# Applying Art-based Embodied Knowledge to Further Artistic Objectives with Technology and Support Creative Thinking in Computing

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(ABSTRACT)

As computers have advanced, their use cases have expanded to support many human-centric activities. Computing's place in the creation and consumption of art has been called into question in recent years with the emergence of generative artificial intelligence (GenAI), which can produce creative works such as paintings, music, and creative writings almost instantly. However, before the introduction of GenAI, software had been used for decades across all vantages of influence to expedite human expression. Society is grappling with the question of how to approach technology's influence on all forms of art: how to effectively apply computing's capabilities without impeding the agency of the artist. Furthermore, there is a lack of influence from the world of art on directing the immense force of technology on the modern world. This dissertation sought to build a tighter bidirectional relationship between art and technology by understanding how technology can further the objectives of the artist through studies 1 and 2 and investigating how embodied logic in art can be used to support the algorithmic thinking required in computing in Study 3.

Study 1 focused on capturing embodied knowledge in the procedures of an art form through motion sensors to communicate physical routines through sound. This work was completed by building a prototype sonification system which dynamically classified segments of a stitch in crochet, and then conducting co-design sessions with stakeholders. Results demonstrated that using novel sensory-perceptual modalities such as audition to express abstract concepts can be used as a novel UX design tool. In study 2 I sought to understand the potential for

human biases against technology's use in art. I built two different technologically-augmented dance performances, one with artificial intelligence (AI) and one without, and withheld information on how the performances were built in order to capture audience responses on the creative merits of the technological components of the two works. Results highlighted significantly higher ratings on questions of artistic merit for the AI performance version when implementation information was withheld compared to when this information was divulged, suggesting a potential for bias. This offered insight into the deployment of AI art in the future. Study 3 focused on teaching and using embodied logic in art to assess analytical thinking skills in computing. The study surrounded teaching individuals how to interpret and write crochet patterns using two different methods: with or without the accompanying physical procedures. After the lessons, written tests on patterns in crochet and computer programming were administered. Results showed a positive correlation between programming and crochet test scores of individuals for the majority of participants across all condition groups. Interview transcriptions pointed to similarities in approaching questions on the two tests and a desire for visual aids from participants who didn't learn the physical procedures.

The present body of work examined how the latest technologies can be used to further the human objectives of art, and how constructs from art can be used to advance computing objectives. The present work offers theoretical insights into using multiple sensory-perceptual modalities as system design tools, as well as practical guidance for how technologies can effectively be applied in creative, art-based contexts.

# Applying Art-based Embodied Knowledge to Further Artistic Objectives with Technology and Support Creative Thinking in Computing

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(GENERAL AUDIENCE ABSTRACT)

People today incorporate computing in nearly all areas of their lives. However, with the rapid developments of GenAI, the adoption of computing into certain domains has been called into question. GenAI can produce creative works like paintings, music, and writing almost instantly with relatively little help from human creators. While computing has contributed greatly to creative domains, some believe that the latest technologies can potentially threaten artistic expression. This is an urgent open question that blends art and computer science (CS), and contributes to a greater discussion of how these fields influence one another. For this dissertation I investigated methods for developing a more balanced relationship between art and technology. In Studies 1 and 2 I sought to use technology to make the artmaking process more fulfilling and enjoyable for the creator, whereas in Study 3 I tried to understand how ideas in art are similar to ideas in computing.

Study 1 focused on capturing patterns in the movements made when producing art in order to make live collaborative music. This was done by building a prototype system that converted data to sound by dividing steps in making stitches in the fiber art crochet and capturing that data in real time. People with different backgrounds in art and technology were asked for their thoughts on the system to improve it in the future. Results showed that sound can be used as a tool to help designers get impressions of activities that do not make sound. Study 2 was done to understand whether people had biases against technology when it is used for art. I built two different dance performances that used technology, one with AI

and one without, and withheld information on how the performances were built to capture audience survey responses on the creativity of the two works. Results showed that people thought the AI performance was more artistic when they were not told about how the performance was built until after the survey; this indicated some bias. This study's results can help people decide whether they want to use AI tools when sharing their work with public audiences. Finally, Study 3 focused on teaching a procedural artistic task using different methods in order to evaluate thinking skills used in computing. In the study individuals were taught how to understand written crochet patterns either with or without physically learning how to crochet. After the lessons, written tests were given on crochet patterns and basic programming. Results showed positive correlations between scores on tests for the majority of participants and similarities in problem solving strategies on both tests. People who did not learn how to physically crochet thought pictures would help on the test as well. This collection of work centered on how the latest technologies can be used to keep humans the focus of art, and how art can positively impact computing. Considering both the benefits and consequences of technology, we can support human creativity as technology advances.

# Dedication

*To mom and dad.*

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I would like to thank my advisor, Dr. Myounghoon Jeon, for his unwavering commitment to my professional development. The grace, patience, and fortitude you have exemplified in drawing out the best from your students is aspirational. I always knew that if I followed your guidance, I would see success. It really was a pleasure to work with you, and I wish you every blessing.

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To all of my study participants, thank you for sharing your most precious resource, your time, with me as I completed this research. I was always so grateful whenever one of you volunteered for one of my studies. This work would not be possible without you.

# Attributions

- **Study 1:**

  This completed study is under review for journal publication in JMUI. A subset of this study has already been published in ACM C&C 2023 as a technical demonstration, and in ICAD 2023 as an extended abstract. This work was also presented in ICAD's 2023 doctoral consortium.

  Bruen, J. & Jeon, M. (Submitted Full Paper). Embodied Knowledge as a Design Probe in a User-Centered Design Study of a Sonification System for Crochet. *Journal on Multimodal User Interfaces (JMUI).*

  Bruen, J., Kwon, H., & Jeon, M. (2023). Cro-create: Weaving sound using crochet gestures. *Proceedings of the 15th Conference on Creativity & Cognition (C&C)*, GatherTown, June 19th – 21st.

  Bruen, J. & Jeon, M. (2023). Cro-create: A collaborative crochet music maker for physical creation together. *Proceedings of the 28th International Conference on Auditory Display (ICAD)*, Norrköping, Sweden, June 26th – 30th.

- **Study 2:**

  Preliminary results from this work were accepted as a workshop and a poster at ACM C&C 2025. The full study has been accepted for journal publication in IJHCI.

  Bruen, J., Jung, S., & Jeon, M. (Recently Accepted). Knowledge of How AI Art is Made Shapes Audience's Valuations of a Technologically Augmented Live Dance Performance. *International Journal of Human-Computer Interaction (IJHCI).*

Bruen, J. & Jeon, M. (2025). What's Behind the Magic? Audiences Seek Artistic Value in Generative AI's Contributions to a Live Dance Performance. *Proceedings of Explainable AI for the Arts Workshop (XAIxArts)*, Virtual, United Kingdom, June 23rd – 25th.

Bruen, J. & Jeon, M. (2025). AI-Supported Dance Performances Provoke Audiences to Seek Creative Merit and Meaning in AI's Artistic Decisions. *Proceedings of the 2025 Conference on Creativity and Cognition (C&C)*, Virtual, United Kingdom, June 23rd – 25th.

- **Study 3:**

  A pilot of study 3 was accepted as a poster to ACM C&C 2025.

  Bruen, J. & Jeon, M. (2025). Algorithms in Art and Code: How Teaching Embodied Artmaking Procedures Can Stimulate Analytical Thinking in Art Crafting and Computer Programming. *Proceedings of the 2025 Conference on Creativity and Cognition (C&C)*, Virtual, United Kingdom, June 23rd – 25th.

# Contents

# Chapter 1

# Introduction

## 1.1 Motivation

Today's technologies can be applied to virtually every aspect of one's life. While Williams acknowledged that computers were initially designed as practical tools to accomplish technical tasks [243], they have so rapidly advanced over the decades that, as Campbell-Kelly et al. found, people now rely on them for wholly humanistic objectives [28]. Franke noted that one of these objectives is the creation and consumption of art [70]. In the academic literature, specifically the works of Dissanayake and Dewey, art is considered to be an expression of "the human experience" [49, 52], a concept that many such as Hertzmann and Lopes argue computers are not equipped to handle [95, 149]. However, the collection of early autonomous artmaking programs of artist Harold Cohen, *AARON*, calls this definition into question. The programs are widely acknowledged as co-creators of valued artistic expression, with viewers' praises directed towards Cohen. Perhaps a better definition of art may be an agreement on expressive value between both the viewer and the creator. For the intents of this body of work, the distinguishing factor which separates art from its contenders is the unspoken contract of a work's implied value that exists between the human creator (of the art-making technology or the art itself) and each individual viewer [36]. I carry this definition of art throughout the three studies described in this dissertation.

With the recent advent of GenAI, the diffusion of technology into the art world is increasingly apparent. With the introduction of many new technological innovations, opinions have often been mixed on how the inventions can further art. What differentiates today's technologies are that they can both capture our physical experiences in the world through sensors and make creative decisions on our behalf through GenAI.

Sensor technologies have been applied in a variety of contexts already. With the wave of the "internet of things," Aheleroff et al. and Dian et al. noted that we have seen sensors used in everyday appliances [9] and wearables [50]. The relative ease of collecting and interpreting information has led, according to Swan, to the "quantified self" movement, whereby people can learn more about themselves using metrics measured by sensors [223]. Systems furthering this movement have been used by researchers such as Metcalf et al. to monitor our health [160], by Passos et al. to track our movement patterns [184], and by Swan to synthesize our habits [223].

The capabilities of sensors that detect changes in our physiology and the environment carry the question of how these technologies can capture the embodied experience of creating art, and how we can use this information to express more about ourselves and the world. Embodied knowledge was described succinctly by Tanaka as "a type of knowledge where the body knows to act" [225]. Creating art requires embodied knowledge: from how the artist holds their tools, to the muscle memory developed to perform the artistic procedures, O'Connor argued that developing embodied knowledge is critical towards honing one's specialized craft [183]. Sensor technologies can provide us with a new lens towards recognizing and applying this knowledge. In the present body of work, I applied sensor technologies to help users enhance the embodied experiences of creating art in Chapter 3. I also used sensors to understand how viewers' valuations of art changed based on the types of technology used to create the art in Chapter 4. In Chapter 5 I applied embodiment theory to understand how knowledge of art-based procedures can help more people understand concepts in computing.

Many researchers, such as Fui-Hoon Nah et al., have acknowledged that GenAI is a new technological innovation that allows its users to rapidly produce artistic media such as music, paintings, and fictional literature [75]. While experts and the general public debate whether this media can be considered "art," GenAI-created pieces sold at auction such as those noted by Jones have yielded high sale prices [120]. For those who make their living from the public consumption of their artwork, understanding the perceived market value of GenAI-created art in this new landscape is critical. A thorough understanding of this can help artists determine whether GenAI should be used in their practice, and help artists form strategies to better direct their personal businesses. In entirely human-created art, there are some tested variables used to arrive at a valuation of a work. According to Kheder, these variables can include rarity, artist's reputation, condition, subject matter, and market trends (i.e., collectors' tastes can change based on the time of sale) [127]. While rarity, artist's reputation, and condition are the more heavily weighted factors in determining a human-made art piece's value, these factors appear to be irrelevant in the sale and production of GenAI-made art. Following my line of research on how technology can further art-based objectives, I wanted to understand whether biases existed in how people perceived art made with or by technology, and how people rationalized these biases. I explored these questions with a study on a set of technologically-augmented dance performances described in Chapter 4.

Technology has so greatly developed that we can now use it to understand our own humanity. Sensors can help us uncover the embodied knowledge of artists and craftsmen, and GenAI leads us to ask whether machines' decisions can have creative merit. Overall in this body of work I aimed to understand how technology can be used to capture and apply embodied knowledge in art to support artists and further interdisciplinary educational objectives. Specifically, the following studies were conducted to answer these two overarching questions:

1. In what contexts are technologies such as GenAI and sensors welcomed in art?
2. How can we use concepts from art to further computing objectives and work towards balancing the symbiosis of computing and art?

The studies this research encompasses are presented visually in Figure 1.1.

Study 1 was an investigation of how a prototype interactive system can enhance how artists create and experience their work. My system, Cro-Create, sonified hand movements as people crocheted. I developed Cro-Create as an application of Wickens' multiple resource theory. According to this theory, individuals can process more information so long as the modalities of the communication channels are distinct. I applied this theory to Cro-Create by adding sound to communicate the artist's actions as they worked by themselves or with a partner. The system had two modes: single user and dual user mode. In single user mode, one user's hand movements were sonified. In dual user mode, two users who crocheted together using different motion sensors on separate machines could create sound that indicated whether they were performing the same crochet subroutines.

I introduced my prototype to three different stakeholders: novice crocheters, experienced crocheters, and experts in sonification, audio technology, and human-computer interaction (HCI). Through a series of demonstrations, tutorials, focus groups, and interviews, stakeholders provided insights into where my system succeeded and what could be improved. Results from this study also yielded generalizable guidelines for user experience (UX) designers of spatial interaction systems.

In study 2, described in Chapter 4, I wanted to understand whether people had biases against specific types of technology when they were used in an art domain that heavily relies on embodied knowledge. In studying this I hoped to inform artists and industry professionals on how the choice of using GenAI art may be received by viewers. To achieve this, I developed two versions of a technologically-augmented dance performance which utilized embodiment data from the dancer via sensors. These performances captured live streams of physiological and locational data from the performer; I used these data streams to alter accompanying visuals and sound during the performance in accordance with data mappings designed using different types of technology. In one version of the performance, creative decisions related to the augmentation were made by myself. In the other version, I used GenAI and neural network models to drive the artistic elements of the augmentation. I held each of these performances twice: in one instance I told audience members how technology was used before they watched the performance, and in the other instance I told them after they had watched the performance and completed a Likert survey about the performance. I ran Mann-Whitney U tests on the survey results of performances where only one variable (technology type or time told) was held constant (i.e., Non-AI/Tell Before vs. Non-AI/Tell After, AI/Tell Before vs. AI/Tell After, Non-AI/Tell Before vs. AI/Tell Before, Non-AI/Tell After vs. AI/Tell After).

I also collected focus group data from audience members after each of the four performances, which I used to create affinity diagrams from the quotes of participants from each experimental condition. Finally, a research assistant (not myself) held an interview with the performer, and as the technologist I wrote a written reflection of my own experience working on the project to understand interdisciplinary collaboration in this context.

Results from this study showed that knowledge of the production of a piece of art impacted people's perception of the work; these results contextualized where people thought GenAI elements were appropriate in art. I explain these results in Chapter 4.4.

For Study 3, described in Chapter 5, I wanted to understand whether different types of knowledge (i.e., embodied or cerebral) of an art-based skill could help improve performance of a technical skill; in this case I chose interpreting crochet patterns as the art-based skill and interpreting pseudocode as the technical skill. Understanding how knowledge of arts can support science, technology, engineering, and math (STEM) education is beneficial from many perspectives. Framing technical problems to novices as exercises of skills they are already familiar with can positively change how novices' perceive challenges in new domains. Furthermore, empirically showing the benefits of learning art towards accomplishing STEM-related tasks can highlight the multifaceted applicability of the arts.

In the main 2x2 between-subjects design of this study, my two independent variables were 1) programming experience and 2) learning method. I recruited both programmers and non-programmers and taught them how to read and write crochet patterns using one of two methods. In one method, participants were taught using text and verbal instructions. In the other method, participants were taught with the text and verbal lessons as well, but also learned the physical procedures (with yarn and hook) used to create the crochet stitches taught in the lessons. After teaching participants in three separate sessions, I tested them on crochet patterns and elementary programming and algorithms in a final, fourth session. I also included an additional comparison group of individuals who were already experienced in crochet who took the two tests but didn't complete the crochet learning interventions. Study 3 results suggested correlations between the two test scores for the majority of participants across condition groups, along with interview data which highlighted shared methodologies for solving test questions and direct mappings between abstractions in crochet and programming.

The research questions addressed in each study of this body of work are as follows:

*Study 1*

- RQ1: How does one learn crochet?
- RQ2: What is challenging about crochet?

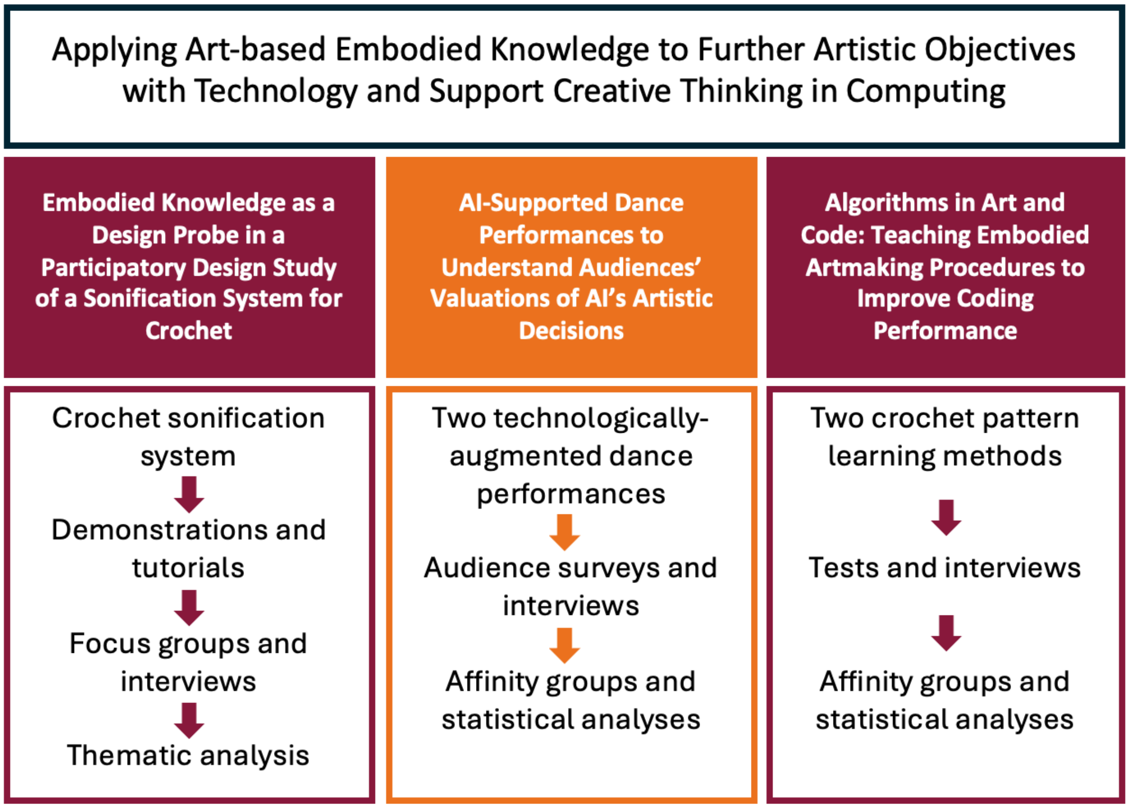



Figure 1.1: Dissertation overview

- RQ3: Why do people crochet?
- RQ4: How can technology improve crocheting?

*Study 2*

- RQ5: Does the type of technology used to help create art impact the viewers' perception of that art?
- RQ6: Does withholding information about how an artwork was made with technology impact how viewers value the work?
- RQ7: How do technologists and artists work together to integrate new technologies into art?

*Study 3*

- RQ8: Do programmers perform better than non-programmers on a procedural art-based assessment (test on interpreting crochet patterns)?
- RQ9: Does physically learning crochet have an effect on participants' performance on a written crochet test or programming test?
- RQ10: Can participants recognize similarities and differences between crochet and programming after exposure to both?
- RQ11: What are participants' impressions of programming after being introduced to the programming-like art practice of crochet?
- RQ12: How do participants perceive their performance on the crochet test and the programming test, compared to their actual performance?

## 1.2 Positionality Statement

In my research I pursued questions of how technology can augment specific art-based activities. This is shaped by my personal interest and knowledge of these activities. I am an avid crocheter, which contributed to my ideation process for Studies 1 and 3. While other similar art activities such as knitting could have been investigated, I utilized my expertise in crochet to more confidently pursue this line of inquiry.

# Chapter 2

# Definitions and Background

## 2.1 Definitions

### 2.1.1 Embodied Knowledge

Embodied knowledge is a person's understanding of their physical contextualization and agency in the world. It constitutes knowledge which can only be understood and utilized through physical presence. The term is said to be derived from Maurice Merleau-Ponty's book, *Phenomenology of Perception* [159]. Tanaka described embodied knowledge succinctly as "a type of knowledge where the body knows how to act [225]."

### 2.1.2 Embodied Cognition

Embodied cognition is a paradigm in cognitive science which centers on the importance of a person's physicality and environment in shaping their thought processes. Embodied cognition emphasizes that natural factors (e.g., biological, chemical, psychological) acting within and outside of us influence our abstract, cerebral reasoning.

### 2.1.3 Declarative Knowledge

Declarative knowledge is knowledge acquired through conscious effort. It can be effectively codified, explained, and recognized. Yun explained that this is the type of knowledge that "knows what everything is:" information that a person is fully aware that they know, and can be easily articulated [246].

### 2.1.4 Implicit Knowledge

Implicit knowledge is knowledge that does not necessarily require conscious effort to draw forth from memory. It develops through continued and varied exposure to the learned phenomena, and is not easily expressed.

### 2.1.5 Kinesthetic Memory

Kinesthetic memory refers to our ability to apply embodied knowledge. This type of memory relies heavily on bodily cues by using sensory and environmental factors. Keele and Ells identified some of these cues as joint position receptors, movement duration, and tendon stretch receptions, among others [124].

