predicting system behavior. Mental models are subjective and based on an individual's beliefs, values and experiences [43]. To harness the full benefits of co-creative AI, it is crucial to understand how users actually perceive these AI systems and how their mental models may vary across different demographics [46]. Literature indicates that the effectiveness of co-creative AI depends on users and their social and cultural influence [127]. Moreover, it is important to investigate whether diverse mental models of AI have an impact on users' ethical stances, as observed in the findings of a design fiction study. This study highlighted that users' perceptions of AI influence their ethical perspectives and concerns regarding the ethical challenges in human-AI co-creation [41]. Ultimately, user perception plays a significant role in shaping the overall user experience with co-creative AI systems.

The existing literature on users' mental models of co-creative AI is notably scarce, leaving several important questions unanswered. For instance, what elements should be incorporated into a comprehensive conceptual model of co-creative AI? Investigating the constructs of conceptual models in co-creative AI is of utmost importance, as it enables a deeper understanding of the diverse mental models held by users. By gaining insights into users' mental models, developers and designers can ensure that the AI systems align with users' needs, preferences, and ethical considerations. It allows for the identification of potential gaps, misconceptions, or concerns that users may have, enabling the development of AI systems that address those issues effectively. To investigate users' mental models of co-creative AI, we identified two research questions.

– RQ4 - What are the constructs of *conceptual* and *mental models* of co-creative AI?
– RQ5 - Is there an association between users *mental models* of AI, *user demographics* and their *ethical stances* in human-AI co-creativity?

To investigate the research questions, we took two different approaches. First, we did a literature review to identify the elements of the conceptual model of co-creative AI. We then propose a framework for the conceptual model of co-creative AI to investigate users' mental models of co-creative AI. To investigate the other research questions, we conducted a survey study with 155 participants from different countries around the world to identify their mental models of co-creative AI. To design the questionnaire for capturing users' mental models of co-creative AI, we used our proposed constructs of mental models of co-creative AI. For the study, we used two popular existing AI, ChatGPT (conversational) and Stable Diffusion, in the context of human-AI co-creation. Participants use the AI to complete the assigned task with each of the AIs and answer the questions about their mental models of the AI. We also collected their perspectives about a few ethical dilemmas in the context of human-AI co-creation and their demographics. We present the findings from the study based on the quantitative data analysis which can be used to develop human-centered ethical and inclusive co-creative AI. The findings can also be useful in developing personalized co-creative AI. This study lays the ground for future research.

6.2 Constructs of the Conceptual Model of Co-Creative AI

We draw heavily on an existing foundation of research when creating our own framework for conceptual models of co-creative AI. First, we need to clarify the definitions of conceptual models. According to Norman, mental models encompass four distinct aspects: the target system(t), which is the actual system a user uses; the conceptual model (C(t)) of the target system, which provides a precise representation of the system developed by experts; the mental model (M(t)) of the target system, which users create in their head through the interaction with the target system and the scientist's conceptualization of the mental model (C(M(t))) [43]. According to Norman, mental models are incomplete, limited, unstable (people forget details of their models or discard them), unscientific (they reflect the people's beliefs upon the represented system), and parsimonious (people frequently choose additional physical operations which require more energy in exchange for less mental complexity) [43].

A good conceptualization of a system is essential before we can investigate an individual's mental model of a system [43]. A conceptual model provides a structure for researchers to design appropriate methodologies for capturing users' mental models of a system. Therefore, for investigating mental models of co-creative AI we consider what a conceptual model (i.e., an appropriate mental model) of co-creative AI would look like. Gero et al. argued that a precise description of the neural network architecture and training procedure does not represent an appropriate conceptual model of an AI [44]. Conceptual models are simplified representations of the target system [124]. Greca and Moreira asserted that a conceptual model can present itself as an analogy or as a mathematical formula [124]. For instance, an analogy between Rutherford's atom and the solar system can be considered a conceptual model. Given the inherent complexity of co-creative AI systems, aligning the conceptual model with the mental model can pose challenges. Thus, our goal is to develop a simplified and high-level conceptual model that captures the essence of co-creative AI, while making it useful for investigating mental models of co-creative AI.

Co-creative AI refers to an AI system that collaborates with humans in the creative process by generating creative artifacts or ideas. This involves both a computational creativity component, an interactive/collaborative component and a utility component. For co-creative AI, we propose three main constructs for conceptual models: the creativity model, the interaction model and the utility model (Figure 6.1). The components of our framework are inspired by the research of Kantosalo et al., where they proposed three key metrics for evaluating co-creative systems: value (utility), novelty (creative divergence) and interaction [26, 21].

6.2.1 Creativity model

The creativity model encompasses the computational creativity aspect of co-creative AI. It focuses on how the AI generates creative content and contributes to the overall creative process. This model represents how a co-creative AI generates content on a high level, the AI ability and how surprising, valuable and novel AI-generated content is. To develop a creativity model for a co-creative AI, the following questions need to be addressed: How does the co-creative AI generate creative content? What can the co-creative AI actually do? How

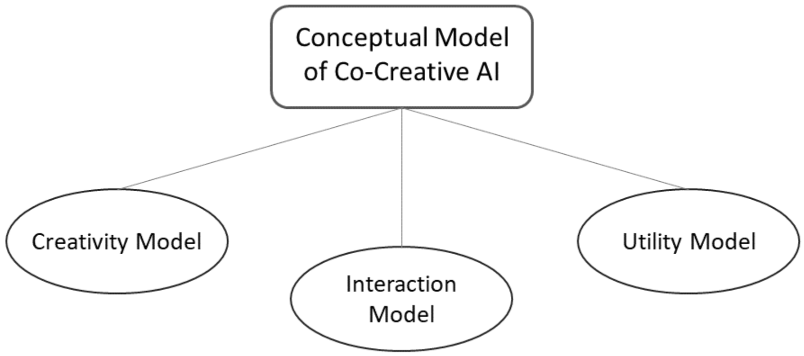


Figure 6.1: Constructs of the conceptual model of co-creative AI

does the co-creative AI contribute to the creative process? How surprising is the contribution of the co-creative AI? How novel is the contribution of the co-creative AI?

Boden asserted that a computational creativity model incorporates a surprise component, a novelty component and also a value component [276]. Also, computational creativity is all about AI contributing to the creative process by generating or evaluating creative artifacts or ideas. Therefore, the creativity model should represent the high-level mechanism of how a co-creative AI generates creative content and in which ways it contributes to the creative process [38]. The formulation of questions aimed at understanding the creativity model of a system has been inspired by the factor statements of the Creativity Support Index [262].

6.2.2 Interaction model

The interaction model represents how the AI interacts and collaborates with humans. It includes the metaphorical representation of collaboration, the communication quality between the collaborators and whether the human-AI interaction is collaborative or tool-like. When developing an interaction model for a co-creative AI, the following questions need to be addressed: What is the appropriate metaphor for the co-creative AI? How is the quality of the communication between humans and co-creative AI? Is the interaction of the co-creative AI collaborative or tool-like?

Even though an interaction model of a co-creative AI can be complex, we want to keep it simple for the conceptual model using analogies. For capturing the dynamics of collaboration between humans and AI, it is necessary to understand the quality of communication between humans and the AI and the metaphor for the AI as a contributor to the co-creation [26]. Kantosalo and Toivonen assert that contrary to how co-creative AI agents are often viewed in the literature, research in computational creativity aims to develop AI agents that are equal collaborators in the creative process [38].

6.2.3 Utility Model

The utility model encompasses the system's usefulness, ease of use, and overall satisfaction when interacting with the co-creative AI. When conceptualizing the utility model, the following questions need to be addressed: How useful is the co-creative AI? How satisfactory is the co-creative AI? How easy is it to use the co-creative AI?

The technology acceptance model (TAM) is a model to understand user acceptance of technology [277]. The two main variables in TAM are perceived usefulness and ease of use. Satisfaction is a major usability variable [278] and is frequently used in the literature to measure the usability or user experience of a system [279, 280].

6.3 Study to Investigate Mental Models of Co-Creative AI

6.3.1 Study Methodology

We used a survey study to investigate our research questions. The survey study took place remotely. The study procedure is summarized in Figure 6.2. At the beginning of the study, participants interacted with two co-creative AI (ChatGPT and Stable Diffusion) to do a simple task with each of them. The survey included embedded links to both freely available co-creative AI systems, enabling participants to access them easily. Following each task, the participants answered questions about their mental models of the AI. At the beginning of the study, participants had to complete a simple creative writing task with ChatGPT and then answer questions about their mental models of it. Then they completed a simple task of creative image generation with Stable Diffusion and answered the same set of questions about their mental models of it. Subsequently, participants responded to a set of questions regarding ethical dilemmas in the context of human-AI co-creation, which were not specific to any particular co-creative AI system but rather encompassed the broader domain of human-AI co-creativity. Lastly, participants responded to a set of questions aimed at collecting their demographic information. We collected participants' demographic information at the end of the study to prevent any potential bias that demographic questions could have had on their responses to the questions regarding mental models and ethical dilemmas. On average, participants took 29.14 minutes to complete the study and on average, each of them received an incentive of $10.3 per hour. The study was approved by the university's

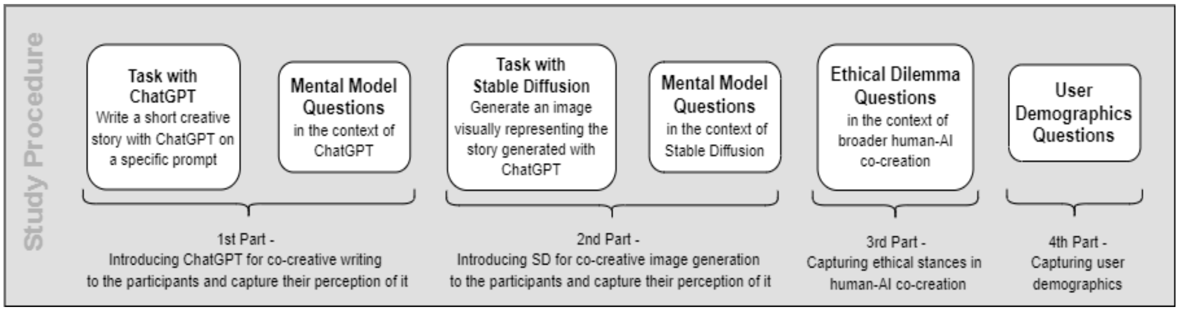


Figure 6.2: Study procedure

Institutional Review Board (IRB).