## 2.2 Background

### 2.2.1 Pre-Computer Technologies in the Arts

Our idea of what constitutes technology is greatly impacted by our place in the timeline of scientific thought. We are more apt today to overlook the fact that writing instruments or the printing press were once astounding technological innovations. Consider the extent to which an inscription tool, such as an early stylus used to record vital information as highlighted by Nissen et al., subsequently prompted the development of early agricultural societies roughly 5000 years ago in the Late Neolithic Period [175]. This early technology led to a cascade of advancements in trade, government, and artistic endeavors which propelled humanity towards higher intellectual pursuits [26].

Much more recently, in the 1400s, Gutenburg's printing press incited the information revolution. Researchers such as Eisenstein have highlighted that this device enabled the efficient reproduction of written materials, which fundamentally altered the structure of society as mass communication became possible [61]. Literacy rates rose sharply amongst common people and antiquated paradigms of power were challenged, setting the stage for the crowning artistic and cultural achievements of the Renaissance in the 16th and 17th centuries.

These technological developments didn't simply enhance human productivity for a few decades or further the objectives of a few well-informed individuals, they completely reshaped the course of human history, drawing forth the thoughts and attention of the masses towards more creative pursuits in science, art, and politics.

Like many great technological triumphs, what we consider to be the first photographic camera was a product of several small scientific findings and rudimentary prototypes developed over time. The oldest surviving photograph from this camera, *View from the Window at Le Gras* was taken by the French inventor Nicéphore Niépce from his bedroom window [177]. While no rival to the great painters of landscapes at the time, the imperfect capture of the cityscape sparked curiosity and widespread adoption by the general public. Sandweiss explained that portraiture was the most exciting use case of the camera for people at the time. While paintings and drawings could render the likeness of a loved one, skillful recreations of a person's likeness by an artist were out of reach for common people [198]. How did artists react to this new tool? An article from 1855 offered some insight into the concerns of the day, "The apprehensions once entertained that this art would... thrust the artist and his vocation aside, are now no longer indulged; but,... it is seen that Photography, so far from being a rival, is in truth a most important auxiliary to the resources of the artist" [3].

### 2.2.2 Computers in Art

#### Early Modern Computers

Computers as the sophisticated mathematical engines we know them as today emerged in 1941 with German Konrad Zuse's Z3 [4]. This earliest programmable machine had minimal memory and no conditional instructions. With developments shortly thereafter in the United States on the EDVAC, John von Neumann published the landmark work on the machine where he proposed the stored-program paradigm in what we know today as the von Neumann architecture [237]. Such architectural developments soon intersected with innovations in computer memory with the Williams–Kilburn tube in 1948, the first random access memory (RAM) [128]. In the 1950s advancements in computing were primarily centered on governmental, military, and business objectives. The versatility in the user's ability to write and run any program, along with sufficient memory to store these programs, were the building blocks that set the stage for the proliferation of computing as a new creative medium in the 1960s. With concentrated efforts that enhanced the ease of running programs and expanded memory chips, computing evolved from a means of conveniently performing sophisticated mathematical operations to the bedrock for completely new genres of creative expression.

### Computer Art

Early instances of computer art can be traced to the first video game, “Tennis-for-Two” developed at Brookhaven National Laboratory as an entertaining activity for guests on the lab’s annual “Visitor’s Day” [179]. This interactive ancestor of the game “Pong” allowed the user to play tennis against the computer [1]. Despite its simple graphics, the staying power of the playful experience is evident in the countless iterations of “Tennis-for-Two,” Nintendo Switch Sports Tennis being a more recent example [174].

SketchPad, a product of Ivan Sutherland’s doctoral thesis in 1963, was one of the earliest interactive drawing applications, and the earliest software to use what we would now consider a graphical user interface (GUI) [222]. While SketchPad was primarily designed to support technical drawings in engineering, the application provided early opportunities to freehand draw on a computer and gave a nod to classical art with its “winking” Nefertiti animation.

Dietrich identified 1965 as the start of the first decade of computer art. Highlighting the exclusivity of computer access at the time, Dietrich explained that early computer art adopted a more academic flavor. Animated simulations were developed for educational purposes, and only those at this cutting edge of technology who also held a joint interest in computers and art began to experiment with computers as artistic tools. Similarly, a subset of artists were receptive to this interdisciplinary collaboration and opened their museums to show these works in three shows starting in the late 1960s: “Cybernetic Serendipity” [192], “Some More Beginnings” [131], and “Software” [25]. Like the more popular artistic movements of the 1950s which preceded computer art, such as minimalism and pop art, these computer-generated artworks were abstract and unrealistic.

Given the need for specific domain knowledge to create computer art, and the proximity of early computing to other STEM subjects, author Dietrich explained that computer art of the 1960s and 70s was often inspired by mathematical principles such as harmonic ratios in Zajec's *Prostor* (1969), sine waves in Csuri and Shaffer's *Sine Wave Man* (1967), and matrix manipulations in Nake's *Matrix Multiplication* (1967). In the pieces of this time, the collaborative elements of computing and art were easily distinguishable. You could see the math and machinery in the artworks—this was part of their gestalt. Artist Harold Cohen's *AARON*, the first AI program for artmaking, emerged at this time [36]. Sheynfeld explained that Cohen proudly pronounced that *AARON* was his "assistant" in artmaking [206]. The software itself was highly novel and arguably an artwork in and of itself.

As computing advanced, the expressive power of machines as a medium to develop art rapidly progressed. Computers slowly began to find their way into homes in the 1980s and 90s. Applications for creating digital art became widely accessible with the hallmark programs being MacPaint [40] in the 80s and Adobe Photoshop [105] in the 90s. Digital art around this time showed less resemblance to its legacy "computer art," and instead became more commonplace as "art made with a computer." With the technical progress in computing, digital art began to become part of the workflow for major commercial artistic endeavors. Computer-generated imagery (CGI) began being used regularly in major Hollywood films such as *Tron* (1982) [146], *Jurassic Park* (1993) [218], and *Toy Story* (1995) [136].

The late 2000s and 2010s brought us mobile computing in the form of smartphones and tablets, and the proliferation of online communities to share videos, images, and thoughts to vast audiences using social media. In this period, lack of digital resources and creativity was not an issue. Rather, deciding what content you wanted to consume and where you could find it, "sifting through the noise" of the online world, became a greater concern.

### Aesthetic Computing

While modern computing has influenced not only the kinds of art we create but also our methods of creation, the computing world has been slow to adopt principles from art. Paul Fishwick and others brought to light this missed opportunity in his *Aesthetic Computing Manifesto* in 2003 by first questioning how aesthetics can be applied to software development, citing a lack of variety in representing computing abstractions [205]. Years later as innovations in other subdomains of computing made new interaction modalities viable and expanded the developmental material for both the artist and the programmer, Fishwick furthered his vision for bringing aesthetics to computing by enlisting embodied cognition towards his greater goal of employing art to further computing [68].

Despite Fishwick's continued efforts to draw attention to the research gap, the majority of interdisciplinary research efforts between art and computing have been in the opposite direction—using computers to make or understand art. With the great public appetite for art and the commercial benefits that come with this demand, the academic literature focuses on what computing can do for aesthetics. In the context of HCI, Edmonds compiled works in a book chapter focusing solely on computing in the design of public-facing experiential artworks [60]. In a more reflective article by LaViola Jr on the evolution of user interaction in video games, the author touted that advances in interface design and controller schemes offered more expressive power to the gaming experience [140]. The infamous graphical processing unit (GPU), now widely known for servicing AI workload, was highlighted by Dally et al. in a history of the processor as having the initial purpose of rendering images quickly [46]. Finally, in the continued drive to introduce computing education to the masses, researchers in CS education have drawn on the universal joy of making art to teach basic computing ideas. Shamir et al.'s work on developing an integrated paradigm for blending art and computing showcased how the complementary nature of the two fields could heighten young students' interests in STEM and improve their performance on a math and computing assessment after the study's interventions [203].

### AI in Art

When we think of AI-made art today, we tend to think of the groundbreaking capabilities of generative large-language models (LLMs) and perhaps our own creative experiences with this technology. These models come from a long lineage of machine learning innovations. While the code for Henry Cohen's *AARON* of the 1970s was closed-source, the program was said to have made artistic decisions based on a set of rules which were expanded and refined over several decades until his passing in 2016 [219]. Cohen's work has been a topic of great discussion and admiration in recent years with the wide availability and low barrier to entry in creating generative art. Decades after the start of Cohen's pioneering work in generative art, computer scientists began using imagery to train and develop new machine learning models and architectures. In a greater effort to improve image recognition techniques as part of the 2014 ImageNet Large-Scale Visual Recognition Challenge, Google engineer Alexander Mordvintsev created DeepDream, a software that essentially reversed the process of finding patterns in images using convolutional neural networks [165]. The software created psychedelic imagery by inserting patterns of recognizable attributes computer vision programs of the time were often trained to search for, such as eyes. If GenAI art today is said to be surreal, its predecessor DeepDream is nothing short of bizarre.

Generative adversarial networks (GANs) were first introduced in 2014 in the seminal work by Goodfellow et al.. The GAN architecture brought two neural networks into competition to generate and discriminate images, leading to more realistic images that could be created in abundance. GANs were regularly used in the research community to overcome the problem of limited image-based datasets. Thus, using GANs to increase the training data for experiments in computer vision and other areas in computing became a common experimental workflow. Four years after the introduction of GANs in academic literature, the painting "Edmond de Belamy" created using GANs by the French AI + Art collective "Obvious" was sold by Christie's for $432,500 [6]. Echoing the earlier adoption of computing as an artistic tool by cutting-edge artists of the late 1960s, the "Edmond de Belamy" painting was created using a computing phenomenon introduced just four years earlier. The painting is cheekily signed with an algorithm. Shortly after the sale, Christie's wrote an article where the author stated, "This portrait, however, is not the product of a human mind. It was created by an artificial intelligence, an algorithm..." [33]. Interestingly, the article acknowledged the three artists in the collective responsible for creating "Edmond de Belamy," and interviewed one of those artists, Hugo Caselles-Dupré, of the piece. Prior to the sale, Christie's estimated the painting would sell for between $7,000 and $10,000.

While GANs played a significant role in generative computer art, LLMs catalyzed the ease of dictating and producing creative ideas with computers. Radford et al.'s GPT-2 (GPT standing for generative pre-trained transformer) was gradually released over 2019 and was considered large for the time with 1.5 billion parameters (knowledge unit connections) [190]. GPT-3, introduced by Brown et al. and the next model in the series, was released just one year later and had 175 billion parameters [23]. As one would expect and could observe through experimentation, imagery produced using larger, more sophisticated models was more realistic. The most recent models are more adept at intelligently filling in the gaps of poorly-worded prompts. Software tools that use this family of LLMs have proliferated and have applications in nearly all domains. Most of these tools have been introduced to the public for free or at very low subscription prices. The barrier to entry for formalizing and actualizing creative ideas with computers today has essentially evaporated for anyone with an internet connection.

For the following three studies I sought to extend this trajectory of using both Non-AI and AI-based technologies to further the user's creative goals. The pressing question today at the intersection of art and computing is not so much one of "how can we improve the technology?" but rather "whether, where, and how do we want to incorporate technology?" To this end I took a mixed-methods approach in carrying out the following works. For study 1 I developed a technological system to allow the artist to communicate more about their practice through a new modality. In study 2 I sought to uncover human biases against technology by withholding information on an augmented artwork. And finally, in study 3 I inverted the relationship between art and technology and sought to uncover means of utilizing the embodied procedures in art to strengthen the logical thinking necessary to advance computing.

# Chapter 3

# Study 1: Embodied Knowledge as a Design Probe in a Participatory Design Study of a Sonification System for Crochet

## 3.1 Introduction

Technology has been cited by Rosner and Ryokai and Massimi and Rosner as having a place in supporting crafting through interpersonal communication [157, 196], by Alves-Oliveira et al. and Frich et al. in creativity [10, 73], and by Smith et al. and Rosner and Ryokai in self-reflection [195, 215]. The domain of craft requires tacit knowledge, which Dormer described as "knowledge that cannot be described very easily but which can often be demonstrated" [53]. Zabulis et al. proposed an approach to represent craft processes through the digitization of contextualized knowledge of craft through heterogeneous sensory dimensions [247]. The value of craft is recognized by the United Nations Educational, Scientific, and Cultural Organization (UNESCO) in its definition of intangible cultural heritage (ICH) as "The totality of tradition-based creations of a cultural community... Its forms are...handicrafts...and other arts [143]." The formalization of ICH by UNESCO has led to preservation efforts of craft in the computing community, such as those by Hou et al. [103]. A study by McCullough envisioned "reuniting hand, eye, tools, and mind, at the level of visual (and otherwise sensory abstraction)" through digital craft [158]. Today's technologies provides more opportunities to realize those goals.

While research has been done by Jeon et al. and Vasey et al. to develop interfaces that use spatial data to help users perform a task [112, 236], spatial user interactions that place minimal or no reliance on visual stimuli from screens are a newer frontier. Gustafson et al. offered one such work on spatial user interaction that demonstrated how users can use gestures as reference points to hold imagined visual interfaces in their working memory [91]. This work demonstrated that interacting in space itself can be used as a medium to illicit meaningful actions by a computer. Furthering this line of research, the prototype system introduced in this study uses sound to communicate the user's actions. Sound as a communicative tool has been shown in the works of Jeon et al. and Ardito et al. to be a powerful medium to convey information [13, 112]. Pairing sound and spatial information in new contexts may bring the research community closer to understanding the role of embodied knowledge in our everyday interactions.

In this participatory design study I used differences in users' craft knowledge as a probe to help improve the design of a prototype spatial user interaction system for the craft crochet. I have provided results that focus on both the tangible and intangible information present in the craft and how this information can impact the future of the prototype's design and the design of similar systems. The long-term effects of this line of work may help champion the use of sound to teach gestural tasks in some disabled communities.

I chose crochet as my craft medium for its inherent algorithmic nature. Edelstein et al. found that crochet follows a set of rules that can be segmented, distinguished, and classified, much like the datasets explained by Gollapudi, which are used to power today's machine learning models [59, 83]. Furthermore, crochet is formalized through patterns that are reminiscent of computer programs. Each group of symbols tells the reader what needs to be completed to reach a greater goal. Crochet, like programming, is both creative and formalized. It is for these reasons that I believe crochet is an ideal medium to blend technology and art to meet objectives in HCI and expand computer science concepts to a wider audience.

Crochet, like many other activities, requires visual attention. Wickens' multiple resource theory predicted that conveying more information at once is possible if the communicative modality is sufficiently different [240]. Though people enjoy crocheting in groups, they can neither share their own experience crocheting nor work on the same artifact as they both crochet. If someone wants to follow along in a spatial user interaction activity like crochet, how are they to know that they are on the right track if they cannot disengage visually and haptically from their work? To answer this question, I built a prototype system to convey crochet state using sonification. Sonification would allow users to convey more about their experience and create an auditory artifact together as they crocheted.

This study surrounds a working prototype I developed to support users in communicating physical state in the creative procedural tasks of crochet through an auditory dimension. I call this system "Cro-Create." Cro-Create included a sonification of crochet that used the palm orientation data of the users' hands to provide ongoing melodic auditory stimuli of the gestures made in crochet as well as auditory signals when two users' gestures were in sync. The Cro-Create system is explained in detail in Subsection 3.3.2.

Many spatial user interaction systems make use of the user's embodied knowledge to achieve a task. Tanaka described embodied knowledge as "a type of knowledge where the body knows how to act," and presented a series of examples where human knowledge is developed through situated interactions with the environment [225]. According to Esteves, in order to inform the design of systems that are intuitive and valuable to users, we should not ignore embodied knowledge [64].

Understanding the perspectives of those who have different experience levels in an embodied task can bring forth novel findings that can inform system design, not only for the crafting domain that I targeted with my prototype, but for any embodied task. Therefore, it was critical for me to understand how this diversity of embodied knowledge contributed to 1) understanding the embodied activity, and 2) understanding how stakeholders used or thought about the prototype system. Therefore, I posed the following research questions (RQs) to guide my investigation:

- RQ1: How does one learn crochet?
- RQ2: What is challenging about crochet?
- RQ3: Why do people crochet?
- RQ4: How can technology improve crocheting?

### 3.1.1 Unique Contributions

In answering my research questions I was able to find pain points and opportunities to improve my prototype, which was built with the goal of enhancing the experience of crocheting alone or with friends by way of auditory feedback. In this chapter I present data on how users of varying experience levels in an embodied task can inform the iterative design of my prototype and spatial user interaction systems like it. I offer recommendations that can support researchers in utilizing differences in embodied knowledge of a task to support their design process. In doing so I expand on the need for investigations into contextualized embodied knowledge to inform wider design objectives as expressed in the works of Khan et al., Smit et al., Zheng and Nitsche, Kalma et al., and Antle et al. [12, 122, 125, 211, 249]. Finally, I explain how my results can inform the next iteration of my prototype's design.

The following describes the organization of this chapter. Section 3.2 outlines the theory that underpins this study and the related work in movement-based design. I describe the features of Cro-Create in Subsection 3.3.2 and the design of the study in Subsection 3.3.3. Subsections 3.3.4 and 3.3.5 describe the procedure for collecting and analyzing the qualitative data, respectively. The results are then presented in Section 3.4 and discussed in Section 3.5. The discussion in Section 3.5 also includes generalizable recommendations to support researchers in utilizing differences in embodied knowledge to design spatial user interaction systems, and how the results could be applied to improve my own prototype.

## 3.2 Related Work

Much research has been done on system design from an embodied perspective. The author of the 2001 seminal work on embodied interaction, Dourish, stated that "social and tangible computing share a common foundation in embodied interaction;" the author then explained that tangible computing specifically deals with activities and the space they occupy [54]. Today, researchers such as Watanabe, Samani et al., and Flechtner et al. apply embodied interaction principles both in the fields of computing [69, 197, 238], while Hook, Sirkin and Ju, and Klemmer et al. have done so in design [100, 130, 209].

According to Groth et al., crafting is an embodied activity which Hosfield argues relies on the development of one or more specialized skills [88, 102]. Authors Zoran and Buechley and Perner-Wilson focused on blending traditional craft and technology to create hybrid craft forms [24, 250]. Other works by Guo et al., Edelstein et al., and Seitz et al. focused on computer-aided representations of physical craft artifacts [59, 90, 202]; in these works, the emphasis was placed less on the experience of the user and more on the user's finished product. A parallel line of research has developed on the processes of crafting by Gore and Gowlland; these works focused on what crafters learned when they engaged in and reflected on the process of making [86, 87]. What was of particular interest to me was the role of embodied knowledge outlined by Macqueen on the design of a spatial user interaction system [153].

In this work I conducted a participatory design study with three participant groups: novice crocheters, experienced crocheters, and experts in sonification, audio technology, and HCI. Participatory design, according to Schuler and Namioka, is a method for eliciting user needs and understanding user experiences in the early stages of development [201]; this research method has been used by Lim et al., Slegers et al., and Frauenberger et al. to support the design of accessible systems for users with diverse needs [72, 145, 210]. Given participatory design's emphasis on the user and its flexibility in participant and activity specifications as explained by Muller and Kuhn, I believed that it would be best suited to help answer my RQs [170].

### 3.2.1 Wickens' Multiple Resource Theory

I used Wickens' multiple resource theory to inform my system's design in communicating information through sound. Multiple resource theory tells us that people can process more information if the sensory-perceptual modalities of these information streams differ across four dimensions: processing stages, perceptual modalities, visual channels, and processing codes [240]. Wickens stated in his seminal work that, "All other things being equal (i.e., equal resource demand or single task difficulty), two tasks that both demand one level of a given dimension (e.g., two tasks demanding visual perception) will interfere with each other more than two tasks that demand separate levels on the dimension (e.g., one visual, one auditory task).” This theory has been empirically tested and applied by researchers in a variety of domains including Jeon et al. in HCI, Smith and Buchholz in advertising, and Tsang et al. in psychology [114, 214, 232]. According to this theory, a system that conveys information between two users who are engaged haptically and visually should utilize a sensory-perceptual modality that differs substantially from those which occupy the users if that system’s aim is to effectively time share cognitive resources. For this reason, I pursued sound as a means of sharing physical state in the embodied task between two users, to transform this individual activity into a shared, social experience.

### 3.2.2 Designing Movement-Based Interaction

Research has been done on how to balance the weight of technology’s capabilities and humans’ capacity for expression in designing systems around embodied interaction. Candau et al. suggested that though sensorimotor processes are complex and can occasionally elude technology, incorporating a multilayered approach by utilizing “multiple modalities, perspectives, and points of view” can overcome this challenge [29]. For this work I saw an opportunity to expand this idea by using sound to convey information about the physical experience of the user.

Loke and Robertson offered a methodology for designing movement-based interactions whereby they emphasized the importance of the mover from both an anatomical and an expressive perspective [148]. From the human perspective, movement can express more than what it may appear as at face value. The emotion of the mover and the mover’s feeling about the movement play a part in the mechanical performance. In this study I applied these findings from Loke and Robertson by seeking to understand how crochet makes participants feel and why experienced crocheters continue to crochet [148].

## 3.3 Methodology

### 3.3.1 Participants

To begin the design of this study, I needed to specify my target users and understand what knowledge they might have that could aid in improving Cro-Create and systems like it. I decided on three participant groups for the study: novice crocheters, experienced crocheters, and experts in sonification, audio technology, and HCI. Each participant group could offer different perspectives and provide me with a more exhaustive set of criteria for improving the system. Table 3.1 outlines the labels and groups of all 25 participants. My goal was not to compare the three groups' statements, but to extract their knowledge and experiences of the domains relevant to the prototype system. Each participant was only included in one group.

I defined a novice crocheter as someone who had never crocheted. Participants in this group consisted of seven males and three females. Participants were recruited from the university community via email announcements sent to students.

I defined an experienced crocheter as someone who had crocheted before and was capable of crocheting without instruction. Participants in this group (nine, all female) were recruited through notices in internal newsletters within the university community. I chose to recruit from the university community because I believed it could offer the greatest chance at capturing a diversity of perspectives. Despite my efforts to recruit participants from a variety of channels, all of the participants in this group were female.

Finally, I consulted five sonification, audio technology, and HCI experts (three male, two

| Participant Details | |
|---|---|
| Identifiers | Description |
| • P1-P10 | • Novice crocheter group participants (have never crocheted before this study) |
| • P11-P19 | • Experienced crocheter group participants (1+ year(s) experience crocheting) |
| • P20 | • Sonification researcher, Professor, Ph.D. |
| • P21 | • Sonification researcher, Postdoc, Instructor, Ph.D. |
| • P22 | • Audio technologist, Composer, Instructor, MFA |
| • P23 | • HCI researcher, Professor, Ph.D. |
| • P24 | • Audio technologist, Researcher, Instructor, MA |

Table 3.1: Participant identifiers and qualifications

female) all with advanced degrees (MA, MFA, and Ph.D.) and at least four years of teaching experience in their respective domains. Of these five expert participants, two were sonification researchers, two were audio technologists, and one was an HCI researcher. Because Cro-Create sought to convey users' state in crochet through sound, experts in sonification could provide insight into how Cro-Create's crochet-to-gesture sound mapping should be evaluated. Experts in audio technology could understand my objectives from a more technical perspective and offer insights into device communication and digital sound protocols, and experts in HCI could help me understand the consequences of my design choices from a UX perspective.

### 3.3.2 Equipment and Stimuli: Cro-Create

The Cro-Create system was built as an application of Wickens' multiple resource theory to allow crocheters to convey the state of their practice in real time. Crochet is unique in that a crochet work consists of repetitions of finite gestural procedures. These gestural procedures can be broken up more easily than those used in other craft and art forms; that is, crochet can be broken up into individual stitches. These characteristics provided a unique opportunity to discretize procedural components of an art form to be processed by technology. Furthermore, crochet patterns are algorithmic with clear pre- and post-conditions, and the physical procedures used to crochet are more predictable than other art forms. By investigating how people learned crochet and interacted with the Cro-Create prototype, I could demonstrate how embodied artistic procedures could be interpreted by technology to convey information about the artmaking process through sound while also enhancing the experience of crocheting for the user.

There are six fundamental stitches in crochet that can be built off of one another to create more complex designs. Even within the six fundamental stitches, the gestures used to make the most complicated stitch, the treble crochet stitch, are found in the simplest crochet stitch, the single crochet stitch. These gestures include pushing the hook through the work, and pulling yarn from the back to the front of the work. The major differences that separate these stitches are the number of times one performs these gestures of pushing and pulling the yarn, and the number of times and direction from which the yarn is wrapped around the hook before it is pushed or pulled through the work. Therefore, the procedure for the simplest stitch, the single crochet, can be found in the other fundamental stitches. This led me to discretize the process of creating a single crochet stitch so I could classify crochet state and compare the states of two users in one of Cro-Create's two user modes (dual user mode) described below. As I built and tested the Cro-Create prototype, I found the design decision of discretizing the simplest crochet stitch advantageous for overcoming some of the idiosyncrasies in how people crocheted. Detecting simpler and shorter gestures yielded better detection accuracy.

The Cro-Create system included two user modes: one mode used by a single user (single user mode), and another used by two users at the same time (dual user mode). The decision to include a single and a dual user mode was drawn from prior research by Taylor et al.

and Hansson and Busch which demonstrated the positive social impacts of creating with and around others [93, 226]. In single user mode, the system created a direct sonification mapping to pitch between the palm orientation scalar values of the user's hands as they crocheted over an infrared motion sensor (Leap Motion Controller) [234]. The two scalar values representing the palm orientations of the two hands were determined by the palms' relative location to the origin of the Leap Motion hand tracking sensor I used to detect hand movement. This origin was centered at the top of the sensor as stated in the system specifications lea. The sensor used a right-handed Cartesian coordinate system and all three axes (x, y, and z) were used in determining the palm orientations of the hands.

Single user mode can be seen in Figure 3.1b. In this mode, the user crocheted over the motion sensor attached to a machine running the system's software to create sound from their gestures in real time. Using the Leap Motion sensor's accompanying software and libraries, the palm orientation values were then sent to a sonification component written in the visual programming language of Max cyc. The palm orientation value pertaining to the location of the dominant hand of the user was scaled to the upper 34 keys on a 48 key piano keyboard (pitch range: $D_3$ - $B_5$; frequency range: 146.83 - 987.77 Hz) to control the pitch, while the palm orientation value pertaining to the non-dominant hand was scaled to control the duration of the note played. Single user mode simply sonified the user's crocheting, allowing them to make sound as they crocheted. Specific gesture recognition was not a feature of single user mode. Single user mode added sound to the process of crocheting, allowing the user to be both a music maker and a crafter. The user in single user mode could in essence "hear" themselves crochet. The sound in single user mode was designed to add an auditory dimension to the playful and creative experience of crochet.

Dual user mode was an extension of single user mode. Dual user mode required two users to work: one user was the "Leader" and the other user was the "Follower." The leading user produced a real time sonification (just as in single user mode) by crocheting over a motion sensor. The following user crocheted over another motion sensor, and when both the leader and the follower were at the same place in making a stitch, an auditory signal was produced that harmonized with the leading user's sonification. This auditory signal was a piano chord an octave below the last note from the ongoing sonification produced by the leading user. Both users were able to hear the ongoing sonification of the leading user as well as the auditory signal indicating that they were both synchronized. Dual user mode allowed two users to determine whether they were in sync and share their joint crafting experience together through sound without needing to take their attention off their work.

I discretized the components of the single crochet stitch into three segments to enable me to develop dual user mode. I used a dynamic time warping model available from the Wekinator software created by Fiebrink and Cook to classify three of the simplest and most common gestures (pre-stitch setup, dip into stitch, and pull through loop) used in making the single crochet stitch [67]. I wrote code that compared the gesture classifications of both users, and if it determined that both users had made the same crochet gestures, a chord an octave below the last note produced from the sonification of the leading user was played. Playing a chord an octave below the leading user's ongoing sonification was a design decision to aesthetically adapt to the movements of the leading user. For this study, participants in the experienced crocheter group used single user mode—the mode where the movements of one user are sonified. This allowed me to collect insights that could help me understand the user's experience at a foundational level, as the sonification for single user mode was critical in both single and dual user modes.

#### System Limitations and Considerations

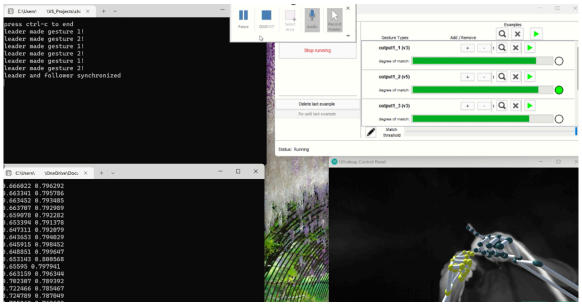
Software components used to build the system, the classification model, and the user interactions, all played a role in the accuracy of the system in classifying gestures. With respect to the sensor (Leap Motion Controller) [234] I used to capture hand movements, Weichert et al. go into depth regarding the sensor's accuracy and robustness [239]. In my particular use case, when a piece of crocheted work became sufficiently large, it would obstruct the sensor's view of the hands.

With respect to the classification model to segment the gestures, there were occasions when the prototype did not accurately classify a crochet gesture. However, my goal for this study was not to make the most accurate recognition system and thus, I did not test my system's recognition accuracy in this study. My questioning of participants on which fingers they used to crochet and how they held the crochet hook during the focus group as described in Subsection 3.3.3 demonstrated that the classification component of dual user mode is a proof of concept. The focus of this study was on the users' interactions with the system. Cro-Create's single user mode, when demonstrated to and used by participants, produced readily apparent changes in sound when hand movement was detected.

While a perfectly accurate classifier is desirable, Cro-Create supported the study's UX goals of elevating the playful experience of crochet alone and sharing the process of crocheting with a partner through sound.

### 3.3.3 Experimental Design

Each participant group took part in group-specific activities during the 60-90 minute sessions that I believed could best reflect their knowledge and diversity of perspectives. Group-specific activity details are provided in Subsection 3.3.4.



(a) Running programs used in dual user mode

(b) The single user mode setup for Cro-Create

Figure 3.1: Cro-Create system artifacts

For novice participants, I wanted to focus on their experiences learning the crochet procedures without introducing the Cro-Create system. I made this choice because I did not want Cro-Create's auditory feedback to influence participants' perception of their learning ability. Cro-Create was built for experienced crocheters to elevate the joy they find in crochet and to share this experience and their patterns of movement with a partner in dual user mode. I sought the insights of novice crocheters to understand crochet from a procedural perspective. Novice crocheters break the process of producing a stitch down to a finer granularity when they are learning than experienced crocheters do when they are teaching. Novice crocheters had no embodied knowledge of the task and thus understood the task at a more rudimentary, procedural level. I included novice crocheters in this study because I believed their insights could be of greater help in the design of the gestural classification model in dual user mode. How the gestures used in crochet are segmented for classification and comparison between two users in dual user mode has a meaningful impact on the accuracy of the system and consequently the UX as a whole. A future iteration of the system could perhaps be used to aid the user in learning the movements through sound. Hearing how novice crocheters tried to learn crochet was beneficial towards this greater objective.

I taught novice crocheter participants how to crochet in a group. This enabled them to learn from each other and allowed me to rotate between participants when they needed help. Learning crochet in a group also allowed me to collect more data during the focus group afterwards, where participants were able to discuss their learning experience with others.

I decided to have participants in the experienced crocheters group use single user mode. I made this decision because this mode had functionality that was extended in dual user mode. Understanding how experienced users interacted with the simplest user mode provided insights that were not obfuscated by the additional features implemented for dual user mode. Experienced users watched a video demonstration of dual user mode at the start of the study and had opportunities to share their thoughts on all materials presented. After experienced crocheters had all tried Cro-Create's single user mode, they engaged in a focus group in which questions were aimed at understanding their knowledge of crochet and their experience with Cro-Create.

Interviewing sonification, audio technology, and HCI experts helped me answer RQ4: How can technology improve crocheting? In building Cro-Create I used sonification and audio technology to facilitate unique human-computer interactions between the system and its users. Interviewing experts in these domains gave valuable perspectives towards improving the system from a technological perspective.

### 3.3.4 Procedure

Before the group-specific activities, participants in all groups completed what I will refer to as the "initial activities" which included: completing a consent form that was approved by the university's Institutional Review Board (IRB) and a screening questionnaire on their experience in the domains relevant to the study (e.g., crochet, sonification, sensor technologies, embodiment theory, and teaching embodied tasks) (5 minutes), learning about the Cro-Create system through a presentation and two short videos demonstrating Cro-Create (10 minutes), and hearing an introduction to the concept of sonification and its applications (10 minutes). For participants whose expertise was in sonification, the 10 minute introduction to sonification was omitted. Figure 3.1a shows the four programs running on a user's machine in dual user mode. Figure 3.1b shows the Cro-Create system setup on a single user's machine. After these initial activities were completed, participants completed the group-specific activities.

#### Novice Crocheters

Participants in the novice crocheter group learned how to crochet together. Participants sat around a large table with me as I taught them how to make a slip knot, chain, and double crochet stitch over the course of 35 minutes. Each participant was given a small ball of yarn and a crochet hook to complete this activity. I demonstrated each crochet procedure using the same materials as the participants, repeating the gestures and verbally describing the movements to help support the participants' learning.

By the end of the 35 minute crochet tutorial, all ten participants were successful in learning the slip knot, chain, and double crochet stitch. Success in learning these stitches was defined as the participant being able to produce each stitch without any guidance from the researcher or other participants. The success determination was made for a participant after the researcher had watched them produce a slip knot, chain, and double crochet stitch without any help.

In the last 30 minutes of the session, novice crocheters participated in a focus group which was led with questions from me. The dialogue from this focus group activity was transcribed by two other researchers. The transcriptions of the dialogue from this session were used to conduct the thematic analysis described in Section 3.4. Questions from this focus group activity can be found in Appendix A.1.

### Experienced Crocheters

Participants in the experienced crocheter group tried Cro-Create's single user mode themselves for 30 minutes. I demonstrated how to use the system before participants tried it. To support participants' use of Cro-Create, I provided each participant with a small ball of yarn and a crochet hook. The participants and I sat around a large table and each participant spent however much time they liked using the system by crocheting over the motion sensor. The motion sensor was a peripheral device that was attached to my laptop which was passed around the table. A picture of the single user mode setup can be seen in Figure 3.1b.

After everyone had a chance to use Cro-Create, the participants engaged in a focus group discussion led by myself with questions that can be found in Appendix A.2 (35 minutes). These questions were different than those posed to the novice crocheter group. Responses from all participants were transcribed by two other researchers.

### Sonification, Audio Technology, and HCI Experts

After the initial activities, each sonification, audio technology, and HCI expert participant took part in a semi-structured interview (50 minutes). All session activities for these experts were conducted one-on-one and virtually. Conducting these sessions virtually allowed me to reach experts with the specific knowledge and experience I sought even if they were from distant places. Questions were prepared ahead of time to lead the discussion. The semi-structured interview for each expert participant was conducted and transcribed by myself.

Questions from this activity can be found in Appendix A.3.

### 3.3.5 Data Analysis

To perform the qualitative analysis on the transcribed data from the focus groups and semi-structured interviews, I ran a thematic analysis in six stages [22]. These stages are outlined below. Data were analyzed by two different researchers independently following the first four steps (preliminary note-taking, coding, generating themes, and defining themes); these researchers were project members (not myself) active in the execution of this study. Figure 3.2 provides a visual representation of the four stages of the thematic analysis. Data were analyzed separately by participant group, so all data collected from experienced crocheters were analyzed together (likewise for the novice crocheters and the sonification, audio technology, and HCI experts). Once two independent analyses were completed for each of the three participant groups (experienced crocheters, novice crocheters, and sonification, audio technology, and HCI experts), I compared the two independent analyses for each participant group, looking for similarities in themes. Final themes and their definitions were generated for each participant group during this iteration of the data analysis. In addition to my participant group-wise theme definitions, I also compared the final themes generated from all three participant groups to arrive at a set of overarching themes.

#### Preliminary Note-Taking

Preliminary note-taking consisted of the two researchers reading through the collected transcriptions and documenting their initial understanding of the dialogue through notes in a separate document.

### Coding

After preliminary note-taking, transcriptions were coded on a per-group basis by the two researchers. List 3.3.5 shows the codes generated from the transcriptions for each participant group. These were all of the codes the researchers generated independently, which explains some of the redundancy; this redundancy was expected and merged in a later stage of the thematic analysis. Dialogue from the transcripts that supported codes were also recorded. After the coding stage, 21 codes were generated from the novice crocheter group, 23 from the experienced crochet group, and 15 from the sonification, audio technology, and HCI expert participants.

- **Novice Crocheter Group**: Handedness, Hand usage, Physical position, Hook usage, Motions, Music/sound usage, Use of visuals, Gestures, Challenges, Concern over hands, Sonification for finding a tempo, Sonification for being distracting, Following researcher when crocheting, Visual information for teaching, Concern about tightness of thread, Difficulty in visualizing holes, Gesture strategies, Fixing mistakes, Frustration with mistakes, Crochet is relaxing, Use of augmented reality/virtual reality for visualization
- **Experienced Crocheter Group**: Sound of crochet, Why crochet?, External stimulation, Movements, Demonstration, Differing techniques, Sound vs. action, Expectations with crocheting, Crocheting for relaxation, Use of crocheting, Crochet learning, Hand movements, Technique, Teaching strategies, Teaching experience, Sound design, Design considerations for the visually impaired, Tracking progress, Opinion of Cro-Create, Role of hand, Teaching challenges, Likes about Cro-Create, Dislikes about Cro-Create
- **Sonification, Audio Technology, HCI Expert Group**: Musical education, Sonification as a method of communication, Requirements of a sonification, Theoretical aspects of music, Developing for the user, Developing pleasant sounds, Visualization's

limited capabilities, Modification of sound, Work experience, Background, Opinion on sonification, Training in music, Teaching, Sound design considerations, Challenges with students

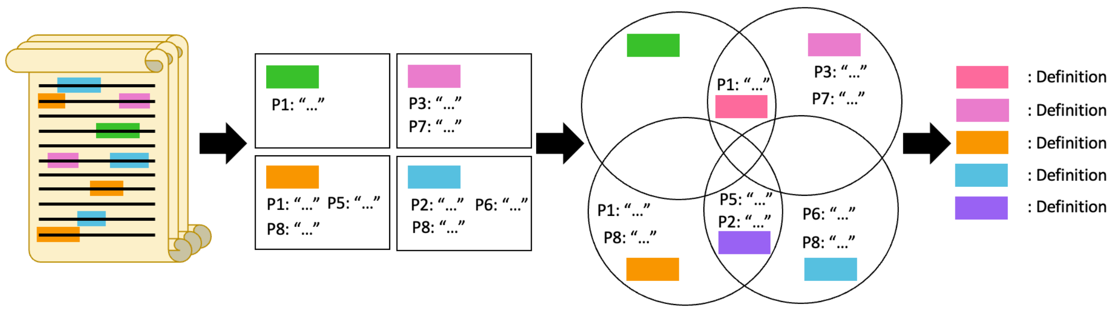



Figure 3.2: A visual depiction of the thematic analysis: dialogue from the interview and focus group transcripts were labeled with codes, codes were organized with all of the dialogue attributed to them, codes were then merged or removed to generate a set of themes, and these themes were then defined.

### Theme Generation

In theme generation, codes were merged, divided, and refined to uncover a more generalizable story from the qualitative data. When the researchers coded the data, they justified each code with specific quotes from the focus group and interview transcripts. To generalize their findings, they looked back at the quotes that supported their codes to find similarities between codes or differences within codes. In most cases, themes were created from merging codes, but in some instances codes were strong enough (e.g., justified by many quotes) to stand on their own as themes. These refinements to the set of codes were grouped into the initial set of themes. Because these themes were generated independently by two different researchers, there was some redundancy shown in the themes at this stage in the analysis 3.3.5; this was expected, as the researchers saw similar patterns in the data. All redundancy was remedied when the two independent analyses were merged in a later stage of the thematic analysis. This stage generated 11 themes from novice crocheters, 10 themes from experienced crocheters, and 13 themes from sonification, audio technology, and HCI experts. Themes for each participant group were as follows:

- **Novice Crocheter Group**: Fine motor skills, Methodology, Sonification, Learning, Challenges, Crocheting procedure concerns, Sonification to reach a flow state, Visual preference, Gesture strategies, Frustration with mistakes, Augmented visualization techniques

- **Experienced Crocheter Group**: Sound design, Why crochet?, Movements, Teaching, Different techniques, Interpretations of crochet, Learning crochet, Crochet technique, Teaching crochet, Opinion on Cro-Create

- **Sonfication, Audio Technology, and HCI Expert Group**: Background in and teaching of music, Difficulty of teaching music, Communicative aspects of sonification, Use cases, User-oriented development, Design aspects of sonification, Theoretical aspects of music, Developing pleasant sounds, Suggestions for sonification, Background, Opinion on sonification, Sound design considerations, Challenges with students

#### Defining Themes

In this stage of the thematic analysis, themes for each participant group were defined. All quotes that were mapped to a specific theme were reexamined to generate more descriptive theme names and definitions. Theme definitions were done independently by two researchers.

#### Merging Independent Per-Group Analyses

As stated earlier in this section, two researchers independently performed preliminary note-taking, coding, theme generating, and theme defining on the data collected. This means that at this point, each of the three participant group data sets had two separate thematic analyses done by two different researchers. At this stage, I went through the two sets of independent analyses and coalesced them by finding codes and notes shared between them. Theme definitions were revised to account for the input of both independent analyses. These themes and their definitions can be found in Table 3.2.

#### Themes Across the Entire Study

In the final stage of the analysis, I then compared the theme definitions across all groups to arrive at a set of theme definitions that captured sentiments that spanned all of the study's participants. Study-wide theme definitions, though less specific than the participant group-specific themes, allowed me to more clearly understand the shared perspectives of the stakeholders of Cro-Create irrespective of their expertise. These themes are defined in Table 3.3.