6.3.2 Co-Creative AI Used in the Study

While the preceding chapters of this dissertation focused on developing co-creative AI prototypes and design fiction for futuristic co-creative AI, recent advancements in large language models and text-to-image generation models prompted us to investigate the mental models of users of existing AI systems. By considering widely-used AI platforms, we sought to identify and explore the diversity of mental models held by users. Furthermore, these AI systems have demonstrated co-creative capabilities that are integrated into people's daily lives, contrasting with the earlier stages of my research where most people lacked access to or familiarity with such systems.

6.3.2.1 ChatGPT

ChatGPT (version 3.5) [11], a state-of-the-art large language model, was used for the study. ChatGPT is widely acclaimed for its conversational prowess and advanced natural language processing capabilities. It has garnered substantial attention in the research community due to its ability to engage in dynamic and interactive conversations with users. Leveraging its impressive generative capabilities, ChatGPT facilitates text-based interactions, allowing users to articulate queries, prompts, and ideas, to which it responds with contextually relevant and coherent messages. The model's aptitude for providing feedback, reasoning, and suggestions positions it as an invaluable collaborator across various domains, including co-creativity.

Task with ChatGPT: We asked participants to write a short creative story from a given prompt. The prompt for the task was: "A little girl named Alice, who is 7, wants to go on an adventure with her dog Lola. One day when both her parents went out for a quick errand, Alice and Lola...". Participants started writing the story in the text-prompt field of ChatGPT by copying and pasting the assigned prompt and then adding a couple of sentences or details to the prompt. Then they had to ask ChatGPT to finish/refine the story. We asked the participants to edit the story and repeat the process until you are happy with the story. The final story had to be at least a paragraph and three paragraphs at max. We also instructed that this task should not take more than 7 minutes. Once they were happy with the story, they had to take a screenshot/photo of the final version of the story on the ChatGPT interface, including their prompts and upload the screenshot/photo.

6.3.2.2 Stable Diffusion

Stable Diffusion (version 2.1) [260], developed as a text-to-image generation model, was used in our study. Stable Diffusion showcases impressive capabilities in generating high-quality visual images based on textual inputs. By leveraging advanced machine learning techniques, Stable Diffusion creates a seamless bridge between textual and visual domains, enabling users to articulate their creative ideas and concepts through natural language descriptions. Unlike ChatGPT, Stable Diffusion does not include two-way conversational interaction and only includes human-to-AI communication.

Task with Stable Diffusion: We asked the participants to generate an image using Stable Diffusion that will visually represent the story created with ChatGPT. Participants wrote a short text prompt summarizing their story in the Stable Diffusion text-prompt field so that they get an image representative of the story. We asked the participants to edit their prompts to improve the AI-generated image. Participants repeated the process until they were happy with the image representing the story. We instructed them that this task should not take more than 6 minutes. Finally, they had to take a screenshot/photo of the image generated and upload it.

6.3.3 Participants

For this study, we recruited 155 participants through Prolific [281], a platform for recruiting participants for online studies. Among the participants, there were 87 men, 64 women and 4 non-binary individuals. We had participants from 22 different countries. The age range of participants spanned from 20 years old to 65+ years old, resulting in an average age of 27.5 years. We had experts and non-experts in AI knowledge based on their self-reported data. Participants were asked to provide justifications for their chosen expertise in AI knowledge and explain how they acquired their knowledge, serving as a validation of their self-reported AI knowledge. Based on participants' self-reports, we had 6 participants who are not knowledgeable at all, 63 participants who are slightly knowledgeable, 58 participants who are moderately knowledgeable, 26 participants who are very knowledgeable and 2 participants who are extremely knowledgeable about AI.

6.3.4 Data Collection

We used surveys to collect data about users mental models of co-creative AI, their ethical stance on a few ethical dilemmas in human-AI co-creation and lastly collecting user demographic data. Therefore, there were three distinct sets of questions. We used our conceptual model framework to create a standardized set of questions for capturing mental models for both AI while adjusting the questions according to the context of each AI. We asked questions about the constructs of the conceptual model of co-creative AI to capture mental models. The ethical dilemma questions were not AI-specific; instead, they pertained to the broader co-creative context. We asked questions about four ethical dilemmas, ownership, anthropomorphism, data collection and AI impact, in human-AI co-creation based on the literature and our preliminary works shown in the previous chapters [41, 83, 282, 87]. Lastly, we collected user demographics. In terms of user demographics, we collected a range of information, including age, gender, ethnicity, highest level of education, first-generation college student status, disability status, annual income, knowledge of AI, field of work/study, profession, and political affiliation.

We presented the survey questions in each set in a randomized order for each participant. This approach aimed to eliminate any potential response biases caused by the order of the questions. We included three attention-checking questions in the survey to check whether the participants were taking the survey seriously and completing the tasks diligently. We rejected a few survey responses in which participants failed the attention check questions and did not complete the tasks with each of the AI properly. We examined whether the participants followed the instructions for each task properly by examining each of the screenshots they uploaded. We rejected a few responses as they took very little time to complete the survey including the tasks, such as 10 minutes.

6.3.5 Data Analysis

For the data analysis presented in this dissertation, we used different quantitative statistical methods to analyze the data. As most of the data we collected are categorical in nature, we used analysis methods for categorical data. We used frequency and percentage analysis presented through histograms to demonstrate the distribution of some variables.

We conducted cluster analysis to identify clusters of mental models of AI, clusters of ethical stances of users and clusters of users based on their demographics. We used K-modes clustering [243, 244] for identifying clusters as the K-modes algorithm is suitable for categorical data which we have. K-modes clustering is an extension of K-means, but instead of means, this algorithm uses modes. For demonstrating the cluster centroids, this algorithm uses modes of all the features used for clustering.

We conducted association analyses using Chi-square between mental models and other variables. Additionally, we conducted multinomial logistic regression to identify not only the association but also the predictors or factors of a specific variable.

6.4 Results

6.4.1 Mental Models of the Co-Creative AI

For identifying different mental models of both AI, we clustered participants based on their mental models of the AI. As the features for the clustering analysis, we used the variables of the creativity model, interaction model and utility model according to our framework. We found two clusters of mental models of ChatGPT and three clusters of mental models of Stable Diffusion. We found the optimum number of clusters using the Elbow method [283], a well-known algorithm for identifying the optimum number of clusters from a dataset. We also measured the quality of the clusters using intra-cluster variance [284]. We found 90% similarity among the data points in each cluster of mental models of ChatGPT and Stable Diffusion.

Table 6.1: Mental models of ChatGPT (cluster centroids)

	Creativity Model								
Cluster Number/Type	Novel Contribution	Unique Story	Surprising Assistance	Unpredictable AI Contribution	Type of Contribution	Story Worth Effort	How it Generates Content	Substitute of Google	Misinformation
1/ Positive Mental Model (75)	Somewhat Agree	Somewhat Agree	Strongly Agree	Strongly Agree	Generation + Transformation + Refine	Strongly Agree	Retrieves Data From Dataset/Web + Synthesizes Original Response	Somewhat Disagree	Strongly Agree
2/ Negative Mental Model (80)	Neutral	Neutral	Somewhat Agree	Somewhat Agree	Generation + Expand + Refine	Somewhat Agree	Retrieves Data From Dataset/Web + Synthesizes Original Response	Somewhat Agree	Strongly Agree

	Interaction Model				Utility Model			
Cluster Number/Type	Good Communication	Collaborative rather than Toollike	Human Substitute	Metaphor	Useful AI	Ease of Use	Satisfaction	Positive Feeling About the AI
1/ Positive Mental Model (75)	Strongly Agree	Somewhat Agree	Somewhat Agree	Tool + collaborator	Strongly Agree	Strongly Agree	Strongly Agree	Strongly Agree
2/ Negative Mental Model (80)	Somewhat Agree	Somewhat Disagree	Somewhat Agree	Tool	Somewhat Agree	Strongly Agree	Somewhat Agree	Somewhat Disagree

6.4.1.1 Mental Models of ChatGPT

We found two distinct clusters of mental models of ChatGPT using k-modes clustering. The first cluster of mental models comprises 75 participants and the second cluster has 80 participants. Participants in the same cluster share similar mental models while not the exact same. Table 6.1 provides an overview of these cluster centroids, highlighting notable feature differences indicated in red. Differences are notable between the clusters, particularly in participants' perception of ChatGPT as either a collaborator or a tool, the metaphor they associate with the AI, the type of contributions expected from ChatGPT, their attitude towards the system, and whether they view it as a potential substitute for Google.

For the creativity model, when it comes to contributions, participants in cluster 1 believe that ChatGPT contributes through generating, transforming, and refining creative content, whereas cluster 2 users emphasize its role in generating, expanding upon, and refining creative content. Additionally, cluster 1 participants somewhat disagree with the analogy of ChatGPT with Google in terms of its purpose and working mechanism, while cluster 2 participants somewhat agree with this notion.