## 3.4 Results

The creation and reduction of codes into themes described in Subsection 3.3.5 gave some insight into the sentiments and ideas expressed by the participants, but they do not paint the whole picture. In this section I will highlight findings that related to a high number of phrases used to create the participant group-specific themes as well as those themes which spanned all three participant groups. Table 3.2 shows the themes derived from data separated by

| Participant Group | Themes and Their Definitions |
|---|---|
| Novice Crocheters | • **Situating Oneself for Learning**: This theme pertains to how participants paid close attention to the pre-conditions of performing the gestures. Ideas such as handedness and location of the instructor relative to themselves affected participants' perception of their ability to succeed even when no noticeable differences in performance of the tasks were observed by the instructor.<br>• **Using Musical Terminology to Describe Flow State**: This theme pertains to the participants' use of musical and engineering terminology to describe their physical experience as they crocheted.<br>• **Dividing Tasks Through Words and Actions**: This theme pertains to how participants divided up the continuous task of making a crochet stitch into components using short phrases or taking small pauses between segments where they decided to divide up the task.<br>• **Sound Design Over Procedural Accuracy**: This theme pertains to participants' greater interest in how the sound of the system should be designed rather than what information the system could convey. |
| Experienced Crocheters | • **Clarity on How the Gestural Activity Should Sound**: This theme pertains to the swift ability of experienced crocheter participants to provide descriptions of how they imagined crochet sounding. Participants provided musical ideas including specific instruments and pitches, while those not well-versed in music offered physical descriptions such as "wavy" or "smooth." Participants shared that they drew these descriptions from how crochet made them feel and why they do it.<br>• **Sound Inconsistency Perturbs Experienced Users**: This theme pertains to participants' feedback on the current sound design. Though these participants were experienced crocheters and were informed that there was no "wrong" way to use single user mode, participants described feeling uncertain of their expertise while using the feature.<br>• **Pointer Finger is the Only Commonality**: Participants explained how they held the crochet hook and positioned their hands. All participants shared that they used the pointer finger of their dominant hand, but also shared that they had seen people hold their hands in unusual ways while still being able to achieve the same results. |

| Participant Group | Themes and Their Definitions |
|---|---|
| Sonification, Audio Technology, & HCI Experts | • **Balancing Complexity and Interpretability for the User**: This theme pertains to participants' discussion of reconciling complexity and interpretability of a sonification for the user. Participants offered methods to alter the sound design to elicit different responses from the users, but noted that this may mandate accuracy or complexity changes.<br>• **Fulfilling a Task Using Sound**: This theme pertains to the participants' recognition of the difference between fulfilling the task of communicating information through sound and making the sound enjoyable to the user. Both objectives must be achieved simultaneously for a sonification to be a success.<br>• **Exploiting Creative Potential Within Your Use Case**: This theme pertains to the idea of the use case of a system being a bottleneck for creativity. When the use case is strict, functionality is paramount. |

Table 3.2: Participant group specific theme names and their definitions

| Shared Themes Across All Participant Groups |
|---|
| • **Describing the Physical Experience Through Sound**: This theme pertains to novice crocheters' novel use of musical vocabulary to describe reaching a flow state in moving their hands as they crocheted, and experienced crocheters' ease of ascribing sound characteristics to the embodied experience of crocheting.<br>• **Using Sound to Perform a Task Colors Users' Perception of the Task**: This theme pertains to the perturbances experienced crocheters felt when they heard the sonification of the prototype's single user mode. This theme also considers what the sonification, audio technology, and HCI experts shared about the duality of a successful sonification's characteristics in conveying information and providing an aesthetic experience for the user. |

Table 3.3: Shared themes across all participant groups

participant group while Table 3.3 shows the themes derived from those shared between all participant groups.

### 3.4.1 Novice Crocheters' Focus Groups

Novice crocheters helped me understand how one learns crochet (RQ1), and what is challenging about crochet (RQ2). These participants created mental checkpoints while learning the crochet gestures and reminded themselves of these checkpoints using short phrases or small pauses.

Participants felt that where they were situated relative to the instructor impacted how easily they learned the gestures. This aligns with the work of Guenther et al. who demonstrated the role of body-centric representations of a target position in adjusting one's relative position [89]. One participant (P3) stated that, "I had to mirror and flip how I would do it [the hand movement]." "Handedness" also played a role in how participants referenced the movements of the crochet instructor. Another participant (P2) who shared the same handedness as the instructor reflected, "I'm left-handed, so I imagine it would be much easier for me to replicate what you do." This participant's statement did not so much indicate a challenge in dexterity, but a challenge in mapping body-centered representations of position to a target position as previously expounded by Guenther et al. [89].

Interestingly, participants just learning crochet used musical terminology to describe a flow state they could reach if they practiced more. Flow is described in the literature by Csikszentmihalyi et al. as "an intense experiential engagement, in the present moment, with an activity which can be physical or mental. Attention is fully invested in performing the activity, and the person performs at his or her highest capacity" [44]. The focus group transcripts indicated that novice participants could see where sonification could enhance their experience to this end. Novice participants were introduced to sonification and the objectives of Cro-Create. Hence, they could offer feedback on their experience through the lens of sound. P10 shared that "for me maybe in the beginning I felt like it [the sonification] would not be as helpful, but maybe as I get into the groove... in the beginning I think my hands are doing nothing, but maybe it [the sonification] would help your hands." P10 extended that point by sharing that "it [the sonification] would help me get in the right tempo." In another focus group session, when discussing how they learned the crochet gestures, P2 shared "I did it right the first time. I replicated the algorithm I used to get it right because I knew that would work." The patterns found in the gestural procedure called for the use of the term "algorithm" from this participant.

### 3.4.2 Experienced Crocheters' Focus Groups

Experienced crocheters provided insight into how and why people crochet, and where sound could enhance the experience. The experienced crocheter focus groups helped me understand the users: why people crochet (RQ3), and the system: how technology can improve crocheting (RQ4). Past works by Nitsche et al., Frankjær and Dalsgaard, and Treadaway have recognized a place for technology in craft and vice versa; [71, 176, 231] are but a few examples by these authors which investigated this connection.

I was particularly interested in experienced crocheters' impressions of the system, and whether they would use it to either connect with others or play with the system by themselves. Three participants told me that they were motivated to crochet for the process of creating itself. "Crochet is a soothing activity (participant P12)," and "I think it's really stress relieving... I do it during finals (participant P13)," were some of several statements expressing the joy of the process itself. These statements support the work of Davies et al.

who found that individuals who engaged in the arts reported having better mental well-being than those who did not [47].

Understanding users' motivations for crocheting provides a good sign that a real-time auditory system has potential to support those with diverse goals. However, these findings do place an increased importance on the sound design of the system. The focus group data gave me helpful insights not only on how Cro-Create's sound design can be improved, but also on the viability of incorporating sound in systems in vastly different domains. When participants were asked how they imagined crochet sounding, they had no shortage of ideas to share. Despite crochet not producing any sound on its own, participants could clearly imagine what it would sound like. For participants who were more musically inclined, they offered ideas on its pitch (P13: "Maybe pick a minor scale"), its timbre (P15: "string instruments," P17: "violin, flute," P19: "piano"), and its genre (P16: "I was thinking classical as well [in agreement with P15] - it seems like it matches the most.") Others described how the sound should be designed by using shapes (P18: "wavy") and feelings (P12: "soothing").

If crochet is considered a soothing activity, does the sound of Cro-Create properly reflect this? Experienced crocheter participants did not think so. Interestingly, despite having ample experience crocheting, some experienced crocheters felt that they were "doing something wrong" (P12) when they crocheted with the system. P13 said that "it was fun to hear what crochet sounded like, but the sounds made me anxious." These anecdotes could be indicative that the system hit an uncanny valley with experienced crocheters. While the physical procedure of creating crochet stitches could be perceived by an expert as deterministic and routine, the sound produced by Cro-Create had some natural variation that comes with our inability to perfectly replicate our own physical movements. Authors Riley and Turvey explained that motor behavior has both deterministic and random components, and that these components do not necessarily imply more control or variability, respectively [194].

This misalignment between the procedural construct of crochet in experienced crocheters' minds and the variation in physically performing those procedures could have been made more apparent by the sound of the system, leading to feelings of anxiety or "doing something wrong."

Certainly this is counter to the objective of the prototype to positively enhance the experience of crocheting. However, in these quotes from participants I find universally applicable kernels of UX design wisdom: aesthetic decisions can have such a profound impact that they can lead experts to question their own abilities.

### 3.4.3 Expert Interviews

Sonification, audio technology, and HCI expert participants brought unique perspectives and helped me understand how technology could improve crochet (RQ4). Interviews with these participants touched on topics such as data mapping to sound, embodied interaction, and methodological techniques.

All participants in this group had various ways of interpreting or expanding the use case of the system. One of the sonification researcher participants (P20) suggested an orchestra of users using Cro-Create's single user mode: "The coolest thing would be single user mode with multiple people. If you have a rich sonification in single user mode and combine it in the dual, it might be too much. I think there is a need to adjust." Past works, such as the work of Jeon et al., similarly utilized sonification to enhance motion-based interactions [113]. An HCI researcher interviewee (P23) suggested using the system as a "logging tool" to better understand one's craft practice through sound, and possibly provide a means of more easily recognizing opportunities for self-improvement. This suggestion follows a body of work on the "quantified self," such as works by Lupton and Swan, which aims to use technology to track aspects of oneself for improvement or self-reflection [151, 224]. The consensus among interviewees suggested that the use case for a system can be a bottleneck for creativity.

Those who had expertise in sonification and HCI emphasized the importance of balancing complexity and interpretability in the sonification. P24 shared that "The danger is balancing complexity and interpretability. I think the design question becomes: at what point do you include too many features? If the use case is really important, then you have to make that the key thing... but to what extent? Think about what the goal or experience of the user is. The goal might not always be to decode everything. How does someone [the user] draw meaning?" P21 offered the same idea from a different perspective "In one way, [if you use] all the parameters you have and if they are giving you more information, it will make it [the sonification] more lively. You can use more information to make things more lively. [Ask yourself] Does it sound nice?"

This co-mingling of complexity and interpretability is ultimately a design decision that should align with the use case of the system. Furthermore, fulfilling the task of communicating a continuous stream of information through sound is distinct from developing a successful sonification that users want to hear. Towards this end, designers must balance complexity and interpretability in developing their sonification by providing clear reasoning to either omit or include variables in alignment with their system's use case(s) and user feedback.

### 3.4.4 Commonalities Amongst All Participant Groups

Two themes appeared across two or more of the participant groups: 1) describing the bodily experience through sound, and 2) how you use sound to help users perform a task colors their perception of the task.

I saw in the novice and experienced crocheter focus groups that participants had no trouble describing their embodied experiences using terms and concepts completely removed from the situations they were experiencing. Additionally, when asked how they imagined crochet sounding, experienced crocheters had no difficulty describing this nonexistent sound. These observations have great implications. Even if a designer has no intention of utilizing sound or sonification in their system, asking users how they imagine an abstract concept or an embodied task with sound can provide a clear probe towards indirectly uncovering users' affective responses and design expectations for the concept or task.

Experienced crocheters shared that they used crochet to relax. These participants all had at least one year of experience crocheting regularly, and all demonstrated that they felt comfortable crocheting without instruction. However, upon hearing Cro-Create's sonification, some participants in this group expressed that they were anxious and felt like they were doing something wrong. I believe this response was the direct result of the prototype's sound design. These participants offered many suggestions on how the prototype's sound design could be improved to better align with their expectations; these suggestions are described in Section 3.5. Participants in the sonification, audio technology, and HCI experts group reinforced this empirical finding by describing how different methods of designing a sonification can elicit different responses from users. Informed sound design is not only about conveying information to the user and sounding aesthetic—it can have a real impact on how users perceive their abilities.

## 3.5 Discussion

### 3.5.1 Insights from Thematic Analysis Themes

#### Novice Crocheter Insights

The novice crocheter group themes in Table 3.2 predominately pertain to crochet learning strategies and the challenges participants faced when learning to crochet. I taught these participants how to crochet using live instruction and verbal cues. What can be inferred from the results is that novice crocheters desired to orient themselves and their materials to exactly mimic the learning tool they were using. P3 shared that, "For me it [the difficulty] was learning from someone who was left-handed, because I'm right-handed and you are across the table from me. I had to mirror and flip how I would do it..."

Systems should establish an orientation frame for the user before starting the task. For applications in virtual reality (VR) this design guideline is easily replicable, as demonstrated by Schuemie et al., as users can be programmatically situated in the desired reference frame [200]. Applications in VR have subsequently led to advancements in motor learning tasks as shown by Le Naour et al. and Joudieh et al. [121, 142].

Transcripts from this participant group indicated that, though participants had different preferences for learning the gestures (verbal or visual), they always tried to divide the gestures into smaller "checkpoints," aligning with the work of Wightman and Lintern [241]; P3 explicated this by saying, "I sort of truncated your explanation. Kind of like: wrap around, pull through. I kind of explained it to myself in my head based on your explanation. After I got the motions down, I could kind of go through the steps to make sure I was right about it." P3 expanded this idea, "I did it [the gestures] right the first time. I replicated the algorithm I used to get it right because I knew that would work." From these observations I recommend UX practitioners learn where their intended users make these delineations within a procedure and design their systems to provide feedback at these divisions. This is especially important in gestural learning tasks.

Participants in this group also provided insights into their bodily experience as they crocheted as well as how sound could help them accomplish the task. P10 shared that “for me maybe in the beginning I felt like it [the sonification] would not be as helpful, but maybe as I get into the groove... in the beginning I think my hands are doing nothing, but maybe it [the sonification] would help your hands.” P10 extended that point by sharing that “it [the sonification] would help me get in the right tempo.” P5 in a different focus group session made similar remarks on the acquisition of an embodied knowledge of crochet: “starting off was a bit difficult, but once I knew it was fine, I could progress.” These sentiments align with the literature on embodied knowledge, with author of a seminal work Johnson, stressing “...the cyclic patternings of our meaningful experience are known rhythmically through our bodies, in the non-reductionistic sense of embodiment developed here” [118].

Participants described their process of learning crochet using musical vocabulary such “groove” and “tempo” as they recognized repeating patterns in the gestures they made; this finding is especially interesting as no musical stimuli was presented to the participants as they learned how to crochet. I believe that this offers positive evidence supporting the inclusion of auditory stimuli as a design probe in spatial user interaction designs which make use of embodied knowledge. From this finding I recommend UX practitioners that intend to design around embodied tasks consult experts and novices of the task to find the “rhythm” of the movements. This study’s empirical evidence and the seminal work by Johnson suggest that users can find rhythm in embodied actions devoid of sound [118].

### Experienced Crocheter Insights

Themes from the experienced crocheter group in Table 3.2 showed that making a stitch in crochet can be done by positioning the fingers and hands in a multitude of ways. While the pointer finger of the dominant hand was unanimously deemed as the key player in creating a stitch, there was still a great deal of diversity in crochet technique. This tells us that developers of more nuanced gestural interfaces should consider including configuration settings so that their interface can more effectively accommodate each user.

Participants in this group heard Cro-Create first hand as they used single user mode. P14 expressed “if it doesn’t sound the same if I’m doing the same thing or the same stitch, then I’m concerned I’m not doing it right.” P14’s feedback was especially interesting to hear as they were an experienced crocheter, but still lacked confidence when using the system. The sound I chose, albeit interesting to the participants, seemed to cause a few participants to question their crochet abilities. As explained in the subsection on Cro-Create 3.3.2, the sonification in single user mode (which these participants tried) did not distinguish between incorrect or correct crochet movements; this user mode was simply designed to make crocheting more enjoyable by adding sound. It is possible that the presence of technology gave the participants the impression that the objective of Cro-Create was to provide binary feedback on their ability, rather than to share their crochet experience through sound. Both single and dual user modes were explained to participants before they used single user mode.

When asked how they imagined crochet sounding, P13 shared that “I expected it to be more soothing” and further suggested using a minor scale. Participant P15 suggested “It’d be cool to have different options for what the sounds are mapped to: string instruments... classical music strings or old-timey vibes.” P16 supported this idea as well “I was thinking classical as well; it seems like it matches the most.” P17 suggested “violin... flute,” and P19 suggested "piano."

It is clear from the participant feedback on the present sound design that it did not match their expectations of what crochet would sound like. Participants described crochet as "wavy," (P18) "delicate," (P17) and "soothing" (P13). Such descriptive words offered from participants provide invaluable insight into sound design to accompany art-based tasks.

The responses I received from participants on their expectations for the sound of the crochet task provided empirical evidence in support of some of the sound design principles used to create immersive experiences in video games offered by Shilling and Krebs and Collins [39, 207]. In Shilling and Krebs's work specifically, the author shared that sound designed for entertainment purposes places a greater emphasis on changing the emotive state of the user, rather than solely focusing on informing them [207]. In this study, I found that when it came to sound, users wanted to be informed by the system in an emotive manner as indicated by their word choice in describing how crochet made them feel and their ideas of how crochet should sound. Thus, I recommend that sound designers of practical systems also make use of the lessons learned by their peers in the entertainment industry by considering incorporating sound design principles that illicit an emotion-driven response.

### Sonification, Audio Technology, and HCI Expert Insights

Sonification, audio technology, and HCI expert participant group themes revealed the expressive capabilities of sound. I discovered that an understanding of music theory can play an important role in communicating information through sound, but also in matching or eliciting an affective response in the user, as explained by P22, "A minor scale gives more of an emotional sense. What gives the notes context is how you use them together. Play around with changing patterns and perhaps change the underlying chord progression." Data from this group aligned with what I had transcribed from the experienced crocheter focus groups—sound can hold a greater expressive power if sound design choices are well-informed by the expectations of the user and the goals of the system. P20 extrapolated this nicely by saying, “Enforce this ambient sonification and determine: what is their [the user’s] feelings? You can attenuate the sound. There are a lot of notes in it [the current design]. Less tones or less accuracy in the tracking of the hands can get more mellow [sound]. It comes down to the goal and the expectations. The use case is very novel.” I recommend practitioners who want to use a sizable amount of auditory stimuli in their designs to consult musicians or music theorists to inform their sound design. I also recommend asking users for their auditory expectations or impressions of the phenomena that motivates the UX system. In all participant groups I found people could quickly ascribe specific types of sound to an activity (crochet) that produced no sound in isolation. These findings demonstrate a unique opportunity to incorporate sound in applications that extend far beyond those used to support artistic endeavors as I have done in this study.

### 3.5.2 Applying My Results to Cro-Create’s Design

This study provided new ideas on how Cro-Create can be improved. As expected, novice crocheters tried to recreate the gestures used to learn crochet stitches by creating simpler mental checkpoints during the process of creating a stitch. These simplified gestural routines would be instrumental in building a more robust classification model for dual user mode in possible future iterations of the prototype. I found the inclusion of novice crocheters to help us understand the crochet task at a finer granularity invaluable, as they found novel methods of recalling the gestural procedures. These recall techniques included rhythm; which provided empirical evidence of elucidations from literature, particularly the work of Johnson [118].

Sonification can offer auditory cues that may serve as checkpoints, according to Khan et al. [126]. Furthermore, I found that even shortly after practicing the crochet stitches, novice crocheters could find patterns or rhythm in their motions. While novices described the process of crocheting using musical vocabulary ("groove" from P9 and "tempo" from P10), and the experienced crocheters were intrigued to "hear" themselves crochet (P13) and could quickly offer descriptive suggestions on how they expected crochet to sound (P13, P15, P16, P17, P18, P19), participants expressed that the sound design of Cro-Create didn't align with their expectations (P12, P13, P14). The data suggests that revisions to the sound design of the prototype would be needed. Nevertheless, the responses from participants on the sound do not account for the extent to which the sonification matched expectations. One could imagine a sonification of crochet that might include contemporary synthesizers, which was an option available to me during the development process. With nothing for the participants to compare Cro-Create's sonification to, the opportunity for improvement became more apparent in the participants' responses. Using sound has shown promise by Ardito et al., in supporting embodied tasks for audiences and applications that span far beyond those of Cro-Create and the wider crafting community [13]. Countless people rely on sound to navigate their world and the systems they use. Building an understanding of the activities where sound can make a positive impact on the experience of the user can help design future tangentially related systems.

### 3.5.3 Limitations

I acknowledge that there is a possibility for bias in conducting the thematic analysis. I have tried to prevent this by having two project members independently analyze the focus group transcripts. After consulting both independent analyses, I then coalesced the ideas of the two other members. Different divisions of the gestures used to train the Cro-Create models as well as the design of the mappings between movement and sound could yield different results if the study were to be reproduced.

## 3.6 Conclusion

In this study I investigated how differences in embodied knowledge of the craft crochet can improve a prototype spatial interaction system and inform future research of embodied tasks. I outlined the study design and methodology, and presented the findings by way of thematic analysis and quotes from participants. Finally, I highlighted the most frequently observed ideas from each participant group, and offered generalized recommendations for future research on systems that seek to utilize variation of embodied knowledge in gestural procedures to inform system design. While this study investigated my system specifically, I believe that the lessons and recommendations I have presented will support more effective and valued system designs.

# Chapter 4

# Study 2: AI-Supported Dance Performances Provoke Audiences to Seek Creative Merit and Meaning in AI's Artistic Decisions

## 4.1 Introduction

In the previous chapter I investigated how technology can use embodied knowledge to enhance the creative process for artists. In this chapter, I will discuss a study on the biases surrounding how viewers of an embodied artwork perceived artistic products made with technological interventions that utilized physiological and environmental data from an artist. The influence of technology on art has driven creative innovations for centuries, as highlighted by Monaco, Bakreski, Moser and MacLeod, and Jeon et al. [17, 115, 164, 168]. Technology is a product of humanity's conscious workings in the world, just as art is. Science historian Smith wrote on this in their seminal work from 1970 [212]: "The study of interplay among [these fields] is not only interesting but is necessary for suggesting routes out of our present social confusion. Humanists have shown a widespread disregard for technology's role in human affairs, but if they had seen technology as an eminently human experience, they could have better guided society's choice of objectives and controls." Certainly this statement has remained applicable, perhaps even more so, with the developments in GenAI.

While the use of computers to help create art has gone on since the 1950s and has been accepted by the general public, GenAI—a new form of computer-based technology—has brought Smith's observations to the forefront again. Epstein et al. found that GenAI can now produce high-quality artistic media [62]. While research by Spennemann, Karpouzis, and Fui-Hoon Nah et al. has been done on the theoretical implications of how GenAI might impact the cultural footprint of society [75, 123, 217], and individuals such as Henriksen et al., Jones et al., and Epstein et al. have written commentary of how this technology can either be a boon or a bane to the art world [63, 94, 119], little research has been done to uncover the biases that underlie how people interpret artwork made by GenAI, or the creative value of that art. In this study, I wanted to understand: (RQ5) whether the type of technology used to help create art would impact the audiences' perception of that art, and (RQ6) whether withholding information about how the art was made with technology would impact how the audience valued the work. I also wanted to understand (RQ7) how an interdisciplinary team consisting of an artist and a technologist could work together to integrate new technologies into a live artistic performance.