For the interaction model, in cluster 1, users lean towards considering ChatGPT as a collaborator rather than merely a tool, while cluster 2 participants tend to hold a contrasting view, perceiving ChatGPT primarily as a tool. Additionally, participants in cluster 1 perceive ChatGPT as both a tool and a collaborator, whereas users in cluster 2 predominantly see it as only tool-like. For the utility model, participants in cluster 1 exhibit a strong positive attitude towards ChatGPT whereas cluster 2 demonstrates a somewhat negative attitude towards the system.

We will categorize the mental model observed in cluster 1 of ChatGPT as the *"Positive"* mental model, as it perceives ChatGPT as a collaborative partner and holds a positive attitude toward the system. Conversely, the mental model identified in cluster 2 will be termed the *"Negative"* mental model, as it exhibits a negative attitude towards ChatGPT and views it as a tool-like rather than collaborative.

6.4.1.2 Mental Models of Stable Diffusion

The mental models of Stable Diffusion (SD) reveal three distinct clusters, with 77 participants in the first cluster, 29 participants in the second cluster, and 49 participants in the third cluster. Table 6.2 provides a visual representation of these cluster centroids, presenting the cluster centroids with the corresponding feature values for each cluster. Participants in each cluster share similar mental models represented by the corresponding cluster centroid. The table highlights the notable feature differences indicated in red. Significant differences are observed among the three clusters concerning unique contribution, surprising assistance, AI being a substitute for human collaboration, communi-

Table 6.2: Mental models of Stable Diffusion (cluster centroids)

	Creativity Model								
Cluster Number/Type	Novel Contribution	Unique Story	Surprising Assistance	Unpredictable AI Contribution	Type of Contribution	Image Worth Effort	How it Generates Image	Can Generate images from any prompt	Can Generate Images of something nobody ever seen
1/ Neutral Mental Model (77)	Somewhat Agree	Somewhat Disagree	Somewhat Agree	Somewhat Agree	Generation	Somewhat Agree	It Synthesizes Image Based On Images On The Web	Somewhat Agree	Somewhat Agree
2/ Positive Mental Model (29)	Somewhat Agree	Strongly Disagree	Strongly Agree	Strongly Agree	Generation	Strongly Agree	Retrieves Data From Dataset/Web + Synthesizes Original Image Based On Training Data	Strongly Agree	Strongly Agree
2/ Negative Mental Model (49)	Neutral	Somewhat Agree	Somewhat Disagree	Somewhat Disagree	Generation	Somewhat Disagree	Retrieves Data From Dataset/Web + Synthesizes Original Image Based On Training Data	Somewhat Agree	Somewhat Agree

	Interaction Model				Utility Model			
Cluster Number/Type	Good Communication	Collaborative rather than Toollike	Human Substitute	Metaphor	Useful AI	Ease of Use	Satisfaction	Positive Feeling About the AI
1/ Neutral Mental Model (77)	Somewhat Agree	Strongly Disagree	Strongly Disagree	Tool	Somewhat Agree	Somewhat Agree	Somewhat Agree	Somewhat Agree
2/ Positive Mental Model (29)	Strongly Agree	Strongly Agree	Somewhat Agree	Tool + Collaborator	Strongly Agree	Strongly Agree	Strongly Agree	Strongly Agree
2/ Negative Mental Model (49)	Neutral	Somewhat Disagree	Somewhat Disagree	Tool	Somewhat Agree	Somewhat Agree	Somewhat Disagree	Neutral

cation quality between users and AI, perception of SD as a collaborator versus a tool, satisfaction level, and overall attitude towards the system.

For the creativity model, participants in cluster 1 somewhat agree with the notion that SD provides surprising assistance, while cluster 2 participants strongly agree, and cluster 3 participants somewhat disagree with this statement. Regarding the effort participants had to exert in producing an image with Stable Diffusion, cluster 2 participants strongly agreed that the generated image was worth the effort, and cluster 3 participants believed the generated image was not worth the effort.

For the interaction model, when it comes to SD as a substitute for human collaboration in co-creative image generation, cluster 1 participants strongly disagree, cluster 2 participants somewhat agree, and cluster 3 participants somewhat disagree with this notion. Participants in cluster 1 hold a somewhat positive view regarding the quality of communication between humans and the AI, while those in cluster 2 strongly agree with the effectiveness of communication and participants in cluster 3 exhibit a neutral stance towards this aspect. Participants in cluster 1 strongly disagree with the idea of SD being a collaborator instead of a tool, while cluster 2 participants strongly agree, and cluster 3 participants somewhat agree with this perspective.

For the utility model, in terms of satisfaction, cluster 1 participants express somewhat satisfaction, cluster 2 participants are not very satisfied, and cluster 3 participants are highly satisfied with SD. Attitudes towards SD also vary, with cluster 1 displaying a somewhat positive attitude, cluster 2 showcasing a strong positive attitude, and cluster 3 participants feeling neutral towards the system.

Based on the centroid features, we will classify the mental model observed in cluster 1 as the *"Neutral"* mental model of Stable Diffusion. Participants in this group exhibit a mixed attitude, showing some level of satisfaction while also expressing some negative perceptions of AI as being tool-like. The mental model observed in cluster 2 will be referred to as the *"Positive"* mental model of Stable Diffusion. Participants in this group demonstrate a strong positive attitude, expressing high levels of satisfaction and perceiving Stable Diffusion as a collaborator with remarkable AI assistance and contribution. Lastly, we will characterize the mental model observed in cluster 3 as the *"Negative"* mental model of Stable Diffusion. Participants with this mental model exhibit a negative attitude, expressing dissatisfaction with the assistance provided by Stable Diffusion, the effort they had to exert, and the contribution of the AI.

6.4.2 Clusters of User Demographics

We tried to find clusters based on different demographics that we collected so that we could find associations between different groups of people and their

Table 6.3: Clusters of participants based on their identities (cluster centroids)

	Identity Demographics						
	Age	Ethnicity	Type community as formative background	Gender	Disability	Annual income	Political affiliation
Cluster 1 (99)	21-24	White	A large city	Men	No	Less than 10,000	No political affiliation
Cluster 2 (39)	25-30	Hispanic/Latinx	A small city or town	Women	No	10,000–19,999	Liberal
Cluster 3 (17)	31-34	Black/African American	A large city	Women	No	30,000–39,999	Moderate

mental models of specific AI.

6.4.2.1 Groups of Participants Based on Identities

We found three clusters of participants using demographics that represent their identities. Specifically for these clusters, we used participants' age, ethnicity, gender, disability, annual income, political affiliation and type of community as their formative background. In table 6.3, we can see the cluster centroids with respective identity demographics as features.

Cluster 1 is the largest cluster consisting of 99 participants among the 155 participants. This cluster predominantly consists of young white men, aged 21-24, who grew up in large cities. They have no reported disabilities and generally have an annual income of less than \$10,000. In terms of political association, most participants in this group do not strongly align themselves with any specific political affiliation.

Cluster 2 consists of 39 participants, mostly identifying themselves as Hispanic/Latinx women aged 25-30. This group tends to have politically liberal views. Most participants in this cluster grew up in small cities or towns as their formative background and typically have an annual income ranging from \$10,000 to \$19,000.

Table 6.4: Clusters of participants based on their educational/professional background (cluster centroids)

	Education, Expertise and Professional Background			
	First-Generation College student	**Highest Level of Education**	**Field of Work/Study**	**Knowledge of AI**
Cluster 1 (104)	No	4-year Degree	Social Sciences/Services	Slightly Knowledgeable
Cluster 2 (51)	Yes	Some College	Technology IT	Moderately Knowledgeable

Cluster 3 consists of 17 participants, primarily comprising black/African American women aged 31-35 without any disabilities. The majority of individuals in this cluster identify themselves as having a moderate political affiliation. They typically earn an annual income ranging from \$30,000 to \$39,000 and have a background of growing up in large cities.

6.4.2.2 Groups of Participants Based on Expertise/Professional Background

We found two clusters of Participants based on demographics about their expertise and professional background. To form the clusters, we used their education level, first-generation college student, field of work/study and knowledge of AI. In table 6.4, we can see the cluster centroids with respective identity demographics as features.

Cluster 1 is the largest cluster among the two, comprising 104 participants. This group primarily consists of individuals with a 4-year college degree and a non-first-generation college background. The majority of participants in this cluster are engaged in work or study related to social sciences or services and have limited knowledge about AI. For the purpose of indicating this group of individuals in various results, we will refer to them as *"Traditional"*.

Cluster 2 comprises 51 participants who are first-generation college students with some college education. The majority of individuals in this cluster are employed or pursuing studies in the field of technology/IT and possess a moderate level of knowledge about AI. The individuals in this group will be referred to as *"Progressive"* while we report several findings about them.

6.4.3 Clusters of Ethical Stances

We found two clusters (Table 6.5) based on users' ethical stances towards four ethical dilemmas/concerns in the context of human-AI co-creation: ownership, anthropomorphism in co-creative AI, data collection by co-creative AI and impact of co-creative AI on society. We found two clusters based on users ethical stances towards these ethical challenges.

Cluster 1, consisting of 114 participants, represents a larger group compared to Cluster 2. The majority of participants in Cluster 1 hold the stance that humans should have sole ownership of the creative product in co-creation. They also exhibit a generally positive perception of AI's impact on society. Therefore, we classify this cluster as the *"Conservative-Positive"* ethical stance. Furthermore, participants in this cluster demonstrate a neutral attitude towards anthropomorphism in AI and hold a moderately positive view regarding data collection by AI for enhancing user experience.

In contrast, Cluster 2, comprising 41 participants, leans towards the belief that both humans and AI should share ownership of the creative product. Participants in this cluster exhibit a somewhat negative perspective on the societal impact of AI, leading us to label this cluster as the *"Liberal-Negative"* ethical stance. Additionally, participants in this cluster hold a somewhat positive attitude towards anthropomorphism in AI and maintain a neutral stance on data collection.

Table 6.5: Two major types of ethical stances (cluster centroids)

Cluster number/Type	Ownership	Attitude towards Anthropomorphism	Attitude towards Data Collection	Attitude towards AI Impact on Society
1/Conservative -Positive Stance (114)	Human	Neutral	Somewhat good	Somewhat Positive
2/Liberal-Negative Stance (41)	Both	Somewhat Good	Neutral	Somewhat Negative

6.4.4 Association between Mental Models of AI and User Demographics

Details about the findings presented below will be found in the Appendix.

6.4.4.1 Association: Mental Models of AI and Identities

We observed a significant association between mental models of Stable Diffusion and Participants' identities. We conducted a chi-square between mental models of Stable Diffusion and clusters of participants based on their identities and found a significant association ($p=0.012<=0.05$). Specifically, we found that white young men (aged 21-24) who have no political affiliation tend to exhibit the "Neutral" mental model of Stable Diffusion. On the other hand, Hispanic/Latinx women aged 25-30 with a liberal political affiliation typically display either the "Neutral" or "Negative" mental model of Stable Diffusion. Lastly, we identified that black/African American women aged 31-34 with a moderate political view generally have the "Positive" mental model of Stable Diffusion.

We did not find any significant association between the mental models of Chat-GPT and participants' identities.

6.4.4.2 Association: Mental Models of AI and Educational/Professional Background

We identified a significant association between the mental models of ChatGPT and Participants' educational/professional backgrounds. We conducted a chi-square and found a significant association ($p=0.05<=0.05$). Interestingly, Progressives tended to exhibit an Positive mental model of ChatGPT, while Traditionals typically held a more Negative view of the system.

We did not find any significant association between mental models of Stable Diffusion and participants' educational/professional background.

6.4.4.3 Association between mental models of AI and knowledge of AI

We also found that there is a significant association between users' knowledge of AI and clusters of mental models of ChatGPT. We conducted a chi-square test and the result showed a significant association indicated by the p-value, which is 0.003. We found that people with little knowledge of AI and very knowledgeable people in AI have the Negative mental model of ChatGPT. On the other hand, moderately knowledgeable people and laypeople tend to have the Positive mental model of ChatGPT.

We also found a significant association between users knowledge of AI and clusters of mental models of Stable Diffusion. Chi-square shows a p-value of 0.01 to indicate the significance of the association. Cluster 1 contains mostly slightly knowledgeable to moderately knowledgeable people. People who are very knowledgeable, extremely knowledgeable and also not knowledgeable at all in AI are seen in the mental model of Stable Diffusion cluster 2. Cluster 2 represents mental models that perceive SD as more like a collaborator than the other mental model clusters that perceive SD as more of a tool. In the third type of mental model of SD, we again see people with moderate to slight knowledge of AI.

We also did a multinomial regression analysis to see if knowledge of AI is a predictor of users' mental models of AI. We found that knowledge of AI is a significant predictor for users' mental models of ChatGPT and Stable Diffusion with a p-value of 0.002 and 0.025, respectively.

6.4.5 Association between Mental Models of AI and Ethical Stances

We found a significant association between attitude toward anthropomorphism and clusters of mental models of both ChatGPT and Stable Diffusion with a p-value of 0.009 and 0.031, respectively. People who feel somewhat bad to extremely bad about anthropomorphism tend to have the Negative mental model of ChatGPT. On the other hand, People who feel somewhat good to extremely good about anthropomorphism tend to have the Positive mental model of ChatGPT. People who feel somewhat bad to extremely bad about anthropomorphism tend to have the Neutral mental model of Stable Diffusion. People who feel extremely good about anthropomorphism tend to have the Positive mental model of Stable Diffusion. People who feel somewhat good about anthropomorphism tend to have the Negative mental model of Stable Diffusion.

There is a significant association between users' mental models of ChatGPT and user attitude towards data collection by the AI with a p-value of <0.001. People who feel extremely good to somewhat good about data collection tend to have the Positive mental model of ChatGPT and people who feel extremely bad to somewhat bad about data collection tend to have the Negative mental model of ChatGPT. We found a significant association between the clusters of mental models of Stable Diffusion and user attitude toward data collection by AI in general, with a p-value of <0.001. Findings show that people who feel bad about data collection by an AI for enhancing user experience tend to have the

Neutral mental model of SD. People who find it extremely good to have their data collected by the AI for user experience tend to have the Positive mental model of SD which perceives SD as a collaborator. People who feel neither good nor bad about data collection tend to have the Negative mental model of SD.

We also found a significant association between users' mental models of ChatGPT and user attitude towards AI impact on society with a p-value of 0.003. The findings show that people with a strongly positive attitude mostly have the Positive mental model of ChatGPT. People with a negative attitude mostly have the Negative mental model of ChatGPT. We also found a significant association between the clusters of mental models of Stable Diffusion and user attitude towards AI impact on society with a p-value of 0.028. People who feel extremely good about AI impact on society tend to have the Positive mental model of Stable Diffusion. People who feel either somewhat positive or somewhat negative about AI impact on society tend to have the Neutral mental model of Stable Diffusion. People who feel extremely negative about AI impact tend to have either the Negative or the Neutral mental model of Stable Diffusion.

Details about the findings presented below will be found in the Appendix.

6.4.6 Association between Ethical Stances and User Demographics

Using a chi-square test, we found a significant association (p-value $= 0.03 <= 0.05$) between the clusters of ethical stances and participants' identities. The findings reveal that white young men aged 21-24, typically without any political affiliation, are more likely to hold the Conservative-Positive ethical stance. Among the participants, Hispanic/Latinx women aged 25-30 with a liberal political view also tend to have the Conservative-Positive ethical stance. On the other hand, Black/African American women with a moderate political view lean towards the Liberal-Negative ethical stance. We also found that user identity is a significant predictor of the user's ethical stance using a multinomial logistic regression ($P=0.04<=0.05$).

Based on our data, we also found that user identity is a significant predictor for the user's attitude towards ownership, anthropomorphism and AI impact on society with a P-value of 0.028, 0.01 and 0.003. However, user identity is not a significant predictor of user attitude towards data collection by AI.

There is a significant association between user attitude towards data collection by AI and users' formative background in terms of childhood community ($p=0.028<=0.05$). Individuals who were raised in large cities generally exhibit a strong to moderately positive sentiment toward data collection by AI. Conversely, those who were brought up in rural areas tend to express a somewhat negative to strongly negative stance regarding data collection by AI. Individuals with a background in either small towns or suburban areas tend to adopt a more neutral attitude towards data collection by AI.

We also found a significant association between the attitude towards data collection by the AI and users' ethnicity, with a p-value of 0.032. Individuals of White ethnicity generally exhibit either a somewhat positive or neutral attitude toward data collection by AI. People who are Hispanic/Latinx usually feel neutral about data collection. Black/African American individuals tend to display a somewhat positive attitude towards data collection. On the other hand, individuals of Middle Eastern/North African descent typically harbor an extremely negative attitude towards data collection by AI. And we found that both the formative community and ethnicity are predictors for user attitude towards data collection by the AI with a p-value of 0.07 and 0.038, respectively.

We also found that user attitude towards AI impact on society and their annual income is significantly associated with a p-value of 0.023. People who have an annual income of less than $10,000 tend to feel positive about AI's impact. People who have an annual income of $10,000 - $19,000 tend to feel neutral or positive about AI impact on society. Interestingly, people who have an annual income more than 19,000 tend to feel somewhat negative about AI's impact on society.

We also found that user attitude toward AI impact on society and their political affiliation is significantly associated with a p-value of 0.005 (<=0.05). Those who feel somewhat negative about AI impact on society tend to have a moderate political affiliation. Among those who feel somewhat positive about AI impact are mostly liberals. Additionally, people who feel extremely positive about it tend to be moderate.

Details about the findings presented below will be found in the Appendix.

6.4.7 Additional Findings: User Perception of Conversational AI vs. Instructing AI

6.4.7.1 Human Substitute (ChatGPT vs. Stable Diffusion)

We asked participants to share their perspectives on whether they believe ChatGPT and Stable Diffusion can serve as substitutes for human collaborators in relevant co-creation scenarios. Notably, we observed significant differences in participant responses for the two AI with a Chi-square test (P=<0.001). A significantly greater number of participants believed that ChatGPT could fulfill the role of a human collaborator compared to Stable Diffusion. Conversely, a substantial majority of participants expressed the view that Stable Diffusion was not capable of serving as a suitable human substitute, in contrast to ChatGPT (Figure 6.3).