For this study I developed two versions of a technologically-augmented dance performance: one using Non-AI software and the other using generative and non-generative AI components. I developed a survey for audience members of these performances which included questions on the creative value and aesthetic choices of the technological components of the performances. To understand whether audience members' responses would be impacted by any biases held about the technologies I used, I withheld this information to half of the audience members until after they had watched the performance and finished the survey. Hence, in my 2x2 between-subjects design with independent variables being the technology type and the time told about the technology, I held four different performances (AI/Tell Before, AI/Tell After, Non-AI/Tell Before, and Non-AI/Tell After). I analyzed the results of the Likert scale Likert surveys using Mann-Whitney U tests Mann and Whitney, Wilcoxon and found interesting trends between different pairs of performance responses which I describe in Section 4.5.

I conducted smaller focus groups of 3-7 audience members after each performance. In these focus groups, I asked participants not only for their thoughts on the performance, but also their thoughts on art, AI, technology, and their intersection. Data from these focus groups consisted of a set of affinity groups from the quotes of audience members from each of the four performances. Finally, I wanted to understand the process of developing an interdisciplinary live performance such as this. To this end, a research assistant on the project (not myself) interviewed the dancer using questions I prepared. As the technologist of the project, I wrote a reflection on my own experiences building the performances. The direct quotes from this data provided insights into the different problem solving strategies of our two disciplines and how the dancer and I worked towards a shared goal.

### 4.1.1 Unique Contributions

This work has both practical and theoretical implications. From a practical perspective, creators of both traditional and digital art can use the findings outlined in this study to inform how they make and present their work. Understanding how subjective works are received by audiences can inform fields that apply art and technology, such as advertising and graphic design. GenAI is already being applied in the field of marketing with mixed responses from consumers, as a recent Coca-Cola commercial illustrated Horvath. From a theoretical perspective, this work serves as an application of the MAIN (Modality, Agency, Interactivity, and Navigability) model proposed by Sundar which can be used to explain how people develop credibility judgments of technology [221]. While I approach the field of art in applying this technology to determine human biases, this study may prompt similar research into biases towards GenAI in other human-centric fields.

## 4.2 Related Work

### 4.2.1 Technology in the Creation of Art

Throughout history, people have brought technology into the production, distribution, and creation of art. Manufacturing techniques used to create the stylistic tools used by artists directly relied on revelations in science and engineering as expressed in the works of Napier and Singhal and Singhal [172, 208]. Lugon highlighted that the invention of the camera allowed artists to distribute their works to wider audiences [150]. After the advent of graphical computers, Paul explained that technology is more closely involved in the creation of art than ever before [185]. Software such as Blender [21], Procreate [108], and Adobe's Creative Cloud [8] have saved artists time and opened them up to new clientele. Distributing their work and marketing their skills is easier than it has ever been with social media platforms like Instagram [107] and YouTube [245].

Specifically in the performing arts, technology has been used to understand audience's reactions to dance in real time through physiological sensors, as expounded by Latulipe et al. [138].

In recent years, we have seen the introduction of a new technology, GenAI. IBM explained on their website that this technology can help its users make creative decisions and can even produce images, music, and text similar to that of humans [106]. Feuerriegel et al. explained that GenAI can perform such feats because it has become familiar with large amounts of past creative work made by humans, including professional artists, musicians, and novelists [65]. What differentiates GenAI from past technological innovations is that it can play an active role as creator, as opposed to past technologies which could offer no more creativity than what the human user could actively exert with their tools. This paradigm shift brings with it a new research gap in HCI. For this work I was interested in how the viewer's perception of art changed based on (RQ5) the types of technologies (AI vs. Non-AI) used to make the art and (RQ6) the time I told the viewer how the art was made (before or after viewing the art).

### 4.2.2 Reception of AI-Made Art

There are mixed sentiments on whether GenAI-made art is beneficial to the art community. Some, such as Mineo, argue that GenAI enables non-artists to produce much more sophisticated works than they would be able to create on their own, and a subset of artists have been receptive to the new technology [163]. These artists have adopted a similar welcoming spirit towards technology as their predecessor, Harold Cohen, whose famed *AARON* program in the 1960s brought computers into the world of high art [206]. Sheynfeld described the evolution of Cohen's reference to *AARON*, first as an assistant, and then later in his career as his "other half" [206]. Another subset of artists today, such as Jiang et al., contest that GenAI hurts artists because it uses artists' work published online for GenAI model training material, and that GenAI diminishes the role of and demand for artists in the marketplace [116].

Esteemed news outlets have published commentary pieces condemning GenAI art. Placido described the extensive natural resources required to keep GenAI performative, and shared the threats it poses to artists [187]. These threats included the devaluation of artists' expertise and the use of their work as training data for the models that power GenAI. Another article by O'brien, described the differences between GenAI-artists and digital and traditional artists in creating a piece of art [180]. While GenAI-artists can create pieces instantaneously by entering prompts, traditional artists gather their own inspiration and utilize their acquired knowledge and personal style over many hours to create a piece that they intend will speak to human viewers. Many artists have expressed their concerns over GenAI-made art through a variety of channels, including the legal system [7].

## 4.3 Methodology

To answer my research questions, I carried out four technologically-augmented dance performances in collaboration with a professional dancer. This study used a 2x2 between-subjects design, with my two independent variables being 1) the presence of AI in the development of the performance, and 2) the time during the study when I revealed to the participants how the performance was developed.

### 4.3.1 Participants

I held each performance at a fixed time and invited participants to choose the time that worked best for them. There was no audience overlap between the four performances. I labeled each performance based on how I altered my two independent variables.

In the "Non-AI, Tell Before" performance, I used Non-AI technology to alter the visuals and a subset of the sound that accompanied the dancer. Participants were told how the technology affected the visuals and sound before the performance started. Eight participants attended this performance, (3 male, 5 female) with an average age of 23.75 ($SD = 4.80$). All audience members of this performance stated that their expertise was in STEM.

In the "Non-AI, Tell After" performance, I also used Non-AI technologies, but participants were told how the technology affected the visuals and sound after the performance ended and they had finished the survey described in 4.3.3. Ten participants attended this performance, (4 male, 6 female) with an average age of 25.30 ($SD = 4.99$). Of these audience members, two had a non-STEM expertise (theater and interdisciplinary arts/political science).

In the "AI, Tell Before" performance, I used AI technologies to alter the visuals and a subset of the sound that accompanied the dancer. Participants were told how the technology affected the visuals and sound before the performance started. Twelve participants attended this performance, (4 male, 8 female) with an average age of 29 ($SD = 7.11$). Of these audience members, two had a non-STEM expertise (dance and political science).

In the "AI, Tell After" performance, I also used AI technologies, but participants were told how the technology affected the visuals and sound after the performance ended and they had finished the survey. Nine participants attended this performance, (2 male, 7 female) with an average age of 23.89 ($SD = 3.89$). Of these audience members, one had a non-STEM expertise (music education).

### 4.3.2 Equipment and Stimuli

In both performance versions (Non-AI and AI), I used a respiratory belt and a 12-camera motion tracking system to obtain live data streams of the dancer's breathing rate and location throughout the performance. I used the Vernier Go Direct Respiration Belt [227] and the Qualisys Track Manager (QTM) system with 12 Qualisys Oqus cameras positioned on the walls of the performance studio [189]. The Qualisys infrared cameras were able to detect the reflective markers I positioned on the dancer's ankles. In alignment with Latulipe et al.'s investigation of temporal integrations of technology in dance performances, all hardware components were setup well before the performance and were tested with and without the dancer's choreography in order to understand live interaction effects [139]. My incorporation of technology consisted of using the live data produced from the motion tracking and respiratory devices to dynamically change the visuals displayed on a large television screen behind the dancer on the performance studio's wall and to create a sonification for the second of the three, four-minute scenes. The dynamic visuals were produced by layering imagery on top of a background image, and moving or altering the visual characteristics (e.g., brightness) of the images on the top according to the live data streams and data mappings designed for each scene of the two performance versions. In consultation with the dancer, the two versions of the performance consisted of the following scenes with the qualities listed below:

**Scene 1: Flowers**

Respiratory data is used in this scene. Imagery of flower petals was projected on the screen behind the dancer in the performance studio. These petals drifted through the sky according to the dancer's respiratory rate. No sound was played during this scene. Figure 4.1a shows the imagery for this scene in the AI version.

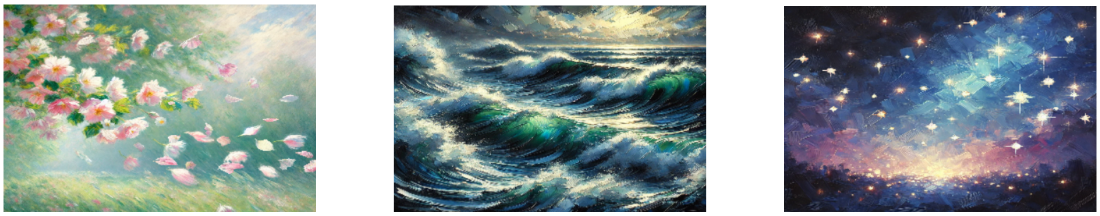
**Scene 2: Waves**

Motion tracking data is used in this scene. Imagery of waves was projected on the screen. Waves moved according to the dancer's position on the dance floor. Sonification of the dancer's position was projected by a speaker in the performance room. Figure 4.1b shows the imagery for this scene in the AI versions.

**Scene 3: Stars**

Respiratory data is used in this scene. Imagery of stars in a night sky was projected on the screen. The stars brightened and multiplied or dimmed and faded in accordance with the dancer's breathing patterns. Music chosen by the dancer was played during this scene.

Figure 4.1c shows the imagery for this scene in the AI version.



(a) AI Scene 1 imagery (b) AI Scene 2 imagery (c) AI Scene 3 imagery

Figure 4.1: Imagery for each scene of the AI performance version

### Human Technologist+Dancer Performance Design

In this performance version, decisions on how to map data streamed from the hardware to produce imagery for Scenes 1-3 and sonification for Scene 2 were made by me.

To begin the design of the dynamic visuals, I sourced imagery from human-produced paintings and photographs. This imagery was then made to dynamically change with the live data being collected from the dancer by layering multiple images on top of one another and altering them conditionally according to data mappings I chose. The effects of the data mappings are described above in the descriptions of each scene.

The data mapping designed to move the petals in Scene 1 consisted of increasing the distance the petals moved from their last position and brightening the sky when the dancer's breathing rate increased, and decreasing the distance and darkening the sky when the dancer's breathing rate decreased. The data mapping designed to move the waves in Scene 2 consisted of moving the waves left and right, up and down, and forward and backward in accordance with the dancer's position in the room along the x, y, and z axes respectively. Finally, the data mapping designed for Scene 3 consisted of increasing the brightness of the stars as the dancer's breathing rate increased and dimming the stars as the dancer's breathing rate decreased.

With respect to the sonification, the data mapping was facilitated by segmenting the stage into five equal sections along each of the x, y, and z axes. Each of these axes was mapped to a subset of a different musical scale of my choosing. The x-axis corresponded to the C minor pentatonic scale, the y-axis corresponded to the C major pentatonic scale, and the z-axis corresponded to the C mixolydian pentatonic scale. Therefore, at any location where the dancer was, the audience heard three notes (one note from each of the three axis scales) played in unison in accordance with the three segments (one segment per axis) of the stage the dancer was located. The timbre of this sonification was like that of a piano keyboard.

### AI in the Loop Performance Design

In this version of the performance, I delegated the production of the imagery as well as the data mapping designs to GenAI (ChatGPT) [181].

When asking the GenAI for data mapping ideas and imagery, it produced a plethora of options, which I consulted with the dancer on to come to a final decision. My prompts to ChatGPT can be found in the Appendix B.1. For Scene 1, I decided to alter the petal movements by taking ChatGPT's suggestion that "the petals could gently rotate based on changes in the breathing depth and they could also rise and fall based on the breathing cycles."

For Scene 2, I used three neural networks to train and classify three different dance movements the dancer would make during that scene. Neural network models were built using Fiebrink and Cook's Wekinator for each of the three dance subroutines in Scene 2 [66]. Each neural network had four connected inputs, one hidden layer, and four nodes per hidden layer. The four inputs to train each model were the x and y coordinate sums for each of the four reflective markers attached to the dancer's ankles (two markers per ankle). The neural networks then provided probabilities of the trained dance subroutines currently happening during the live performance. Thus, I needed to make mappings to visuals from the models' live resemblance classifications for each of the three trained dance movements for Scene 2.

For Scene 2's visuals, ChatGPT suggested I "assign one probability [of a dance move currently happening] to control the height or amplitude of the waves... another probability could influence the wave's direction or angle." I took these suggestions for two of the three classified dance movements. Dance move one's resemblance was mapped to the height of the waves along the y-axis. The change of the waves' height along the y-axis ranged from -50 to 50 pixels. A higher y value corresponded to a higher probability of the live dance move resembling the movements I trained the model on for dance move one. Dance move three was mapped to a change in angle of the waves; when what the dancer was doing live increasingly resembled the third dance move I trained the model on, the wave's angle increased up to two radians. The rotation angle theta ranged from 0 to 2 radians. For dance move two's resemblance probability, I took ChatGPT's suggestion that "you could also experiment with the mappings to see what creates the most engaging visual experience." I took this liberty by mapping dance move two's resemblance probability to the theta-dependent horizontal cosine offset of the waves, ranging from 0 to 0.6 pixels. As the angle of the waves changed, the horizontal offset of the cosine rotation wave was altered to a higher degree when the live dance movement greatly resembled the trained data for dance move two.

For Scene 3, I consulted ChatGPT for the data mapping of the visuals and implemented the following suggestion: "make the stars move more rapidly across the sky, suggesting heightened energy for a higher respiration rate. Their [the dancer's] movement could be subtle or more dynamic, depending on how you want to emphasize the breathing. For a slower respiratory rate, the stars can move more slowly or remain still for a tranquil effect."

For Scene 2 I took ChatGPT's suggestion for the sonification that I "assign each probability a scale or a set of pitches... Movement A can map to a pentatonic scale... Movement B can use a minor scale, and Movement C can use a chromatic scale." ChatGPT also suggested I use a C major pentatonic scale, an A minor scale, and a chromatic scale from D to A for each of the trained movements, respectively. The timbre of this sonification was like that of a light organ and was chosen by myself.

While ChatGPT supported the ideation process, differences in the required time and effort to implement the data mappings for the Non-AI and AI performance versions were negligible. Imagery for the AI performance was created over several iterations where prompts were refined and outcomes were weighed. Imagery for the Non-AI performance was sourced by myself through careful internet searches, and choices were similarly tabulated for alignment with the artist's vision.

### 4.3.3 Experimental Design

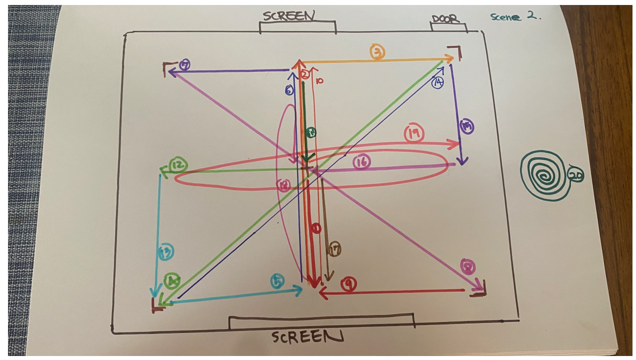
#### Performances

The study materials included the two performance variations and the data collection tools. The data collection tools included a survey and a semi-structured focus group for audience members, as well as an interview for the professional dancer and a written self-reflection prompt for myself as the technologist.

Through several meetings with the dancer, I aligned the incorporation of technology with her vision for the performance. Figure 4.2a shows the dancer during a rehearsal and Figure 4.2b shows a draft of her choreography given to me to aid in developing the performance.

The dancer's choreography and the structure of the performance into three scenes were kept the same in both performance versions. These performances differed in their use of

(a) Dancer rehearsing during an experimentation of different projection strategies




(b) Outline of the choreography for Scene 2

Figure 4.2: Artifacts from the iterative process of developing the two performances

technology as a creative collaborator. In the Non-AI version, the creative decisions made in mapping live sensor data collected from the dancer's respiration rate and location to imagery and sound were made by myself; this is described in 4.3.2. In the version of the performance where AI was involved, some of the creative portions of my work were made or supported by AI; this is described in 4.3.2. The imagery produced by AI was prompted to align with the dancer's desires. That is, Scene 1 imagery included floating petals, Scene 2 included rough waves, and Scene 3 included stars in a night sky.

#### Survey

The survey was designed to collect audiences' feedback across three core dimensions that could help me answer RQ5 and RQ6. These core dimensions were:

- Artistic value of technological components

- Technological components' influence on the coherency of the whole performance
- Observation of changes produced by technology in the performance

The survey can be found in the Appendix B.2 and consisted of 29 five-point Likert scale questions (with answer choices on a scale of - 1: Not at all, 5: Absolutely) for the two audiences in the "Tell Before" condition. For the two audiences in the "Tell After" condition, I added six additional Likert scale questions (with answer choices on scales of - 1: Not at all, 5: Absolutely; 1: The visuals mostly seemed to guide the dancer, 5: The dancer mostly seemed to guide the visuals; 1: The sound mostly seemed to guide the dancer, 5: The dancer mostly seemed to guide the sound). I added these additional questions to understand whether audience members could determine what the data mappings were before I informed them after the survey.

#### Focus Group

After all participants had finished taking the survey, I invited 3-7 participants to join in a focus group interview after every performance. Participants of the focus groups were self-selected and either indicated via email beforehand that they were interested in participating, or decided to join in the focus group when it was announced after the performance. Focus group questions changed slightly according to the study condition participants had just experienced. The focus group outline can be found in the Appendix B.3.

#### Interview with Dancer

To understand the artist's perspective of working with technology, a research team member (not myself) interviewed the dancer after the performances for one hour, which allowed ample time to answer and freely discuss the interview questions. These data contributed to answering RQ7. Interview questions can be found in the Appendix B.4.

#### Written Reflection from the Technologist

To explain my perspective as the technologist on developing software systems to further artistic goals, I produced a written reflection after the technology had been developed but before the performances were ran. I timed myself to spend one hour writing this reflection. I set this one hour constraint to give equal time for myself and the dancer to sharing our opinions. These data contributed to answering RQ7.

### 4.3.4 Procedure

The research materials and design of this study was approved by Virginia Tech's IRB. The procedure across all four performances was the same with the exception of the time I informed participants of what technology was used. For the performances assigned the "Tell Before" condition, I informed participants of the technology before the performance started. For the "Tell After" performances, I informed them after they had taken the survey. The information I shared with the audiences included what hardware and software were used in each scene, how the dancer's location and breathing changed the visuals and sound of the performances, and how these data mapping decisions were made and justified.

Audience members were led into the performance studio where they sat around the dance floor. For five minutes, audience members of the "Tell Before" performances heard an explanation of technology's role in to what they were about to see. The performance then began and lasted for 15 minutes. After the performance, informed consent documents for the study were distributed to interested audience members; individuals who verbally consented to the researcher were then given a QR code to the survey, which took approximately 10 minutes to complete. After completing the survey, audience members of the "Tell After" performances heard an explanation of how technology was used. Interested audience members were invited to also participate in a small focus group. This semi-structured focus group included 3-7 audience members per performance, took an additional 20 minutes, and was audio recorded for later transcription and analysis. Consent for this focus group was implied by the participant joining in the activity.

### 4.3.5 Data Analysis

To analyze the survey results, I performed Mann-Whitney U tests on the non-parametric data. I performed these tests comparing the following sets of audience survey results:

- AI, Tell Before vs. Non-AI, Tell Before
- Non-AI, Tell Before vs. Non-AI, Tell After
- AI, Tell Before vs. AI, Tell After
- AI, Tell After vs. Non-AI, Tell After

Therefore, I only included the 29 baseline questions in the Mann-Whitney U tests for all but the last comparative case (AI, Tell After vs. Non-AI, Tell After). In this case, both audiences experienced the "Tell After" condition, so I could include the six additional Likert questions in that survey comparison's Mann-Whitney U test.

Focus group data were audio recorded and transcribed. Quotes from each performance audience's focus group were made into affinity diagrams by copying the quotes onto sticky notes and grouping them according to the similar sentiments the quotes shared. An affinity diagram was produced for each of the four performances. The groups in each affinity diagram are named in Table 4.1.

The dancer's interview data were audio recorded and transcribed, while the technologist provided a written reflection. These data were compared to contextualize the collaborative process and provide insight into the team dynamics of interdisciplinary projects.

## 4.4 Results

### 4.4.1 Statistical Analysis of Audience Surveys

I found there to be statistical significance (confidence interval = 95%) for a selection of questions when conducting Mann-Whitney U tests for the four performance set comparisons in which one independent variable was held constant.

When I told the audience how technology was incorporated in the performance BEFORE the performance started, the following survey questions had statistically significant answer differences between the audience members who experienced the AI and Non-AI versions.

- The projected visuals enhanced the performance. ($Z$ = -2.667, $p$ = .008, the Non-AI performance rated higher, [AI version: $M$ = 2.00, $SD$ = .739; Non-AI version: $M$ = 3.25, $SD$ = .886])
- The projected visuals were distracting. ($Z$ = -2.025, $p$ = .043, the Non-AI performance rated higher, [AI version: $M$ = 2.00, $SD$ = 1.348; Non-AI version: $M$ = 3.13, $SD$ = .991])
- The projected visuals appeared random. ($Z$ = -2.130, $p$ = .033, the AI performance rated higher, [AI version: $M$ = 3.67, $SD$ = 1.073; Non-AI version: $M$ = 2.62, $SD$ =

.916])

When participants experienced the Non-AI version of the performance, the following survey questions had statistically significant answer differences between the audience members who were told how technology was incorporated before the performance and those told after the performance and survey.

- The projected visuals were distracting. ($Z$ = -3.333, $p$ = <.001, the "Tell Before" performance rated higher, [Tell before: $M$ = 3.13, $SD$ = .991; Tell after: $M$ = 1.30, $SD$ = .483])
- I tried to see if there was a pattern in the visuals. ($Z$ = -2.789, $p$ = .005, the "Tell Before" performance rated higher, [Tell before: $M$ = 4.88, $SD$ = .354; Tell after: $M$ = 3.60, $SD$ = 1.075])
- I thought about how the visuals were created. ($Z$ = -3.180, $p$ = .001, the "Tell Before" performance rated higher, [Tell before: $M$ = 4.50, $SD$ = .756; Tell after: $M$ = 2.30, $SD$ = 1.160])
- I tried to make a connection between what the dancer was doing and the visuals. ($Z$ = -2.049, $p$ = .040, the "Tell Before" performance rated higher, [Tell before: $M$ = 4.88, $SD$ = .354; Tell after: $M$ = 3.90, $SD$ = 1.370])

When participants experienced the AI version of the performance, the following survey questions had statistically significant answer differences between the audience members who were told how technology was incorporated before the performance and those told after the performance and survey.

- The projected visuals complemented the performance. ($Z$ = -2.411, $p$ = .016, the "Tell

After" performance rated higher, [Tell before: $M$ = 2.33, $SD$ = .778; Tell after: $M$ = 3.33, $SD$ = 1.00])

- The projected visuals enhanced the performance. ($Z$ = -2.007, $p$ = .045, the "Tell After" performance rated higher, [Tell before: $M$ = 2.00, $SD$ = .739; Tell after: $M$ = 2.89, $SD$ = 1.054])

- The projected visuals demonstrated artistic merit. ($Z$ = -2.501, $p$ = .012, the "Tell After" performance rated higher, [Tell before: $M$ = 2.83, $SD$ = 1.030; Tell after: $M$ = 4.11, $SD$ = 1.054])

- The projected visuals appeared random. ($Z$ = -2.698, $p$ = .007, the "Tell Before" performance rated higher, [Tell before: $M$ = 3.67, $SD$ = 1.073; Tell after: $M$ = 2.22, $SD$ = .972])

When I told the audience how technology was incorporated in the performance AFTER the performance and survey, the following survey questions had statistically significant answer differences between the audience members who experienced the AI and Non-AI version.

- The projected visuals were distracting. ($Z$ = -2.008, $p$ = .045, the AI performance rated higher, [AI version: $M$ = 2.56, $SD$ = 1.509; Non-AI version: $M$ = 1.30, $SD$ = .483])

- I thought about how the visuals were created. ($Z$ = -2.795, $p$ = .005, the AI performance rated higher, [AI version: $M$ = 4.11, $SD$ = 1.054; Non-AI version: $M$ = 2.30, $SD$ = 1.160])

- I wondered why the visuals were chosen. ($Z$ = -2.162, $p$ = .031, the AI performance rated higher, [AI version: $M$ = 4.44, $SD$ = .726; Non-AI version: $M$ = 3.50, $SD$ = .972])

- The sound in part 2 complemented the performance. ($Z$ = -2.061, $p$ = .039, the Non-AI performance rated higher, [AI version: $M$ = 3.56, $SD$ = .882; Non-AI version: $M$ = 4.30, $SD$ = .483])
- The sound in part 2 enhanced the performance. ($Z$ = -2.253, $p$ = .024, the Non-AI performance rated higher, [AI version: $M$ = 3.78, $SD$ = .667; Non-AI version: $M$ = 4.50, $SD$ = .527])
- The sound in part 2 fit with the other sounds in the performance. ($Z$ = -1.973, $p$ = .048, the Non-AI performance rated higher, [AI version: $M$ = 2.44, $SD$ = .882; Non-AI version: $M$ = 3.50, $SD$ = 1.269])
- I wondered what caused the visuals to change. ($Z$ = -2.201, $p$ = .028, the AI performance rated higher, [AI version: $M$ = 4.33, $SD$ = .707; Non-AI version: $M$ = 3.20, $SD$ = 1.135])

### 4.4.2 Affinity Diagramming of Audience Focus Groups

| Performance | Affinity Groups |
|---|---|
| Non-AI, Tell Before | • Underlying meaning and dancer's aesthetic choices<br>• Looking out for technical augmentations during the performance<br>• Fluidity and responsiveness of technology's response to the performer's actions<br>• The novelty of tech + art<br>• AI as a tool to further artists' goals/Artist-centric collaboration with AI<br>• People can find meaning in anything, and AI art is no exception<br>• Ownership concerns in AI<br>• Physical art is deemed to have higher intrinsic value |
| Non-AI, Tell After | • The focus was on the dancer; audience ignored the screen<br>• Preference to identify a "deeper meaning" in the work<br>• AI as an artist-driven tool<br>• Reflecting on the performance post-explanation<br>• Forming questions and theories during the performance<br>• Skills required to create art should influence its value<br>• Purpose of the art determines its value<br>• AI content sourcing concerns<br>• Limitations in guiding AI as it creates limits its ability to produce quality art |
| AI, Tell Before | • Using AI as a tool (to overcome deficits of skill, or provide uninhibited inspiration)<br>• AI art can't meet the objectives of human-made art (e.g., self-expression, the human experience)<br>• Copyright and natural resource concerns of AI<br>• Need to hear dancer's objectives to situate the whole performance and draw meaning<br>• Visuals should not deter attention from the performer<br>• Difficulty remembering or interpreting how the technology would behave<br>• Sensitivity and responsiveness of technology should be more apparent to match the performer<br>• Being informed about the production of a piece of art would impact its monetary value |

| Performance | Affinity Groups |
|---|---|
| AI, Tell After | • The visuals were not as fluid as the performer; occasionally they lacked responsiveness<br>• Expectations and trying to find patterns during the performance<br>• Reinterpreting the performance with new information<br>• Using technology subtly with the performer as the focal point<br>• Art is art because the human creator brings meaning to it<br>• AI can be used as a peripheral tool to support the artist<br>• Concerns about AI with respect to consumption of natural resources, compensation of artists, and discouragement of thinking creatively |

Table 4.1: Affinity groups developed from each performance focus group

### 4.4.3 Comparing Perspectives of the Dancer and Technologist

Results from the dancer's interview and the technologist's written reflection provided anecdotes that demonstrated how the collaborators' shared objective of developing the performance was realized using two different approaches.

The technologist was primarily concerned with the viability of developing creative ideas proposed by the dancer: "I started the project by making sure that the overarching idea could be done with the equipment and software I had on hand." While developing the work, the technologist occasionally found that technology presented itself as a bottleneck to realizing certain artistic ideas: "At some moments while I was developing, I would be able to make one idea for the visuals work much more easily than another idea, but the later idea would be slightly more attractive visually... I always managed to figure out how to implement the more attractive idea." The technologist also seemed to rely on the dancer in making artistic decisions. The following quotes illustrate the clear separation of roles the technologist drew in her mind: "I tried the best I could to achieve imagery similar to that of the illustrations she [the dancer] showed me..." and "...but we both went away from the meeting with homework in our respective area—she would think about the choreography and music, and I would develop some data—mapped visuals taking inspiration from the illustrations she shared."

The dancer was similarly focused on using her domain expertise to develop the performance, but held a more fluid delineation of responsibilities than the technologist. In portions of the interview the dancer shared that she sought creative input from the technologist: "So for the first one [Non-AI version of the performance] mostly I tried to give her [the technologist] what I'm thinking about: what I have imagined and then she [the technologist] tried to make, you know, actual, actual one like the visuals. That's the kind of like... we tried to communicate, but I feel like mostly I'm talking to her and then she's, like, accepting..." The dancer explained that in the creative arts, all collaborators can and should contribute artistically: "For making the creative arts it is definitely ideally good to work together. Like not only one side is working for the other side, you know? Means collaboration. Yeah. That's the like good balance to work together." Interestingly, one situation that the technologist deemed a setback—when the sonification did not match the artistic vision—the dancer used as a new creative opportunity, "...the second one [scene]... when we used sonification... then I just... it, it's not expected that I hear that sound and it's pretty cool... then I just changed my whole choreography relying on the data or like the technology so that thing is just literally... I can say it's collaboration, like what I wanted." The dancer emphasized this point by sharing, "It's clearly...for the second scene my choreography is definitely influenced by technology. Like 100%." Gonzalez et al. explained through a set of case studies that the mark of a truly successful collaboration is an active exploration and deepened understanding of each partner's domain [84]. During the rehearsals leading up to the performance, the dancer had requested to spend some time alone with the technology, to better understand how it would react to her breathing and movements. This supports the work of Latulipe et al., which highlighted how performers working with technology used it as a boundary object to align their choreography in the context of a greater performance [137]. This solo experimentation with the technology could have also shaped how the dancer reacted to the visual and auditory changes during the live performances. These data points helped me answer RQ7.

## 4.5 Discussion

### 4.5.1 Survey

When comparing the results for audience groups who experienced the Non-AI condition but were told how the performance was built at different times, those told before the performance began rated significantly higher on questions pertaining to thinking about patterns in the visuals during the performance (i.e., I tried to see if there was a pattern in the visuals; I thought about how the visuals were created; I tried to make a connection between what the dancer was doing and the visuals). This audience group also considered the visuals to be more distracting than the audience in the "Tell After" condition. These results were in line with the work of Anderson et al. on the effects of learned value on attentional capture [11]; once the audience was made aware of the value of the visuals on the screen behind the dancer, those visuals became more salient to them.

When comparing the results for audiences who experienced the AI condition but were told how the performance was built at different times, those told after the performance and survey ended rated significantly higher on questions pertaining to the artistic value the visuals added to the performance (i.e., The projected visuals complemented the performance; The projected visuals enhanced the performance; The projected visuals demonstrated artistic merit). The audience members in the "Tell Before" condition rated significantly higher on the question: "The projected visuals appeared random." This data contributed towards my answering of

RQ6.

These results reflected similar findings to those presented by Mikalonyte and Kneer in [162], in which participants who were told how an artwork was created were more likely to consider a human creator of the work an artist than they would consider a robot to be. The present study differed in that I temporarily obscured information about the production of art. In doing so, I could further isolate the biases observed by Mikalonyte and Kneer. Even when both performances used artistic decisions made by AI, participants not yet informed of technology's use rated the performance significantly higher on questions pertaining to artistic merit. These results suggest that those openly using GenAI for artistic or commercial purposes consider the potential outcome of a negative response from viewers. These results indicate that viewers' awareness of how a creative work is produced affects their perception of the work's artistic value.

When comparing the results for audience groups in the "Tell After" condition that experienced different types of technology (AI vs. Non-AI), those who experienced the AI performance rated significantly higher on questions related to their curiosity about the performance (i.e., I thought about how the visuals were created; I wondered why the visuals were chosen; I wondered what caused the visuals to change). Audience members who experienced the Non-AI performance rated higher on questions pertaining to the complementary nature of the sound of the performance (i.e., The sound in part 2 complemented the performance; The sound in part 2 enhanced the performance; The sound in part 2 fit with the other sounds in the performance). This data contributed towards my answering of RQ5.

These results align with research on the behavior of GenAI and art interpretation. GenAI has been shown by Kim et al. and Prather et al. to make mistakes [129, 188] and Oppenlaender et al. found that prompters lack fine-grained control in driving the output of their requests [182]. At the same time, Bayles and Orland highlighted that those lacking context when viewing art can perceive any product made by an artist as intentional [20]. Thus, there is potential for an audience to attribute meaning to artistic products of GenAI that were wholly unintended by the prompter. Terzidis et al. specifically examined the intentionality of art made by AI and argued for a shift in the placement of intentionality towards the final product, thereby allowing AI "mistakes" to be considered intentional artistic decisions [228].

Participants who experienced the AI version of the performance but were told how technology was integrated at the end of the study were significantly more curious about why certain artistic decisions were made compared to those who watched the Non-AI performance. These participants may have been searching for artistic intention in the AI performance which could have been more apparent to the audience of the Non-AI performance. The reader can further see from the higher audience ratings on the complementary nature of the sound in the Non-AI performance that participants could draw relational conclusions between the artistic elements of the Non-AI performance more easily than the AI performance.

The MAIN model proposed by Sundar explicates that two technologies can offer the same affordance (Modality, Agency, Interactivity, or Navigability), but cue different heuristics and ultimately lead to different value judgments [221]. In the case of this study, the technologies used in the two performances offered the interactivity affordance. Participants may have been cued by the visuals and sound of the Non-AI performance to attribute the "Responsiveness" heuristic to that performance because the relationship between the dancer's actions and the system's reactions might have been clearer. The AI performance on the other hand might have cued the "Contingency" heuristic, which suggests a more subtle relationship between the performer and the technology. These heuristics could have ultimately led to different heuristic-based judgments on the creative merits of the two performances.

Finally, I saw statistical significance in survey responses to the statement, "The projected visuals were distracting," in three of the four Mann-Whitney U tests. These tests compared audience responses between those who were told about technology beforehand but saw different versions, those who saw the Non-AI version but were told at different times, and those who were told about technology afterwards but saw different versions. Results showed that when told before, participants rated the Non-AI version as more distracting, whereas when told after, people rated the AI version as more distracting. While this result conflicts with the premise that knowledge of AI's presence lowers audience members' impressions of the work's artistic merit, it is important to contextualize these results with respect to the other questions which produced statistical significance within the specific performance comparisons. Looking at the other question responses which produced statistical significance when comparing those performances where audiences were told before, individuals who saw the Non-AI version also rated higher than the AI performance on the statement that the projected visuals enhanced the performance, indicating that there were conflicting impressions of those who saw the Non-AI version. Whereas the only statement where those who saw the AI version in this comparison rated significantly higher than the Non-AI version was that, "the projected visuals appeared random." Thus, there was no significantly positive response from those who saw the AI performance as compared to the Non-AI performance when told about technology before.

### 4.5.2 Focus Groups

The focus group data yielded four affinity diagrams (one for each performance audience). Three out of the four affinity diagrams included a group of quotes that pertained to using AI as a tool to further artists' goals; participants qualified this artist-centric collaboration with technology with quotes such as P3's statement, "the key with an artist is that they're able to consistently bring meaning to a design... so I think when an artist is able to use technology to bring more meaning... it could be very powerful." Coeckelbergh contributed this same idea to the literature: that the meaning the observer attributes to a work affects the work's status as a piece of art [35]. P10 spoke about how AI can be more uninhibited than humans, and how this can be used to an advantage, "It doesn't have human emotion, but I do like that it doesn't strictly stay to the laws or the rules that we have. Like certain artists have certain styles, and so it doesn't really care about those certain rules and so it can kind of blend and create new styles of art..." Moroni et al. showed this to be true empirically by demonstrating how interactions with machines can allow people to create entirely new varieties of art [167]. P13 used the AI version of the performance to contextualize where technology could support artists' objectives: "I think that it [technology's artistic output] needs some form of human expression underneath of it... In the sense of like music created by a human's movements, I think that's really unique and very different, something that you can't necessarily do without technology..." These quotes aligned with Jeon's work, which argued that machine-creativity can be accepted by humans, but this creativity is primarily situated in the interaction between the machine and the human creator [111].

I asked participants how something is determined to be art. Much of the literature in this domain frames art as an expression of the "human experience," with Dissanayake and Dewey's works [49, 52] being two examples. All of the focus groups responded to this question with multiple quotes tied to the meaning or purpose only the artist can uniquely bring to the work, or the meaning ascribed to the piece by the observer. P14 shared that art is used "...to express human desires and emotions, and also to communicate messages to other people." In a different focus group P7 shared, "...because AI doesn't really have emotions... I know a lot of art is about expression, and about trying to convey a deeper meaning to it. I think that it makes a lot more sense for people to be able to do that..." P11 provided a more specific meaning to the purpose of art "I think [the purpose of art is] definitely self expression," and later stated "I think art making is inherently political." Works in the literature by Mouffe et al. and Edelman have also made this argument, as politics have long been an important facet of the human experience [58, 169]. P3 shared the same sentiments about meaning driving the purpose of art, but took a more neutral stance: "...and so when I think about art, it's just something that people place meaning towards..., and I mean that could be generated by anybody honestly..."

The emphasis on finding meaning was carried by participants in how they experienced the performances. Three of the four affinity groups included a group of quotes pertaining to the focus group participants' desire to understand the dancer's objectives, aesthetic choices, and the underlying meaning behind her choreography. P9 summarized the multiple quotes on this item nicely by saying, "if she [the dancer] were to explain just a little bit, give us a little bit of background insight to the dance before she performed, I think it would have definitely made the performance feel differently." Stolnitz shared that it is common practice to contextualize an artwork by learning more about the artist [220], and participants similarly wanted more attention given to the dancer of the performances.

### 4.5.3 Dancer's and Technologist's Reflections

The technologist heavily relied on the dancer to make aesthetic judgments on the performance. This could be explained by the technologist's understanding of the dancer's high level of expertise in her field, which contributed to the technologist's greater confidence in the dancer's creative decisions. This relationship between expertise and confidence has been empirically observed by Trafimow and Sniezek in [230]. The technologist's confidence in the dancer's judgments could be in part due to the technologist's trust in the dancer, as can be explained by Sniezek and Van Swol in [216].

The collaborators began developing trust well before the implementation of the performances began. The technologist met with the dancer to demonstrate the various technological options available to bring the dancer's creative vision to life. The dancer discussed the meaning of what she wanted to deliver artistically. She also shared that she was specifically touched by a children's book about girls in Korea under the Japanese colonial period, and wanted to use the imagery of this book as inspiration for the imagery augmented by technology, as well as her own choreography.

One could infer that the project's interdisciplinary team developed a strong relationship of trust. Research by Costa et al. on trust in team dynamics has demonstrated that building trust can positively impact perceived task performance, team satisfaction, and relationship commitment [42]. The results lead me to emphasize the importance of building trust between members of an interdisciplinary team. In such teams, members may feel less equipped to make decisions outside of their domains, thereby placing greater reliance on the expertise of the other team members.

The collaborators' reflections highlighted that problem solving techniques can differ. What the technologist considered to be a problem (the sonification not matching the initial artistic vision), the dancer saw as a solution (closer collaboration with technology). Research by Glaser et al., Nazzal, and Bassok has been done in determining how problem solving techniques can be translated across domains [19, 78, 173]. In these works, problem solving methodologies are associated with one or more fields, and have varying degrees of transferability across fields as determined by some sets of shared characteristics. Other works from psychology by Reiter-Palmon et al. and D'Zurilla et al. suggest that problem solving techniques are influenced by one's personality [57, 193]. While a closer examination of the problem solving techniques utilized in interdisciplinary teams is beyond the scope of this work, interaction effects between one's personality type and field of expertise could be expounded on in future work, following the same line of research as Jiang et al. and Reed et al.

[117, 191].

### 4.5.4 Holistic Findings

In this mixed methods study, data was collected from audience members and the interdisciplinary collaborators. It can be inferred that the act of creating art is still considered to be a chiefly human endeavor, even in the age of GenAI. Focus group data showed that participants were open to the possibilities of GenAI art so long as the technology furthered the goals of the human creator. Collaborator reflections highlighted that the process of developing the performances required flexibility and iterative creative decision making. Analysis of the audience surveys showed that participants unaware of the presence of GenAI attributed artistic merit to that performance's augmentation at significantly greater levels than participants who were aware of GenAI's use before the performance began. These data points lead to the conclusion that artmaking continues to live in the minds of many people as a primarily human experience.

### 4.5.5 Limitations

Though I took precautions in developing, conducting, and analyzing all materials for this study, I also acknowledge that there is always a possibility for bias. There were some technical issues while implementing the performance. It should also be noted that our past experiences color how we see the world. Those with a dance background could have had interpreted the visuals differently. However, I did not specifically ask participants whether they had a background in dance. This could be an interesting variable to explore in future research studies.

Finally, mapping choices between live data streams and visual and auditory augmentation made by myself and the dancer had an impact on the results. Changes to these design choices would likely yield slightly different findings.

## 4.6 Conclusion

In this study I collected insights from audiences to understand how people's impressions of an embodied artwork are impacted by the type of technology used to augment the art (RQ5), and one's awareness of how the art was made (RQ6). I collected data from the dancer and technologist to understand the interdisciplinary process of integrating live streams of physical data captured by sensors in a performance (RQ7). Using data collected from audience surveys and focus groups, I found trends highlighting the consistent desire for audience members to understand the meaning of art in order to situate its creative value, and that withholding information about an artwork's production can influence audience members' evaluations of the aesthetic choices of the artist. In an interview with a professional artist and a reflection from the technologist, I found that problem solving strategies in interdisciplinary teams can vary, but a willingness to adopt the other's strategy can offer unplanned creative opportunities.

# Chapter 5

# Study 3: Algorithms in Art and Code: How Teaching Embodied Artmaking Procedures Can Stimulate Analytical Thinking in Art Crafting and Computer Programming

## 5.1 Introduction

In previous chapters, I investigated how technology can be used to further objectives in art. In this chapter I discuss a study I designed that uses embodied knowledge and procedural abstractions in art to improve analytical thinking skills used in computer science.