Regarding ChatGPT, a majority of participants (n=86, %=55.28) agreed that

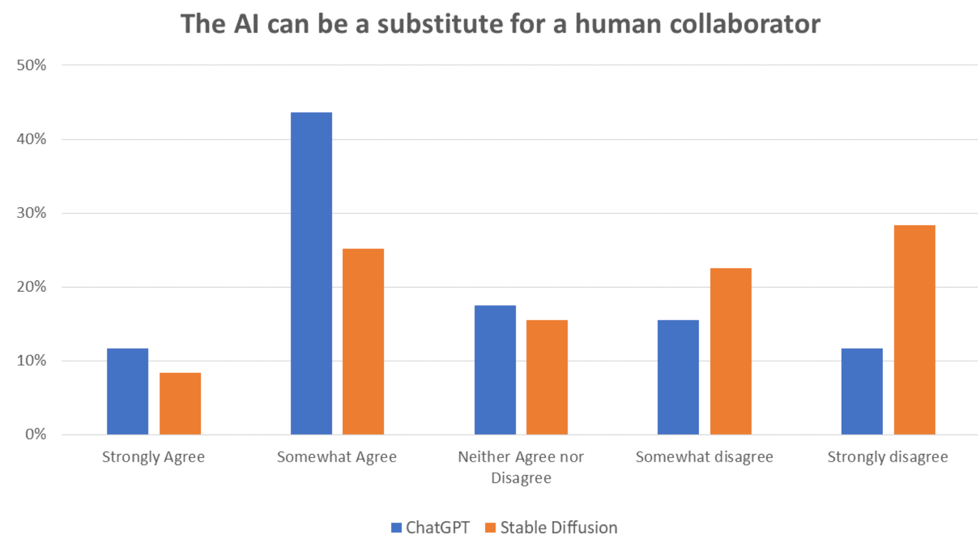


Figure 6.3: Can the AI be a human substitute? (ChatGPT vs. Stable Diffusion

ChatGPT can serve as a substitute for a human collaborator. Among them, 18 participants (11.61%) strongly agreed, while 68 participants (43.67%) somewhat agreed. In contrast, approximately 27% of the participants expressed disagreement with the idea of ChatGPT being a suitable human substitute, while over 55% agreed with ChatGPT's potential as a human substitute. Conversely, for Stable Diffusion, most participants disagreed (n=79, %= 50.97) with the notion that it can replace a human collaborator. Specifically, 44 participants strongly disagreed (%=28.39), and 35 participants somewhat disagreed (%=22.58). Thus, more than 50% of the participants disagreed with the idea of Stable Diffusion being a human substitute, while around 33% agreed with the potential of Stable Diffusion as a human substitute.

6.4.7.2 AI Metaphor (ChatGPT vs. Stable Diffusion)

We asked the participants about the appropriate metaphor for both the AIs. A Chi-square analysis was conducted to examine the differences in participants' perceived metaphors for the two AI and it revealed a significant difference (Chi-

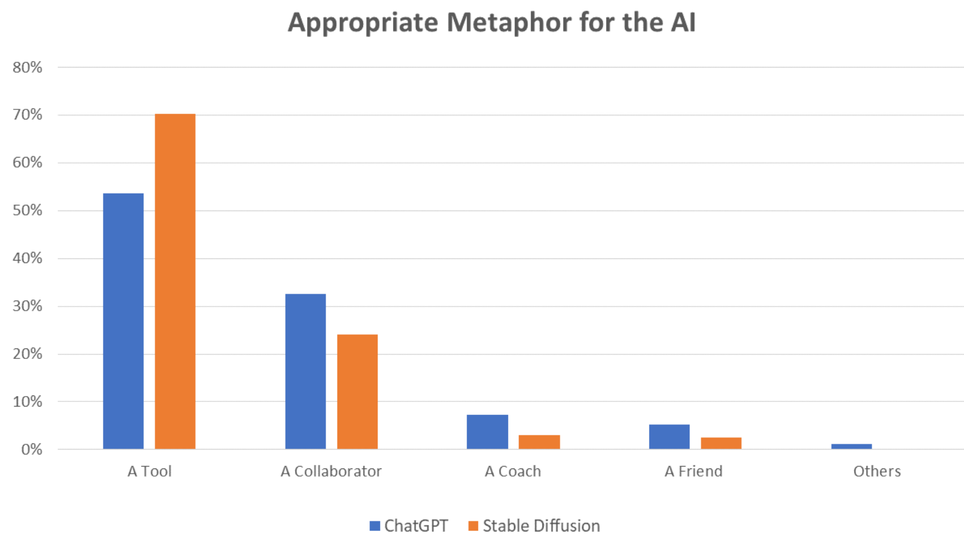


Figure 6.4: What is the appropriate metaphor for the AI? (ChatGPT vs. Stable Diffusion

square, p= < 0.001) in participants' perceptions. Notably, a considerably larger proportion of participants regarded Stable Diffusion as a tool compared to ChatGPT, while conversely, a significantly greater number of participants considered ChatGPT to be a collaborator in comparison to Stable Diffusion (Figure A.15).

Among the participants, 53.66% perceived ChatGPT as a tool, while a higher percentage of 70.26% viewed Stable Diffusion as a tool. On the other hand, 32.52% of the participants considered ChatGPT to be a collaborator, whereas 23.1% of the participants perceived Stable Diffusion as a collaborator.

These results again validate the results we got from the Creative PenPal study, where conversational co-creative AI was perceived as a collaborator, whereas non-communicative AI was perceived as a tool.

6.5 Discussion

We develop and describe a framework for conceptual models of co-creative AI for investigating users' mental models of co-creative AI. Our framework for conceptual models of co-creative AI provides a structured approach to understanding and representing key components of users' mental models. Researchers can design surveys, interviews and other methods based on the framework's constructs to gather information about users' mental models of co-creative AI. Additionally, the construct of conceptual and mental models facilitates the comparison and analysis of users' mental models across different contexts and user groups.

This research identified associations between mental models of co-creative AI and user groups based on demographics. People's identities and expertise/professional backgrounds are associated with their mental models of AI. This finding highlights the need for tailored designs that are human-centered and value-sensitive, taking into account the specific requirements of different user groups. While generating AI explanations and responses, capturing users' mental models would help co-creative AI to adapt its contribution, communication, and collaboration approaches to cater to the diverse needs of users. Recognizing the influence of user demographics on mental models informs user-centered design practices, allowing designers to consider diverse backgrounds, experiences, and cognitive styles when designing the system. Future work is necessary to dig deep into understanding mental models across different user groups for developing human-centered co-creative AI.

Additionally, we discovered a significant association between user identities and mental models of Stable Diffusion, whereas no significant association was observed for mental models of ChatGPT. Conversely, we identified an association between mental models of ChatGPT and user expertise/professional background, while no such association was found for mental models of Stable Diffusion. These findings prompt further investigation into whether these differences stem from the interaction designs of the systems, conversational vs instructing. It is also worth considering the role of familiarity and exposure to these systems, as they may influence the maturity of users' mental models. It is possible that users have more developed mental models of ChatGPT and less mature mental models of Stable Diffusion, which could contribute to the observed differences.

The study revealed an association between users' knowledge of AI and their mental models of co-creative AI. We also identified that knowledge of AI is a significant predictor of users' mental models. Recognizing the relationship between users' knowledge of AI and their mental models highlights the importance of AI literacy among the general public and training initiatives. Users with limited knowledge of AI may have incomplete or inaccurate mental models. Providing accessible and comprehensive education about AI concepts, capabilities, and limitations can help users develop more informed and accurate mental models of co-creative AI. Designers should consider users' varying levels of AI knowledge when designing co-creative AI to enhance engagement and satisfaction. Users' AI literacy might be used for appropriate suggestions and contributions from a co-creative AI in the realm of personalized co-creative AI.

The associations between mental models of AI and their ethical stances further validate previous findings of the design fiction study in chapter 5.1 [41]. Understanding the relationship between users' mental models and their ethical stances allows for increased ethical awareness among users. Users with accurate mental models of co-creative AI are more likely to recognize and consider the ethical implications and potential risks associated with its use. This awareness empowers users to make informed decisions about ethical boundaries and responsibilities while engaging with co-creative AI systems. Also, when users' mental models align with the ethical principles of co-creative AI systems, it is likely to build trust and increase user engagement with co-creative AI. Finally, education and training programs for educating the general public about AI ethics and risks will help bridge the gap between users' mental models and the ethical challenges of the technology. User demographics, including type of community as a formative background, annual income and political affiliation, influence a wide range of ethical perspectives. Recognizing this association emphasizes the importance of inclusivity and cultural sensitivity when addressing ethical challenges in co-creative AI. It calls for considering multiple viewpoints and avoiding biased assumptions about ethics.

Furthermore, our research revealed significant associations between users' ethical stances and user demographics, including user identity, annual income, political affiliation, and formative background community. These associations signify that distinct cohorts of individuals possess diverse understandings of ethical dilemmas and concerns within the domain of human-AI co-creativity. Consequently, it underscores the significance of considering multiple viewpoints and avoiding presumptions regarding ethical behavior. These findings also have implications for personalization and promoting equity in the field of human-AI co-creativity. By recognizing and considering these demographic differences, tailored approaches should be developed to address the specific perspectives of diverse user groups, fostering a more customized, inclusive and equitable co-creative experience.

Additionally, the study revealed notable differences in user perceptions between conversational and instructional co-creative AI. A larger number of participants believed that ChatGPT, a conversational AI, could effectively fulfill the role of a human collaborator compared to Stable Diffusion. Conversely, a majority of participants expressed that Stable Diffusion was not suitable as a human substitute in co-creation, unlike ChatGPT. Additionally, participants largely viewed Stable Diffusion as a tool while perceiving ChatGPT as a collaborator. These findings further support the results of our previous study on the impact of AI-to-human communication in human-AI co-creativity, where participants identified AI with communication ability as a collaborator and AI without communication ability as a tool.

Policymakers can use these findings to shape regulations and guidelines that protect user interests, ensure fairness, and address potential biases or discrimination in the deployment of co-creative AI systems.

6.6 Limitations

The sample size and the specific sample we used for our study does not represent the entire population. Therefore the findings might not be representative of the entire population. In addition, our study focused on two widely-used existing co-creative AI systems, which may not fully capture the mental models across all co-creative systems in diverse contexts. Nevertheless, we believe that the findings provide valuable insights into users' mental models of co-creative systems, transcending specific domains. Lastly, we did not collect any in-depth qualitative data on users' mental models of co-creative AI, which might provide additional insights and validation to the findings.