Prominent figures such as Knuth working in computer science can attest to the creativity required in their field [133]; elegant solutions in computing are highly revered and studied by scientists such as Knuth and Cormen et al. [41, 132]. While the inherent creativity of CS described by Saunders and Thagard and Peteranetz et al. may be obvious to computer scientists, it can elude the uninitiated [186, 199]. Once more, ideas of what CS is have been built up over the years and have left impressions on the general public, as noted by Cheryan et al. and Turkle and Papert [31, 233]. Individuals who exhibit the qualities of a great computer scientist may not see how their skills translate to computing.

While researchers such Jawad et al., Magerko et al., and DesPortes et al. have made efforts to promote CS from an art-based perspective, these projects often focus on using CS to enhance, change, or build art [48, 110, 155]. These projects divide CS and art such that computing is the cause and art is the effect. Little has been done to utilize art as both the cause and effect in demonstrating analogous qualities between the two.

Smith explained that showcasing the similarities between art-making and computing may provide opportunities for building computing confidence in the many individuals who already enjoy practicing art [213]. My approach to using art as a catalyst to drive new, creative perspectives to the tech sector is novel in its focus on highlighting the procedural aspects of creating art, and framing CS techniques as a new flavor of the art-making strategies individuals already see themselves as being successful at.

Crochet is a popular fiber art whereby the crocheter can design and create items like sweaters or toys by following a crochet pattern. A crochet pattern consists of symbols representing stitches and syntax which communicate conditional procedures and repetitions. Thus, crochet patterns can exhibit similar characteristics to computer programs. The similarities between the two, and the addition of crochet patterns having accompanying physical procedures which make use of embodied knowledge (i.e., by reproducing the crochet patterns with yarn and hook), led me to design this study. In this work I seek to use the process of learning crochet patterns as a proxy for learning simple algorithms in computing. Furthermore, I can apply embodiment theory in teaching crochet patterns for a subset of participants to understand how adding a physical dimension to learning art-based algorithms might improve one's understanding of algorithms in a classical STEM domain such as computing. In the present work I apply this concept of an "embodied algorithm," where a sequence of distinguishable gestural procedures reliably realizes a physical goal, to draw parallels to computing.

### 5.1.1 Unique Contributions

This work has both practical and theoretical implications. From a practical perspective, my findings can motivate novel teaching methods in CS and similar fields. This study offers two new approaches towards this end: 1) artmaking is used as a medium to practice analytical thinking, and 2) physical interaction is used to support this thinking. The concept of embodied cognition outlined by researchers such as Wilson and Shapiro suggests that cognition takes place in the central, perceptual, and motor systems of the body, and that our physical interactions can lend themselves towards cognitive objectives such as learning [204, 244]. Empirical studies by Glenberg and Robertson and Jang et al. on learning tasks have supported these claims [79, 109]. Thus I utilized embodied cognition in this study by incorporating physical interaction in learning as one of my two independent variables.

My work's theoretical contribution comes as an application of Holyoak and Thagard's multiconstraint theory [98, 99], which posits that similarity, structure, and purpose constrain our ability to develop and understand analogies. My study's design seeks to draw out from participants through tests and interviews whether these constraints are upheld in building analogies between computing and crochet.

In this study, I taught participants with and without programming experience how to read, write, and interpret crochet patterns using two different learning methods (with or without gestures) over the course of three separate sessions. I then tested them on crochet patterns and simple programming and algorithms in two separate tests in a final fourth session. Afterwards, I interviewed the participants to try to understand their perceptions of the tests and their own analytical abilities. Participants who had prior crochet experience also took the tests and interview without any learning interventions as a baseline to compare against the condition groups in the aforementioned 2x2 between-subjects design. My research questions were as follows:

- RQ8: Do programmers perform better on the crochet test?
- RQ9: Does learning the crochet gestures have an effect on participants' performance on the crochet test or programming test?
- RQ10: Can participants recognize similarities and differences between crochet and programming?
- RQ11: What are participants' impressions of programming after introducing them to the programming-like art practice of crochet?
- RQ12: How do participants' perceive their performance on the crochet test and the programming test, compared to their actual performance?

## 5.2 Related Work

### 5.2.1 Crochet

Crochet is a fiber art where the artist repeats a series of foundational stitches to create physical objects. There are six foundational stitches which can be grouped together, alternated, or rotated to make increasingly intricate designs. Crochet objects can be made by following a written or graphical pattern. Written and graphical patterns convey the same information: which stitches to use, how many to use, and how to arrange them. Graphical patterns do this through symbols and spacing, while written patterns use abbreviations, syntax, and occasionally natural language. By understanding and following a crochet pattern, the artist can reproduce a physical object. In this study, I taught all participants inexperienced with crochet the abbreviations, syntax, and stitch symbols found in written and graphical crochet patterns. Half of these participants learned these items along with the accompanying crochet stitches with hook and yarn.

### 5.2.2 Analogies in Learning

As Gentner and Forbus and Dreistadt explained, scientists make use of a variety of analogies to explain ideas in their fields [55, 76]. Researchers such as Coll et al. have recognized the potential of analogies and have applied them to teaching topics in science [37]. While some researchers such as Halpern et al. and Glynn have used analogies to promote recall or clarify an idea [80, 92], others like Heywood have claimed that analogies can support learning by serving as a medium for discourse on complex topics [96]. Work in the field of psychology on building analogies, specifically multiconstraint theory by Holyoak and Thagard, outlined three core requirements in building a successful analogy in someone's mind [98, 99]. These included similarity between the compared elements, consistent parallels in the roles the two elements serve, and clear goals in developing the analogy. The analogies between crochet and programming used in this study meet these three criteria and thus, I used them to investigate how teaching crochet can help build computational thinking skills.

The act of building and recognizing analogies between disparate fields to support learning is an application of constructivist learning theory, the antecedent of what we would today call active learning. Bada and Olusegun contextualized constructivism in the learning sciences, explaining that constructivist learning theory is rooted in the idea that what individuals have already experienced will impact how they build connections with new information [14]. Therefore, actively building engaging experiences with new information can not only help cement the information in one's mind, but can also make learning new things easier. Michael surveyed the literature in active learning and presented numerous studies which highlighted the benefits of the approach [161]. While supporting the benefits of active learning, the author also argued that although the learner takes a more active role in forging connections in their learning, the educator's responsibility in providing an environment to facilitate the learner's understanding remains equally critical. Outlining information to help learners make the jump in bridging art and computing was central to the design of the present study.

### 5.2.3 Embodied Cognition

Embodied cognition is a theory which posits that thinking is an activity served by the entire body in the context of a wider, interactive world. Research by Macrine and Fugate, Jang et al., and Kontra et al. applying the theory has demonstrated the value of utilizing multiple modalities of perception to support learning [109, 134, 154]. Goldin-Meadow noted that the use of hand gestures to convey information related to tasks, ourselves, and the world around us [82] has been used as an effective learning tool in an array of contexts, from early childhood exercises in counting as reported by Goldin-Meadow in [81] to training professional athletes as highlighted by Zourbanos et al. in [251]. In this work's application of embodied cognition, I taught half of the participants inexperienced with crochet the gestural routines that conveyed the written crochet material. While it was not necessary for participants to learn the gestures to master the written material, the aforementioned literature in embodied cognition suggested that incorporating the additional modality could improve learning.

## 5.3 Methodology

### 5.3.1 Participants

Fifty-eight participants (21 male, 37 female) with an average age of 25.38 ($SD = 5.63$) were recruited to partake in the study. Of these 58, 52 did not have prior crochet experience. Half (26) of these 52 participants identified themselves as programmers. Programmers were identified after they had expressed interest in the study; they were asked if they had either taken a semester long computer science course or could program by themselves without help. These individuals were divided into two groups where crochet was taught either with or without gestures. The other half of participants (26) identified themselves as "non-programmers" by their lack of experience or confidence in programming independently; these participants were similarly divided into two learning groups. The remaining six participants of the total 58 were experienced in crochet and did not partake in the crochet learning activities. These individuals had varying degrees of programming experience.

### 5.3.2 Equipment and Stimuli

In the first three sessions with participants who did not have prior crochet experience, I taught them how to read and understand written crochet pattern using a curriculum I designed. This curriculum consisted of lesson plans, flash cards, and review questions. Participants learned using written lessons and verbal instruction from myself, but half of these participants also learned how to create the crochet stitches taught in the written lessons. Lesson plans for those who learned without the gestures can be found in Appendix C.1, and plans for those who learned with the gestures can be found in Appendix C.2. Details of what each condition group did on a per-session basis are explained in Subsection 5.3.4.

To determine causal effects of embodied learning on understanding written crochet language, I used a crochet test. To detect correlations between crochet and programming, I used a programming test. Finally, I used a set of interview questions to understand participants' perceptions of the two subjects and their perceived ability in each subject. These evaluation materials were administered to the participants who learned crochet in the final, fourth meeting. The six individuals with crochet experience prior to the study did not complete any learning activities; instead, these individuals had just one session where they took the same two tests and interview. The crochet test, which can be found in Appendix C.3, was designed by myself and consisted of nine multiple choice questions which only tested participants on the application of material covered in the previous sessions' written lessons. Note that these written lessons were presented to all but the six participants with prior crochet experience and an understanding of how to physically make the crochet stitches taught in the lessons was not required to earn a perfect score on the crochet test. Individuals with crochet experience prior to the study were not screened for an ability to read crochet patterns before taking the tests. Notation on the crochet test and in the curricula followed the US standard crochet notation commonly used in marketable crochet patterns. The computer programming and algorithms test, which can be found in Appendix C.4, consisted of nine (eight multiple choice and one multiple selection) mock questions [43] from the AP Computer Science Principles exam [38]. This exam is a standardized test taken by high school students to earn credit for a college-level introductory computer science course. Questions on this exam are written in a mock programming language; thus, the programming test was also written in this mock language. This was advantageous for the study, because writing the test in a particular programming language would risk capturing experienced programmer participants' familiarity with the language rather than their problem-solving skills.

Interview questions can be found in Appendix C.5 and covered topics including participants' perception of their performance on the tests, whether they would like to learn more about the topics covered on each test, whether they believed that they were capable of expanding their knowledge of the topics covered on the tests, and what similarities or differences they noticed between the two tests (apart from the subject matter itself).

### 5.3.3 Experimental Design

A 2x2 between-subjects experimental design with an additional comparison group was applied to answer the research questions. The two independent variables of the 2x2 between-subjects component were 1) crochet learning method, and 2) programming experience. The additional comparison group consisted of individuals with prior crochet experience and varying levels of programming ability. I defined someone as having programming experience by them having taken at least one programming course or knowing how to write code in any language, unaided. Of the 26 participants **with** programming experience but without crochet experience, half of them (13) learned crochet with gestures and written materials, while the other half (13) learned crochet by only using written materials (i.e., they learned the written syntax and symbols of crochet patterns, but they did not learn how to physically make the crochet stitches). The 26 participants **without** programming experience were assigned to the two conditions in the same way. Each participant experienced only one set of conditions with no overlap. The six participants with prior crochet experience did not engage in the learning activities.

The dependent variables included the results of the two tests on crochet language and introductory programming and algorithms and the interview data collected afterwards. In these interviews participants shared the similarities and differences they observed between the two tests, their perceived ability to succeed on the tests, and whether they could see themselves learning more about the content of the tests. All participants took these assessments.

### 5.3.4 Procedure

Each participant in the groups that learned crochet met individually with me on four separate occasions. These meetings occurred no less than 24 hours apart for all participants and lasted approximately 30 minutes each. Figure 5.1 highlights the study activities for the different condition groups.

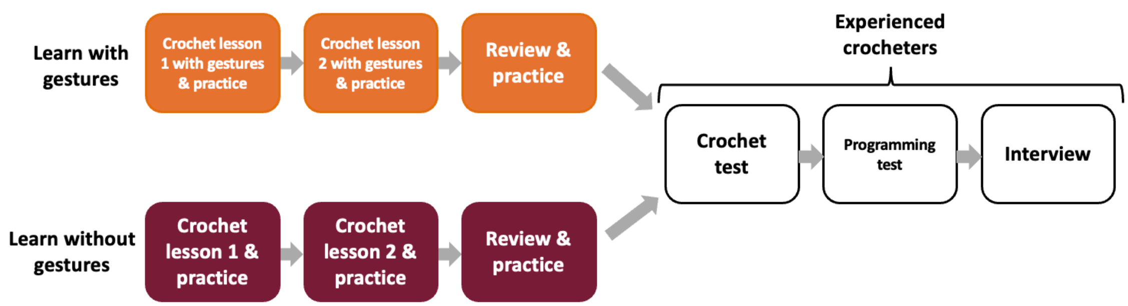



Figure 5.1: Study activities flowchart

At the start of the first meeting, individuals were given an informed consent document approved by the Virginia Tech IRB. Interested and eligible individuals then read this document and signed it if they consented to participate. In the first two meetings, participants heard and read a lesson (10 minutes) on the syntax and rules of written crochet patterns and were introduced to the abbreviations and symbols for three foundational crochet stitches. After the lesson, the participant was quizzed on the material with three questions which included short crochet patterns (5 minutes). Questions included "How many stitches are in this pattern?" and "Can you walk me through what happens in this pattern?" If the participant answered incorrectly, I would demonstrate how to answer the question. After answering the questions, participants reviewed flashcards on all of the material they had learned up to that point. After flashcards, participants assigned to the groups which only learned crochet with the written materials were finished with that day's session. Participants in the groups assigned to learn with the written materials and gestures remained in the study room and learned two crochet stitches in each of the first two sessions. Participants who learned how to make these crochet stitches were provided with yarn and a crochet hook, and sat side by side with me as I demonstrated how to make each stitch. All participants who learned crochet stitches were successful in replicating each stitch without my aid at least one time.

In the third session, participants in the groups that learned crochet reviewed the two sets of flashcards they had seen from the previous two sessions. They were then asked questions about three short written crochet patterns that included all of the syntactical and notational information they had learned in the previous two sessions. After answering the questions, participants assigned to the groups that learned with gestures were asked to recreate a simple crochet pattern alongside me. Participants assigned to the groups that learned using only the written material were asked to write their own crochet pattern and explain it to me.

In the fourth and final session for participants who learned crochet, and the only session for participants who had crochet experience prior to the study, participants took two written multiple-choice tests (20 minutes). The first test was on the written crochet language and the second test was on simple computer programming and algorithms. Participants were given 10 minutes to complete each test and were provided pen and paper to work out the problems. All participants completed both tests within the allotted time. After participants finished the two tests, they completed a semi-structured interview with me (10 minutes).

### 5.3.5 Data Analysis

#### Crochet and Programming Tests

To analyze the quantitative test results I ran a series of statistical tests. Two one-way analyses of variance (ANOVA) was ran for each of the programming and crochet tests; for these ANOVAs the single factor used to assess changes in the response variable was the condition group participants were in. The condition groups were:

- Programming experience, learned with gestures
- Programming experience, learned without gestures
- No programming experience, learned with gestures
- No programming experience, learned without gestures
- Crochet experience, no learning activity

Descriptive statistics separated by the five condition groups above were also calculated for each of the two tests.

I then performed two two-way ANOVAs omitting those with crochet experience who did not take part in the learning activities; an ANOVA was ran for each of the two tests. The two factors for these ANOVAs were 1) crochet learning method and 2) programming experience.

Next, I ran one sample t-tests comparing the scores of the expert crocheters who did not participate in any learning activities to the scores of the four other condition groups. In running these one sample t-tests I considered the average scores of the six crocheters for each of the two tests as the baseline to compare against my study's interventions.

Finally, I ran a Pearson's correlation test between the scores of the crochet and programming tests which considered all participants.

#### Interviews

To analyze the qualitative interview data I developed affinity diagrams (introduced as an interview analysis technique by Holtzblatt and Beyer) on a per-condition group basis using quotes from participants [97]. All relevant quotes from participants were written on cards and grouped by shared sentiments. These groups were then descriptively named. In some instances quote groups became too broad and were further refined, and in other instances a single quote could not stand alone as its own group and had to be removed. In the end I arrived at a set of affinity groups for each of the five participant conditions.

## 5.4 Results

### 5.4.1 Crochet and Programming Tests

As stated in subsection 5.3.5, several statistical tests were run to determine potential correlations between individuals' test scores and causation of score differentials between the condition groups.

To begin, the two one-way ANOVAs which compared the scores on the two tests across the five condition groups rendered no between group significances. Descriptive statistics of crochet and programming test scores comparing the condition groups can be found in tables 5.1 and 5.2, respectively. These descriptive statistics contributed towards answering RQ8. I found that there were trivial differences in average scores on the crochet test when comparing programmers to non-programmers.

Two two-way ANOVAs which omitted the six participants with crochet experience who had no learning intervention, sought to find potential main or interaction effects on crochet and programming test scores due to programming experience and learning intervention. These ANOVAs did not show statistical significance.

Next, four one sample t-tests were run using the average crochet test scores of those with crochet experience as a benchmark against the four other condition groups. This procedure was similarly repeated comparing the programming test scores.

Considering the crochet test scores, a one sample t-test (one-tailed) showed that the mean score ($M = 85.472$, $SD = 11.461$) of those with programming experience who learned with gestures was significantly higher than the mean score ($M = 79.63$, $SD = 23.745$) of crocheters with no learning intervention, $t(12) = 2.31$, $p = .045$, $d = 0.51$. Another one sample t-test (one-tailed) showed that the mean score ($M = 86.326$, $SD = 12.131$) of those without programming experience who learned without gestures was significantly higher than the mean score ($M = 79.63$, $SD = 23.745$) of crocheters with no learning intervention, $t(12) = 1.990$, $p = 0.035$, $d = 0.55$.

Considering the programming test scores, a one sample t-test (two-tailed) showed that the mean score ($M = 84.617$, $SD = 14.008$) of those with programming experience who learned with gestures was significantly higher than the mean score ($M = 61.113$, $SD = 25.094$) of crocheters with no learning intervention, $t(12) = 6.050$, $p < 0.001$, $d = 1.678$. Another one-sample t-test (two-tailed) indicated that the mean score ($M = 74.361$, $SD = 17.792$) of those without programming experience who learned with gestures was significantly higher than the mean score ($M = 61.113$, $SD = 25.094$) of crocheters with no learning intervention, $t(12) = 2.685$, $p = 0.020$, $d = 0.745$.

Finally, the Pearson's correlation test indicated a significant positive correlation ($r(56) =$

.513, $p < .001$) between the scores on the two tests when considering all participants.

| Condition Group | N | Mean | Std. Dev. | Std. Err | Min | Max |
|---|---|---|---|---|---|---|
| Programming Experience, With Gestures | 13 | 85.472 | 11.461 | 3.179 | 55.56 | 100.00 |
| Programming Experience, Without Gestures | 13 | 82.907 | 26.688 | 7.402 | 11.11 | 100.00 |
| No Programming Experience, With Gestures | 13 | 84.616 | 14.726 | 4.084 | 44.44 | 100.00 |
| No Programming Experience, Without Gestures | 13 | 86.326 | 12.131 | 3.365 | 66.67 | 100.00 |
| Crocheters | 6 | 79.630 | 23.745 | 9.694 | 44.44 | 100.00 |

Table 5.1: Crochet test descriptive statistics for each condition group

| Condition Group | N | Mean | Std. Dev. | Std. Err | Min | Max |
|---|---|---|---|---|---|---|
| Programming Experience, With Gestures | 13 | 84.617 | 14.008 | 3.885 | 66.67 | 100.00 |
| Programming Experience, Without Gestures | 13 | 73.505 | 25.875 | 7.177 | 22.22 | 100.00 |
| No Programming Experience, With Gestures | 13 | 74.361 | 17.792 | 4.935 | 44.44 | 100.00 |
| No Programming Experience, Without Gestures | 13 | 68.379 | 14.939 | 4.143 | 44.44 | 100.00 |
| Crocheters | 6 | 61.113 | 25.094 | 10.245 | 11.11 | 77.78 |

Table 5.2: Programming test descriptive statistics for each condition group

### 5.4.2 Interviews

Table 5.3 displays the affinity groups produced from the interview analysis. The process of arriving at these groups is described in Subsection 5.3.5. During the interview, participants were asked to estimate their scores on both tests. These estimations were then compared to their actual scores. Per condition group counts of score estimates can be found in Table 5.4.

| Condition Group | Affinity Groups |
|---|---|
| Programming Experience, With Gestures | • Methodical nature of crochet<br>• Mixed impressions of the programming test's difficulty<br>• Referenced math when describing both tests<br>• Thought crochet was easy<br>• Both tests used symbols and assignments.<br>• Tests required thinking ahead or in sequences.<br>• Tests pertained to following steps.<br>• Saw no differences between the tests (besides subject matter)<br>• One or more tests were described as logic tests.<br>• Both tests had routines.<br>• People didn't feel confident in performing the crochet gestures or taking the crochet test. |
| Programming Experience, Without Gestures | • Visualizing would help in crochet.<br>• Thinking sequentially on both tests<br>• Crochet was easy/easier than programming.<br>• Mindset/thinking processes were similar in crochet and programming.<br>• Math was a component on both tests.<br>• Mixed impressions of programming test's difficulty<br>• Mastery of programming requires more lessons and thinking.<br>• Crochet was fun/interesting.<br>• Both tests required logical thinking.<br>• Both tests required breaking down problems into pieces.<br>• Mapping specific programming constructs to crochet (e.g., loops, arithmetic operators) |

## 5.5 Discussion

### 5.5.1 Learning Interventions Showed Improved Performance on Both Tests

I found statistical significance in a subset of the one sample t-tests I ran which considered the average test scores of the experienced crocheter condition group against the other condition groups. Examining these statistical tests for the crochet test scores, I found that the

| Condition Group | Affinity Groups |
|---|---|
| No Programming Experience, With Gestures | • Crochet is relaxing and gives a sense of fulfillment.<br>• Immutability of constructs in crochet<br>• Couldn't find similarities between tests<br>• Programming was a greater logical exercise.<br>• Programming was more difficult than crochet.<br>• Programming required some background knowledge to comprehend.<br>• Both tests had sequential operations.<br>• Both tests included some math.<br>• Both tests had conditional statements.<br>• Used visualizations to understand the crochet test; lack of visualizations made programming harder<br>• Programming test had mutable variables<br>• Test order mattered (i.e., people liked the crochet test first as a primer)<br>• The study caused some to became interested in programming.<br>• Programming would be an important skill to learn; people suspected they would need to learn it eventually.<br>• Saw few/no conceptual differences between the tests |
| No Programming Experience, Without Gestures | • Programming was harder than crochet because there was more to infer.<br>• Programming had conditionals and variables that could change.<br>• Participants would learn programming for their career.<br>• Crochet and programming both produced a final outcome.<br>• Logic was core to understanding the crochet and programming tests.<br>• Crochet and programming are both types of languages.<br>• Saw no fundamental differences between the two tests<br>• Both tests had repetitions.<br>• Both tests required following steps.<br>• Having the physical element would have been helpful on the crochet test.<br>• Both tests used numbers. |

| Condition Group | Affinity Groups |
|---|---|
| Crochet Experience, No Learning Intervention | • Crochet isn't cognitively demanding.<br>• People's crochet experiences differed (some knew how to read patterns while others didn't).<br>• Both tests were like logical reasoning tests.<br>• Both tests required you to follow sequences.<br>• Math was used on both tests.<br>• Participants pulled from their varying degrees of programming experience.<br>• Desire to make/work on physical things<br>• Belief in growth mindset<br>• Lesser interest in programming<br>• Written instructions in any language (programming or crochet) are abstract and hard to imagine |

Table 5.3: Affinity groups developed from each condition group

| Participants' Overestimation of Scores by Condition Group | | |
|---|---|---|
| Condition Group | Crochet Test | Programming Test |
| Programming Experience, With Gestures | 12 of 13 participants | 10 of 13 participants |
| Programming Experience, Without Gestures | 8 of 13 participants | 10 of 13 participants |
| No Programming Experience, With Gestures | 6 of 13 participants | 0 of 13 participants |
| No Programming Experience, Without Gestures | 7 of 13 participants | 4 of 13 participants |
| Crochet Experience, No Learning Intervention | 2 of 6 participants | 3 of 6 participants |

Table 5.4: Per condition group counts of participants who overestimated their scores on the two tests

group with programming experience that learned with gestures as well as the group without programming experience that learned without gestures had scores significantly higher on average than those of the crocheter group with no learning intervention and diverse programming experience. This result brings to light an important consideration: people do not need to read patterns to crochet. People use crochet patterns to recreate others' designs or share their designs with others, but this is not necessary for success in the same way that one does not need to know how to read a recipe to cook.