6.7 Conclusions

In this chapter, we develop a framework for the conceptual model of co-creative AI for capturing users' mental models of co-creative AI. We then conduct a survey study using our framework with 155 participants to investigate users' mental models and their association with other variables, such as user demographics and ethical stances. The results show an association between mental models of AI and their demographics. We also identified that AI literacy is a significant predictor for a person's mental model of co-creative AI. Additionally, we found associations between mental models of AI and users' ethical stances and attitudes. We also found associations between several demographic variables and the ethical stances of users. Finally, we found significant differences between users' attitudes towards conversational vs. instructing co-creative AI.

CHAPTER 7: GENERAL CONCLUSIONS & FUTURE WORK

7.1 Conclusions

The field of human-AI co-creativity is rapidly expanding, driven by the increasing prevalence of human-AI collaboration in creative domains and advancements in generative AI technology. The progression of this field requires the creation of co-creative AI systems that go beyond technological advancements and prioritize human values, user experience, and ethical considerations. This dissertation delves into various aspects of human-AI co-creativity, contributing valuable theoretical and empirical insights into design considerations, ethical implications, and user-centered perspectives. By examining interaction designs, AI-to-human communication, human-centered ethical considerations, and mental models of co-creative AI, this research uncovers valuable insights that contribute to the design of engaging and ethically-driven human-centered co-creative AI.

In response to our first research question regarding the identification of essential interaction components in co-creative AI, this dissertation contributes to the development of the COFI framework. COFI describes interaction components as a space of possibilities for designing and interpreting interaction models in co-creative systems. This research also identifies trends and gaps in the interaction designs of existing co-creative AI. The analysis using COFI revealed a general lack of communication in co-creative systems within the dataset. The research gaps indicate opportunities for future work in developing more collaborative and effective co-creative AI.

To investigate the second dissertation question, this dissertation also contributes by identifying the impact of AI-to-human communication on collaborative experience, user engagement and also user perception of co-creative AI. Including AI-to-human communication along with human-to-AI communication improves the collaborative experience and user engagement by fostering a perception of co-creative AI as a collaborative partner. Moreover, AI-to-human communication positively influences user perception of co-creative AI as users perceive it as more intelligent and reliable. This research leads to new insights into designing engaging and effective human-AI co-creative systems and lays the groundwork for future studies.

Furthermore, this research identifies ethical stances and perspectives of users around ethical dilemmas in human-AI co-creativity using a design fiction study as a response to the third research question. Insights from this study include users' stances and expectations regarding ownership, leadership, accountability, anthropomorphism of AI, data collection/management, evaluation from AI, training data, and AI access to public data. The findings from the study highlight the influence of users' perceptions of co-creative AI on their ethical stances related to ethical dilemmas. The findings from the research provide insights and considerations into designing ethical human-centered co-creative AI and recommendations for policymakers.

Finally, this dissertation contributes to the advancement of human-centered co-creative AI with the exploration of users' mental models of co-creative AI to investigate the last two research questions about conceptual and mental models of co-creative AI. The dissertation presents a framework for conceptual models of co-creative AI, serving as a tool for investigating users' mental models. Through a survey study, we identify diverse mental models of two co-creative AI, associations between mental models of co-creative AI, user demographics, and their ethical stances. Findings provide crucial insights into human-centered design principles and ethical considerations, offering valuable guidance for the development of co-creative AI systems.

Insights from this dissertation contribute to the growing body of knowledge in the field of human-AI co-creativity. The findings serve as a foundation for the design of human-centered, engaging, ethical and value-sensitive co-creative AI. The implications of this research extend beyond the creative domains, offering transferable insights for human-AI interaction and collaboration in fields such as education, entertainment, and professional work.

7.2 Future Work

COFI can be used as a tool to identify emerging interaction design trends and research gaps in commonly used interaction designs in recent co-creative AI. Through our analysis, we identified several research gaps that call for further exploration. One such area is investigating the impact of human-to-AI consequential communication, such as users' facial expressions and postures on user experience. Additionally, there is a need to examine the role of AI as a definer of the creative space, going beyond its traditional role as a generator and evaluator, as commonly observed in existing co-creative AI systems. Analyzing emerging gaps in the current rapidly advancing and increasingly sophisticated co-creative systems is crucial. Conducting further analyses with the COFI framework can yield valuable insights into these gaps.

Given our findings on the positive impact of AI-to-human communication on collaboration, user engagement, and user perception of co-creative AI, further research is needed to investigate which modalities of AI-to-human communication work best in different co-creative contexts. Specifically, exploring the effectiveness of various communication modalities in co-creative AI based on large language models, which exhibit more conversational capabilities, would be of great interest.

As we investigated users' perspectives and stances around ethical challenges in human-AI co-creation through a design fiction approach, it is important to acknowledge that the specific context and ethical issues presented in the design fiction may have influenced the findings. It is necessary to conduct further studies in diverse contexts and with recent advanced co-creative systems to gather insights that are based on users' interaction experiences with the technology rather than hypothetical scenarios.

Further studies are needed to investigate ways to utilize users' mental models of co-creative AI to generate appropriate explanations, feedback and contributions. Furthermore, future works can include conducting studies with larger samples that include more diverse user demographics. Additionally, longitudinal studies can provide valuable insights into how users' mental models of co-creative AI evolve over time. Investigating the impact of intersectionality on mental models of co-creative AI can inform culturally sensitive and value-sensitive design.

By pursuing these future research directions, significant contributions can be made to the development, understanding, and responsible implementation of human-centered co-creative AI systems. These contributions can shape the future of human-AI collaboration, leading to more engaging, ethical and effective co-creative experiences.

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APPENDIX A: ADDITIONAL DATA REGARDING THE MENTAL MODEL STUDY FINDINGS

In this appendix, we include the details of the findings from the association analysis presented in Chapter 6 (study about mental models of co-creative AI).

Each table consists of three sub-tables, each describing different aspects of the association tests. The first sub-table displays the contingency table of Chi-Square, showcasing the count and percentage of variables between which associations were observed. These contingency tables form the basis for statistical inference, where tests question the relationship between variables based on observed data.

The second sub-table provides information on the statistical significance of the association tests. A high level of statistical significance indicates that the observed relationship is unlikely to be a result of chance.

Lastly, the third sub-table demonstrates the effect size or the strength of the statistical significance. Measures such as Phi and Cramer's V gauge the strength of association of a nominal by nominal relationship.

Table A.1: Details of the association between mental models of ChatGPT and users' AI expertise using Chi-Square test

Clusters of MMs ChatGPT * Knowledge of AI Crosstabulation

			Knowledge of AI					
			Extremely knowledgeable	Moderately knowledgeable	Not knowledgeable at all	Slightly knowledgeable	Very knowledgeable	Total
Clusters of MMs ChatGPT	0	Count	2	20	1	33	19	75
		Expected Count	1.0	28.1	2.9	30.5	12.6	75.0
		% within Knowledge of AI	100.0%	34.5%	16.7%	52.4%	73.1%	48.4%
	1	Count	0	38	5	30	7	80
		Expected Count	1.0	29.9	3.1	32.5	13.4	80.0
		% within Knowledge of AI	0.0%	65.5%	83.3%	47.6%	26.9%	51.6%
Total		Count	2	58	6	63	26	155
		Expected Count	2.0	58.0	6.0	63.0	26.0	155.0
		% within Knowledge of AI	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	15.789[a]	4	.003
Likelihood Ratio	17.099	4	.002
N of Valid Cases	155		

a. 4 cells (40.0%) have expected count less than 5. The minimum expected count is .97.

Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	.319	.003
	Cramer's V	.319	.003
N of Valid Cases		155	

Table A.2: Details of the association between mental models of Stable Diffusion and users' AI expertise using Chi-Square test

Clusters of MMs SD * Knowledge of AI Crosstabulation

			Knowledge of AI					
			Extremely knowledgeable	Moderately knowledgeable	Not knowledgeable at all	Slightly knowledgeable	Very knowledgeable	Total
Clusters of MMs SD	0	Count	0	31	2	33	11	77
		Expected Count	1.0	28.8	3.0	31.3	12.9	77.0
		% within Knowledge of AI	0.0%	53.4%	33.3%	52.4%	42.3%	49.7%
	1	Count	2	6	2	9	10	29
		Expected Count	.4	10.9	1.1	11.8	4.9	29.0
		% within Knowledge of AI	100.0%	10.3%	33.3%	14.3%	38.5%	18.7%
	2	Count	0	21	2	21	5	49
		Expected Count	.6	18.3	1.9	19.9	8.2	49.0
		% within Knowledge of AI	0.0%	36.2%	33.3%	33.3%	19.2%	31.6%
Total		Count	2	58	6	63	26	155
		Expected Count	2.0	58.0	6.0	63.0	26.0	155.0
		% within Knowledge of AI	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	20.203[a]	8	.010
Likelihood Ratio	17.531	8	.025
N of Valid Cases	155		

a. 7 cells (46.7%) have expected count less than 5. The minimum expected count is .37.

Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	.361	.010
	Cramer's V	.255	.010
N of Valid Cases		155	

Table A.3: Details of the association between mental models of ChatGPT and users' educational/professional expertise using Chi-Square test

Clusters of MMs ChatGPT * Experience Clusters Crosstabulation

			Experience Clusters 0	Experience Clusters 1	Total
Clusters of MMs ChatGPT	0	Count	56	19	75
		% within Clusters of MMs ChatGPT	74.7%	25.3%	100.0%
	1	Count	48	32	80
		% within Clusters of MMs ChatGPT	60.0%	40.0%	100.0%
Total		Count	104	51	155
		% within Clusters of MMs ChatGPT	67.1%	32.9%	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	3.772[a]	1	.052		
Continuity Correction[b]	3.137	1	.077		
Likelihood Ratio	3.805	1	.051		
Fisher's Exact Test				.061	.038
Linear-by-Linear Association	3.747	1	.053		
N of Valid Cases	155				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 24.68.

b. Computed only for a 2x2 table

Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	.156	.052
	Cramer's V	.156	.052
N of Valid Cases		155	

Table A.4: Details of the association between mental models of Stable Diffusion and Users' Identity using Chi-Square test

Identity Clusters * Clusters of MMs SD Crosstabulation

			Clusters of MMs SD 0	1	2	Total
Identity Clusters	0	Count	55	14	30	99
		% within Identity Clusters	55.6%	14.1%	30.3%	100.0%
		% within Clusters of MMs SD	71.4%	48.3%	61.2%	63.9%
	1	Count	19	7	13	39
		% within Identity Clusters	48.7%	17.9%	33.3%	100.0%
		% within Clusters of MMs SD	24.7%	24.1%	26.5%	25.2%
	2	Count	3	8	6	17
		% within Identity Clusters	17.6%	47.1%	35.3%	100.0%
		% within Clusters of MMs SD	3.9%	27.6%	12.2%	11.0%
Total		Count	77	29	49	155
		% within Identity Clusters	49.7%	18.7%	31.6%	100.0%
		% within Clusters of MMs SD	100.0%	100.0%	100.0%	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	12.788[a]	4	.012
Likelihood Ratio	11.849	4	.019
Linear-by-Linear Association	3.049	1	.081
N of Valid Cases	155		

a. 1 cells (11.1%) have expected count less than 5. The minimum expected count is 3.18.

Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	.287	.012
	Cramer's V	.203	.012
N of Valid Cases		155	

Table A.5: Details of the association between mental models of ChatGPT and users' ethical stance towards AI impact on society

Clusters of MMs ChatGPT * AI Impact Crosstabulation

			AI Impact					
			I feel extremely negative about it	I feel neutral	I feel somewhat negative about it	I feel somewhat positive about it	I feel strongly positive about it	Total
Clusters of MMs ChatGPT	0	Count	1	13	8	34	19	75
		Expected Count	1.9	12.1	13.1	36.8	11.1	75.0
		% within AI Impact	25.0%	52.0%	29.6%	44.7%	82.6%	48.4%
	1	Count	3	12	19	42	4	80
		Expected Count	2.1	12.9	13.9	39.2	11.9	80.0
		% within AI Impact	75.0%	48.0%	70.4%	55.3%	17.4%	51.6%
Total		Count	4	25	27	76	23	155
		Expected Count	4.0	25.0	27.0	76.0	23.0	155.0
		% within AI Impact	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	16.002[a]	4	.003
Likelihood Ratio	17.014	4	.002
N of Valid Cases	155		

a. 2 cells (20.0%) have expected count less than 5. The minimum expected count is 1.94.

Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	.321	.003
	Cramer's V	.321	.003
N of Valid Cases		155	

Table A.6: Details of the association between mental models of Stable Diffusion and users' ethical stance towards AI impact on society

Clusters of MMs SD * AI Impact Crosstabulation

			AI Impact					
			I feel extremely negative about it	I feel neutral	I feel somewhat negative about it	I feel somewhat positive about it	I feel strongly positive about it	Total
Clusters of MMs SD	0	Count	2	13	14	42	6	77
		Expected Count	2.0	12.4	13.4	37.8	11.4	77.0
		% within AI Impact	50.0%	52.0%	51.9%	55.3%	26.1%	49.7%
	1	Count	0	5	4	9	11	29
		Expected Count	.7	4.7	5.1	14.2	4.3	29.0
		% within AI Impact	0.0%	20.0%	14.8%	11.8%	47.8%	18.7%
	2	Count	2	7	9	25	6	49
		Expected Count	1.3	7.9	8.5	24.0	7.3	49.0
		% within AI Impact	50.0%	28.0%	33.3%	32.9%	26.1%	31.6%
Total		Count	4	25	27	76	23	155
		Expected Count	4.0	25.0	27.0	76.0	23.0	155.0
		% within AI Impact	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	17.252[a]	8	.028
Likelihood Ratio	15.620	8	.048
N of Valid Cases	155		

a. 5 cells (33.3%) have expected count less than 5. The minimum expected count is .75.

Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	.334	.028
	Cramer's V	.236	.028
N of Valid Cases		155	

Table A.7: Details of the association between mental models of ChatGPT and users' ethical stance towards data collection by AI

Clusters of MMs ChatGPT * Data Collection Crosstabulation

			Data Collection					
			Extremely bad	Extremely good	Neither good nor bad	Somewhat bad	Somewhat good	Total
Clusters of MMs ChatGPT	0	Count	2	15	18	9	31	75
		Expected Count	5.3	7.3	22.7	13.1	26.6	75.0
		% within Data Collection	18.2%	100.0%	38.3%	33.3%	56.4%	48.4%
	1	Count	9	0	29	18	24	80
		Expected Count	5.7	7.7	24.3	13.9	28.4	80.0
		% within Data Collection	81.8%	0.0%	61.7%	66.7%	43.6%	51.6%
Total		Count	11	15	47	27	55	155
		Expected Count	11.0	15.0	47.0	27.0	55.0	155.0
		% within Data Collection	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	25.785[a]	4	<.001
Likelihood Ratio	32.001	4	<.001
N of Valid Cases	155		

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 5.32.

Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	.408	<.001
	Cramer's V	.408	<.001
N of Valid Cases		155	

Table A.8: Details of the association between mental models of Stable Diffusion and users' ethical stance towards data collection by AI

Clusters of MMs SD * Data Collection Crosstabulation

			Data Collection					
			Extremely bad	Extremely good	Neither good nor bad	Somewhat bad	Somewhat good	Total
Clusters of MMs SD	0	Count	8	2	22	20	25	77
		Expected Count	5.5	7.5	23.3	13.4	27.3	77.0
		% within Data Collection	72.7%	13.3%	46.8%	74.1%	45.5%	49.7%
	1	Count	1	10	6	2	10	29
		Expected Count	2.1	2.8	8.8	5.1	10.3	29.0
		% within Data Collection	9.1%	66.7%	12.8%	7.4%	18.2%	18.7%
	2	Count	2	3	19	5	20	49
		Expected Count	3.5	4.7	14.9	8.5	17.4	49.0
		% within Data Collection	18.2%	20.0%	40.4%	18.5%	36.4%	31.6%
Total		Count	11	15	47	27	55	155
		Expected Count	11.0	15.0	47.0	27.0	55.0	155.0
		% within Data Collection	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	34.676[a]	8	<.001
Likelihood Ratio	29.500	8	<.001
N of Valid Cases	155		

a. 4 cells (26.7%) have expected count less than 5. The minimum expected count is 2.06.

Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	.473	<.001
	Cramer's V	.334	<.001
N of Valid Cases		155	

Table A.9: Details of the association between mental models of ChatGPT and users' ethical stance towards anthropomorphism

Clusters of MMs ChatGPT * Anthropomorphism Crosstabulation

			Anthropomorphism					
			Extremely bad	Extremely good	Neither good nor bad	Somewhat bad	Somewhat good	Total
Clusters of MMs ChatGPT	0	Count	3	11	26	7	28	75
		Expected Count	5.8	6.8	25.2	12.6	24.7	75.0
		% within Anthropomorphism	25.0%	78.6%	50.0%	26.9%	54.9%	48.4%
	1	Count	9	3	26	19	23	80
		Expected Count	6.2	7.2	26.8	13.4	26.3	80.0
		% within Anthropomorphism	75.0%	21.4%	50.0%	73.1%	45.1%	51.6%
Total		Count	12	14	52	26	51	155
		Expected Count	12.0	14.0	52.0	26.0	51.0	155.0
		% within Anthropomorphism	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	13.453[a]	4	.009
Likelihood Ratio	14.083	4	.007
N of Valid Cases	155		

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 5.81.

Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	.295	.009
	Cramer's V	.295	.009
N of Valid Cases		155	

Table A.10: Details of the association between mental models of Stable Diffusion and users' ethical stance towards anthropomorphism

Clusters of MMs SD * Anthropomorphism Crosstabulation

			Anthropomorphism					
			Extremely bad	Extremely good	Neither good nor bad	Somewhat bad	Somewhat good	Total
Clusters of MMs SD	0	Count	9	4	25	17	22	77
		Expected Count	6.0	7.0	25.8	12.9	25.3	77.0
		% within Anthropomorphism	75.0%	28.6%	48.1%	65.4%	43.1%	49.7%
	1	Count	1	7	10	3	8	29
		Expected Count	2.2	2.6	9.7	4.9	9.5	29.0
		% within Anthropomorphism	8.3%	50.0%	19.2%	11.5%	15.7%	18.7%
	2	Count	2	3	17	6	21	49
		Expected Count	3.8	4.4	16.4	8.2	16.1	49.0
		% within Anthropomorphism	16.7%	21.4%	32.7%	23.1%	41.2%	31.6%
Total		Count	12	14	52	26	51	155
		Expected Count	12.0	14.0	52.0	26.0	51.0	155.0
		% within Anthropomorphism	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	16.951[a]	8	.031
Likelihood Ratio	15.027	8	.059
N of Valid Cases	155		

a. 5 cells (33.3%) have expected count less than 5. The minimum expected count is 2.25.

Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	.331	.031
	Cramer's V	.234	.031
N of Valid Cases		155	

Table A.11: Details of the association between users' identity and users' ethical stances

Identity Clusters * Clusters of Ethical Concerns Crosstabulation

			Clusters of Ethical Concerns 0	1	Total
Identity Clusters	0	Count	75	24	99
		% within Identity Clusters	75.8%	24.2%	100.0%
		% within Clusters of Ethical Concerns	65.8%	58.5%	63.9%
	1	Count	31	8	39
		% within Identity Clusters	79.5%	20.5%	100.0%
		% within Clusters of Ethical Concerns	27.2%	19.5%	25.2%
	2	Count	8	9	17
		% within Identity Clusters	47.1%	52.9%	100.0%
		% within Clusters of Ethical Concerns	7.0%	22.0%	11.0%
Total		Count	114	41	155
		% within Identity Clusters	73.5%	26.5%	100.0%
		% within Clusters of Ethical Concerns	100.0%	100.0%	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	7.087[a]	2	.029
Likelihood Ratio	6.344	2	.042
Linear-by-Linear Association	3.148	1	.076
N of Valid Cases	155		

a. 1 cells (16.7%) have expected count less than 5. The minimum expected count is 4.50.

Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	.214	.029
	Cramer's V	.214	.029
N of Valid Cases		155	

Table A.12: Details of the association between users' ethical stance towards data collection by AI and users' ethnicity

Data Collection * Ethnicity Crosstabulation

			Ethnicity						
			Asian	Black/African-American	Hispanic/Latinx	Middle Eastern/North African (MENA)	Other	White	Total
Data Collection	Extremely bad	Count	0	1	3	2	0	5	11
		Expected Count	.2	2.3	3.0	.4	.1	5.0	11.0
		% within Ethnicity	0.0%	3.1%	7.1%	40.0%	0.0%	7.0%	7.1%
	Extremely good	Count	0	8	1	1	0	5	15
		Expected Count	.3	3.1	4.1	.5	.2	6.9	15.0
		% within Ethnicity	0.0%	25.0%	2.4%	20.0%	0.0%	7.0%	9.7%
	Neither good nor bad	Count	2	9	18	0	0	18	47
		Expected Count	.9	9.7	12.7	1.5	.6	21.5	47.0
		% within Ethnicity	66.7%	28.1%	42.9%	0.0%	0.0%	25.4%	30.3%
	Somewhat bad	Count	0	4	5	1	0	17	27
		Expected Count	.5	5.6	7.3	.9	.3	12.4	27.0
		% within Ethnicity	0.0%	12.5%	11.9%	20.0%	0.0%	23.9%	17.4%
	Somewhat good	Count	1	10	15	1	2	26	55
		Expected Count	1.1	11.4	14.9	1.8	.7	25.2	55.0
		% within Ethnicity	33.3%	31.3%	35.7%	20.0%	100.0%	36.6%	35.5%
Total		Count	3	32	42	5	2	71	155
		Expected Count	3.0	32.0	42.0	5.0	2.0	71.0	155.0
		% within Ethnicity	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	33.226[a]	20	.032
Likelihood Ratio	30.495	20	.062
N of Valid Cases	155		

a. 19 cells (63.3%) have expected count less than 5. The minimum expected count is .14.

Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	.463	.032
	Cramer's V	.231	.032
N of Valid Cases		155	

Table A.13: Details of the association between users' ethical stance towards data collection by AI and their formative background

Data Collection * Type of community as formative background Crosstabulation

			Type of community as formative background				
			A large city	A rural area	A small city or town	A subarb near a large city	Total
Data Collection	Extremely bad	Count	2	1	4	4	11
		Expected Count	5.0	.4	3.0	2.6	11.0
		% within Type of community as formative background	2.9%	16.7%	9.5%	10.8%	7.1%
	Extremely good	Count	10	0	2	3	15
		Expected Count	6.8	.6	4.1	3.6	15.0
		% within Type of community as formative background	14.3%	0.0%	4.8%	8.1%	9.7%
	Neither good nor bad	Count	18	2	12	15	47
		Expected Count	21.2	1.8	12.7	11.2	47.0
		% within Type of community as formative background	25.7%	33.3%	28.6%	40.5%	30.3%
	Somewhat bad	Count	7	3	9	8	27
		Expected Count	12.2	1.0	7.3	6.4	27.0
		% within Type of community as formative background	10.0%	50.0%	21.4%	21.6%	17.4%
	Somewhat good	Count	33	0	15	7	55
		Expected Count	24.8	2.1	14.9	13.1	55.0
		% within Type of community as formative background	47.1%	0.0%	35.7%	18.9%	35.5%
Total		Count	70	6	42	37	155
		Expected Count	70.0	6.0	42.0	37.0	155.0
		% within Type of community as formative background	100.0%	100.0%	100.0%	100.0%	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	23.003[a]	12	.028
Likelihood Ratio	25.292	12	.013
N of Valid Cases	155		

a. 10 cells (50.0%) have expected count less than 5. The minimum expected count is .43.

Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	.385	.028
	Cramer's V	.222	.028
N of Valid Cases		155	

Table A.14: Details of the association between users' ethical stance towards AI impact on society and their political affiliation

AI Impact * Political affiliation Crosstabulation

			Political affiliation				
			Conservative	Liberal	Moderate	No political affiliation	Total
AI Impact	I feel extremely negative about it	Count	1	1	1	1	4
		Expected Count	.1	1.6	1.1	1.1	4.0
		% within Political affiliation	20.0%	1.6%	2.3%	2.3%	2.6%
	I feel neutral	Count	0	16	5	4	25
		Expected Count	.8	10.0	7.1	7.1	25.0
		% within Political affiliation	0.0%	25.8%	11.4%	9.1%	16.1%
	I feel somewhat negative about it	Count	0	8	13	6	27
		Expected Count	.9	10.8	7.7	7.7	27.0
		% within Political affiliation	0.0%	12.9%	29.5%	13.6%	17.4%
	I feel somewhat positive about it	Count	3	33	14	26	76
		Expected Count	2.5	30.4	21.6	21.6	76.0
		% within Political affiliation	60.0%	53.2%	31.8%	59.1%	49.0%
	I feel strongly positive about it	Count	1	4	11	7	23
		Expected Count	.7	9.2	6.5	6.5	23.0
		% within Political affiliation	20.0%	6.5%	25.0%	15.9%	14.8%
Total		Count	5	62	44	44	155
		Expected Count	5.0	62.0	44.0	44.0	155.0
		% within Political affiliation	100.0%	100.0%	100.0%	100.0%	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	28.223[a]	12	.005
Likelihood Ratio	26.203	12	.010
N of Valid Cases	155		

a. 8 cells (40.0%) have expected count less than 5. The minimum expected count is .13.

Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	.427	.005
	Cramer's V	.246	.005
N of Valid Cases		155	

Table A.15: Details of the association between users' ethical stance towards AI Impact on Society and users' annual income

AI Impact * Annual income Crosstabulation

			Annual income												
			$10,000 - $19,999	$100,000 - $149,999	$20,000 - $29,999	$30,000 - $39,999	$40,000 - $49,999	$50,000 - $59,999	$60,000 - $69,999	$70,000 - $79,999	$80,000 - $89,999	$90,000 - $99,999	Less than $10,000	More than $150,000	Total
AI Impact	I feel extremely negative about it	Count	0	0	1	1	1	1	0	0	0	0	0	0	4
		Expected Count	.6	.0	.5	.5	.2	.2	.1	.0	.1	.1	1.8	.1	4.0
		% within Annual income	0.0%	0.0%	5.3%	5.6%	14.3%	16.7%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	2.6%
	I feel neutral	Count	9	0	1	3	0	1	0	0	1	0	10	0	25
		Expected Count	3.7	.2	3.1	2.9	1.1	1.0	.5	.2	.3	.3	11.5	.3	25.0
		% within Annual income	39.1%	0.0%	5.3%	16.7%	0.0%	16.7%	0.0%	0.0%	50.0%	0.0%	14.1%	0.0%	16.1%
	I feel somewhat negative about it	Count	2	1	8	2	0	1	0	0	1	0	12	0	27
		Expected Count	4.0	.2	3.3	3.1	1.2	1.0	.5	.2	.3	.3	12.4	.3	27.0
		% within Annual income	8.7%	100.0%	42.1%	11.1%	0.0%	16.7%	0.0%	0.0%	50.0%	0.0%	16.9%	0.0%	17.4%
	I feel somewhat positive about it	Count	8	0	7	10	6	3	3	1	0	1	37	0	76
		Expected Count	11.3	.5	9.3	8.8	3.4	2.9	1.5	.5	1.0	1.0	34.8	1.0	76.0
		% within Annual income	34.8%	0.0%	36.8%	55.6%	85.7%	50.0%	100.0%	100.0%	0.0%	50.0%	52.1%	0.0%	49.0%
	I feel strongly positive about it	Count	4	0	2	2	0	0	0	0	0	1	12	2	23
		Expected Count	3.4	.1	2.8	2.7	1.0	.9	.4	.1	.3	.3	10.5	.3	23.0
		% within Annual income	17.4%	0.0%	10.5%	11.1%	0.0%	0.0%	0.0%	0.0%	0.0%	50.0%	16.9%	100.0%	14.8%
Total		Count	23	1	19	18	7	6	3	1	2	2	71	2	155
		Expected Count	23.0	1.0	19.0	18.0	7.0	6.0	3.0	1.0	2.0	2.0	71.0	2.0	155.0
		% within Annual income	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	64.571[a]	44	.023
Likelihood Ratio	59.971	44	.055
N of Valid Cases	155		

a. 53 cells (88.3%) have expected count less than 5. The minimum expected count is .03.

Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	.645	.023
	Cramer's V	.323	.023
N of Valid Cases		155	