For the programming test, I found that both condition groups that learned with gestures (i.e., groups with and without programming experience) had significantly higher scores than the experienced crocheter condition group with no learning interventions. One factor which could have contributed to these results is the fact that participants who identified themselves as programmers had different levels of experience. While the programming test was derived from a standardized tests for an introductory course in computer science, a small number of individuals in the experienced programmer condition groups shared doubt about their performance on the test; P53 who learned crochet with gestures and text shared, "...I have some coding experience and some of the questions were a bit tricky, but I had seen them many times before, so I hope I did well." These nuanced results helped me to answer RQ9—whether learning with gestures had an effect on participants' performance on the tests.

### 5.5.2 Crochet and Programming Test Scores Were Positively Correlated Across All Participants

Looking across all condition groups, crochet and programming test scores had a statistically significant positive correlation, as reported in Section 5.4. This suggests that crochet and programming may be applications of logical reasoning, and success on one might imply success on the other. Future studies may be devised to investigate shared characteristics of these thinking patterns at a finer granularity.

Various tests have been created and applied to assess logical reasoning skills. The Test of Logical Thinking (TOLT) derived from Lawson's work and validated by Tobin and Capie was one such test [141, 229]. While questions on the test did not pertain to domain-related knowledge, scores reliably increased with age, fluctuating between high school and college age groups. Morgan and Morgan administered the Morgan Test of Logical Reasoning whereby they found that though participants with formal educational training in logic scored significantly higher on average than those who did not, the scores of those not formally trained were higher than a chance average [166].

The results of these previous experiments suggest two important points to contextualize the present study's results. The first is that prolonged training and exposure to logic does help on tests of the subject. This exposure can be built up over time or with concerted effort in a formal setting. These results are especially encouraging, as they support Dweck and Leggett's concept of a growth mindset in learning [56]. The second is that such tests are subject-matter agnostic. The tests utilized exercises and puzzles which did not necessitate domain-specific knowledge. Interestingly, in the interviews of the present study, both non-programmers and programmers shared that they thought the programming test was easy. It is important to note that participants' ages ranged from 18 to 43, and major of study was not controlled. What is particularly interesting is the correlation between the crochet and programming test scores across all participant groups. This correlation suggests the broader impact of individual participant differences.

Had participants been given more time and training, it could be supposed that the average scores on both tests would have increased, but present results suggest that these interventions would not negate the unique strengths of individual participants as evidenced by the correlations between the two scores irrespective of condition group; personal characteristics do likely play a role in performance on such tests.

An open question in computer science education research is how to predict the future success of aspiring computer scientists [27, 135]. Tests in more familiar domains which include analogues of abstractions found in computing may provide a solution. The present work applies analogues in crochet to assess analytical thinking commonly applied in computing. Following Holyoak and Thagard's multiconstraint theory, other diagnostic assessments could possibly be configured to answer this open question [98]. Recognizing one's unique strengths and weaknesses through such diagnostic assessments can help lead individuals in the direction where they are most capable to make a meaningful contribution to society and find personal satisfaction.

### 5.5.3 Majority of Programmers Overestimated Their Scores on Both Tests

During the interviews I asked participants to give their estimated scores on both tests to help me in answering RQ12. I then compared these scores to their actual scores; Table 5.4 shows score overestimations by condition group. It is interesting to note that the vast majority of those with programming experience overestimated their scores on both tests, whereas those without this experience (not considering crocheters who had a diverse programming background) are usually split on the crochet test and conservative on estimating their performance on the programming test. While this confidence from the experienced programmers did not materialize in the form of higher scores, research from Norman and Hyland has shown confidence to be a motivating factor in learning [178].

### 5.5.4 Programmers Described Specific Examples of How Crochet and Programming Were Related

In my post-test interviews with programmers I found specific examples of what concepts in programming are similar to crochet. P6, a teaching assistant for an introductory programming class shared, "...I saw a lot of similarities. So first, if you want to repeat an instruction or a set of instructions [in crochet] $n$ number of times it's very similar to, you know, doing for loops in programming...and yeah there are a set of instructions like single crochet, double crochet. We have similar instructions in programming that we want to, you know, repeat to achieve a bigger task. And they are reusable [in crochet] just like functions in programming." P1 shared that they used the same strategies while taking the two tests, "so they both were... to count and find the answers. So they had pretty, like, big similarity... like how we use arithmetic operators when we learn in any programming language, it was just like that." P2 highlighted the procedural aspects of both subjects by sharing, "I think the process itself... even though we're programming there's always math involved. So... [on the programming test], how many, whether you're moving forward, or... how many turns; and with the crochet [test], like how many chain or how many double crochet. So I think math is the element that has a similarity in both."

These quotes from programmers aligned with the multiconstraint theory of Holyoak and Thagard for building analogies, in that participants described how crochet and programming were similar in form and usage despite not being exactly the same [98, 99]. Thus, as the theory predicted, participants were able to fill in the gaps of dissimilarity to recognize how the two disparate domains could be used in tandem to support their success on the tests. Works by Chiu and Lin and Hunter such as [32, 104] have also tested multiconstraint theory to support learning tasks across domains with positive results.

Programmers also explained that while crochet and programming have shared qualities, crochet is similar to just a subset of programming. Programming is more expansive and descriptive. P6 stated, "So the crochet test... the first difference that I saw was it was limited to some vocabulary while the programming test had no limits: could be anything. Other than that, I didn't see much difference. It... is a kind of algorithm, crochet, that you repeat some number of times, so it's very similar to programming or algorithms." P3 compared their experience learning the two subjects by saying, "If I need to compare, then I think crochet was easier to learn because in programming to get the basics you need to have more lessons than the crochet lessons. That's my feeling." These quotes suggest that drawing on crochet could provide a sampling of early programming ideas to novices; this data helped me answer RQ10.

The ease to which programmers could draw connections from a new domain to their own was illuminating. Conclusions drawn from work on schema induction by Gick and Holyoak may suggest that, having been exposed to many instances of puzzles in their own area of expertise, programmers could more easily recognize manifestations of these puzzles in the new domain of crochet [77]. Some, such as Fries et al., take this concept further by proposing a framework extending the use of analogies to concrete learning efforts [74]; Fries et al.'s work focused on helping students build connections between disparate domains partly by introducing simple representations and variation in data. Over the course of the three crochet learning sessions programmers were exposed to the basics of crochet with plenty of varied examples. The present study supports the findings of both Gick and Holyoak and Fries et al.'s work: programmers could offer many mappings from crochet to programming, but the basics of crochet which they learned seemed limited compared to their own area of expertise.

### 5.5.5 Participants Took Similar Approaches to Interpreting Crochet Patterns and Pseudocode

Participants from all condition groups shared similarities they noticed in the process of arriving at answers on each test. Many explained that finding the output of a pattern or program required them to sequentially trace elements in the routine. Non-programmer P68 said of the crochet test, "[it was] very number-based, and very detail-oriented. You have to specifically know what part you're on, and if you lose counts or anything, you'd have to start over. And I feel like that mixed a little bit onto the programming one, but obviously I didn't really know what was going on in that test, but it seemed like it was the same." Programmer P60 compared how they approached both tests, "so the way of interpreting or arriving at the answer, that is the step by step breaking down of the problem that was similar in both." Participants explained that there was a method to understanding the procedures on both tests, and though the contexts were different between the tests, that shared method could still be applied.

Tracking the effects of lines of code in a program is a core skill early computer scientists must develop to improve their debugging skills; results from a multi-national study of program tracing skills by Lister et al. found that it can also be a learning bottleneck for some students [147]. A study by Vainio and Sajaniemi found that novice programmers struggled with four main categories of difficulties in tracing: 1) single value tracing, 2) confusing function and structure, 3) inability to use external representations, and 4) inability to raise abstraction level [235]. While programming allows for storing variables beyond their use in loops, which is a relevant concern for challenges 1 and 2 listed above, challenges 3 and 4 have equivalences in crochet. External representations in programming are ways of organizing ideas and data beyond the lines of code themselves, which is part of a broader obstacle cited related to difficulties with abstractions. Crochet patterns share these two hurdles with programming. In interviews with crocheters I found that some participants could physically crochet, but were not familiar with interpreting patterns: P79 shared, "...I just know how to do it [crochet] manually. I don't know the, all of the words and letters that... they're associated with it." The crochet and programming tests exercised this need to organize and abstract operations:

in crochet these operations were physical, whereas in programming these were technical.

### 5.5.6 All Condition Groups Equated Both Tests to Math and Causal Relationships

Participants used subfields of mathematics to describe both the similarities and differences between crochet and programming. Participants tended to equate crochet to arithmetic or algebra, and programming to logic. When describing how they thought they performed on the crochet test, non-programmer P7 stated "...I don't want to say equations, but that's the best word I can come up with..." non-programmer P9 shared, "The difference is the crochet tests had more calculations. Addition, subtraction, multiplication... but the programming test was more intuitive—understanding codes—and it's logical also but there was no calculation. Both involved letters and numbers and maybe some special symbols..." Non-programmer P11 explained, "Crochet felt more like algebra, and the coding was kind of [like] critical thinking or logics. And I felt like those were very different things. One's more straightforward." Responses such as these helped me answer RQ11: what were people's impressions of programming after being exposed to crochet?

Programmers also noticed this relationship, with P55 sharing, "They both required logic, but the crochet one was more, mathematics inclined for me. I had to do a lot of summing in multiplication and the programming tests required more logical understanding of variables and... data structures." Programmers also recognized that while there were similarities between the two tests, the programming test required more thought, with P53 suggesting that their background in computing could not guarantee a perfect score, "I think I did good because I have some coding experience... some of the questions were a bit tricky, but I had seen them many times before, so I hope I did well." These associations helped me answer

RQ10.

Understanding whether individuals could recognize these logical similarities was a core objective in designing the present study. While interpreting code requires more study, practice, and precision than reading crochet patterns, participants suggested that crochet was a more forgiving exercise of the same logic used in programming. Rather than using crochet patterns as a one-to-one mapping to teach programming, which could be possible at the elementary level, patterns could serve as a springboard for students to further explore other logic-based activities.

### 5.5.7 Visual Aids Were Desired for the Crochet Test

Non-programmers who learned with gestures shared the benefits of their hands-on experience with crochet; P7 explained, "I don't know exactly what the variables are [in programming]; I had a hard time visualizing it. Whereas with the crochet, I could visualize it and I was like counting through the steps... I'm a very visual person, especially with math." This statement goes back to the need to build external representations in programming which Vainio and Sajaniemi found to be a challenge for novice programmers [235]. The lack of non-textual cues in programming can be a hurdle in creating visual abstractions, whereas the presence of multimodal cues in crochet for those who learned with gestures may have helped participants feel more confident during the tests. Interestingly, six of the nine programming test questions had visuals, compared to one question on the crochet test. These visuals included maps to be used in interpreting some navigation-related pseudocode, and portions of code circled to highlight organizational similarities. P33 of the same condition group made a similar assessment of the two tests, implying crochet was easier to visualize: "the major difference was the clarity and the ability to visualize it." Why is it that individuals who learned with gestures said that crochet was easier to visualize than programming when the programming test had more visual cues than the crochet test, and crochet visuals were not required to ace the test? Perhaps the value in physically learning crochet wasn't the visuals, but recognizing the context and meaning of the abbreviations in the patterns. Similar results were found by comparing rote memorization to semantic mapping in a study on foreign language learning by Badr and Abu-Ayyash. Badr and Abu-Ayyash's work showed that semantic mapping produced significantly higher test scores for students than the rote method [15], demonstrating that visuals and context certainly play a positive role in learning. As Balsam and Tomie succinctly stated, "all learning occurs in context" [18]. When the learner is increasingly exposed to new information through a variety of modalities, familiarity and comfort with the information begins to develop.

Non-programmers who didn't physically learn crochet considered the benefits of that missed experience, with P63 stating "...but doing it, I feel like, is a lot different than knowing what you're supposed to do." What did programmers who didn't learn how to physically crochet think of the perceived value of the visuals? Programmer P47 shared, "Yeah, the [crochet] test was more visual and more closer to what I can do with my own hands. Whereas the programming test was more on what happens on the system; it was finding out something out of an array..."

### 5.5.8 Limitations

While the present study's design was grounded in embodiment theory and applications thereof, some experimental factors could have been more controlled. For one, while the programming test was derived from a standardized test on elementary programming, some participants with programming experience expressed they had some difficulty on the test. In hindsight, a shorter variation of the test could have been given as a screener before assigning individuals to the experienced programmer condition groups. Additionally, the inclusion of experienced crocheters brought about complications in qualifying crochet experience. While knowledge of crochet patterns was fundamental to succeeding on the crochet test, to some in the experienced crocheter group the test became something like the programming test became to non-programmers, an exercise of piecing together new information to draw conclusions. Screening for an ability to read crochet patterns in the individuals who had no learning interventions could have remedied this. Future work should take care to develop screeners for experience on broad subjects such as the ones investigated in the present study.

## 5.6 Conclusion

In this chapter I explained my motivation to bring computational thinking to wider audiences and outlined my experimental design and research questions to this end. I collected both quantitative and qualitative data to provide a holistic picture of how people perceived their abilities in, and related the characteristics of, patterns in the art form crochet and computer programming and algorithms. I found learning interventions with gestures improved the average scores of a subset of programmers and non-programmers on the crochet and programming assessments when compared to experienced crocheters with varying degrees of programming experience. I observed a significant positive statistical correlation between scores on the two tests across all participants. In the interviews I uncovered specific mappings between elements of introductory computer science and crochet. Finally, I discovered similarities in the approaches participants across groups used to interpret and solve the problems on the two tests.

# Chapter 6

# Societal Impacts

As Lyytinen and Yoo suggested, technology now serves us in all areas of life [152]. As today's technologies are increasingly applied by researchers such as Civit et al., Bai et al., and Cetinic and She to some of the most subjective activities of our existence—such as creating [30, 34] and explaining art [16]—there is a need to assess where and how technology can be successfully applied here. In this body of work, I presented three studies that sought to understand how technology can be used to capture and apply embodied knowledge in art to support artists' creation and dissemination processes and further interdisciplinary educational objectives between the arts and sciences.

With the recent introduction of GenAI as outlined by Fui-Hoon Nah et al. in [75], and the wide usage of sensors to capture details of our physical presence and environment as explained by Swan in [223], society asks how these technologies can help us fulfill our subjective needs. This body of work seeks to understand how these technologies can lead us towards reaching our goals of creating and communicating art, while also illuminating possibilities to apply art procedures and abstractions to reason about technology.

The societal impacts of this work can inform decisions made in industry on how art can be created and used by technology. Companies today are eager to find novel uses for technology. Though the capabilities of GenAI and sensors are extensive, how consumers perceive the roles these technologies can meaningfully play in their lives is paramount to their adoption. One can find numerous examples of products which utilized the latest technologies, but failed to succeed in the marketplace because they did not align with consumers' values and expectations. Technologies today can accomplish creative tasks, but do people want them to? If so, how can they be designed well?

I studied how technology could help artists communicate and enhance the process of creating art by applying embodiment theory using sensors to build a prototype spatial sonification system which was central to a participatory design study described in Chapter 3. In Chapter 4 I explained how I applied AI and Non-AI elements to augment a live dance performance in order to understand the limits and biases surrounding technology's use in artmaking. Finally, in Chapter 5 I described a study where I taught a subset of embodied procedures and written instructions found in crochet in order to understand whether art can be used to introduce and improve analytical thinking skills in a technical field like computer science.

The present body of work focuses on building a stronger bidirectional relationship between computing and art. Chapter 2 highlighted some of the most impactful points of computing history, and how these have contributed to our production and consumption of art over the past several decades. Our reliance on computing to help create art has shifted dramatically over this period, with the recent introduction of LLMs to support GenAI causing some to question whether computing is encroaching on art. Our society has already established that art is important; we would not be so keen on using our most powerful technologies to create it, otherwise. Unfortunately, the knowledge that comes with creating art has not received as much attention compared to the resultant finished products. What we now have is a weak bidirectional relationship between technology and art, where computing heavily influences art, but art has little impact on computing. I sought to strengthen art's weaker influence on technology by exploring 1) where technologies are welcomed in art (in Studies 1 and 2), and 2) how art can be used to advance computing objectives (in Study 3).

Study 1 revealed, by way of technology, an uncanny valley where mapping artistic procedures through quantitative measures became unsettling for artists. I found that the physical operations of creating art are simply one small component of the process as a whole, and calling the artist's attention to this mechanical process through sound can color the confidence they have in their craft. Tangentially, participants of this study could clearly describe how they thought the mute artistic activity should sound. Whatever prompted participants to offer these suggestions highlights the importance of the gestalt of creating art, which carries intrinsic emotional and perceptual capital clearly understood to the artist, but not easily received by the audience.

This importance of perception informed the design of Study 2, where I withheld how a technologically-augmented dance performance was developed to understand whether audience members had biases against how different forms of technology were used to create art. I found there to be statistically significant differences in how audience members evaluated the creative merits of the work that was created using GenAI when they were told about the use of technology at different times. Complementing these results with focus group data, I found that audience members qualified the survey results better in discussions following the performances. It was not that they wanted less technology in the performances; rather, they wanted to hear more from the performer and understand what drove her to create the work. The problem did not seem to be a lessened demand for technology in this domain, but rather a desire for a recentering of the relationship between art and computing in creative works. These results returned me to my greater objective for carrying out this body of work: to build a stronger bidirectional relationship between art and computing by shining a light on what art can do for technology.

In my final study, I wanted to investigate how learning to make a particular type of art might improve performance on another logical thinking task—interpreting pseudo-code in computing. Quantitative results from the tests showed a significant positive correlation between scores on the art-based and pseudocode assessments for the majority of participants across condition groups. Test results also showed increased scores on both tests for a subset of participants both with and without programming experience as compared to experienced crocheters with no learning interventions. Qualitative results brought about specific examples of equivalent abstractions found in programming and crochet, along with similar participant perceptions of the two assessments as logical exercises across all participant groups. Furthermore, methodologies for arriving at the answers on the two tests were shown to be similar for programmers and non-programmers, with individuals who experienced the learning intervention without hands-on crochet activities expressing that visuals could have helped them on the crochet test despite the test lacking any questions that required visual or tactical understanding of the procedures.

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# Appendices

# Appendix A

# Cro-Create Study Materials

## A.1 Novice Crocheter Focus Group Questions

- What was most difficult about learning crochet?
- Do you think adding sound feedback would help in learning crochet?
- What strategies did you use to help you make the gestures?
- Was there anything that felt unclear or confusing to you?
- What fingers did you use most to learn crochet?
- What did you do when you made a mistake?
- How did you feel when you made a mistake?
- What do you think would have been most helpful to you in learning crochet?

## A.2 Experienced Crocheter Focus Group Questions

- How would you envision crochet sounding like?
- What movements and fingers are most important in crochet?
- Do the movements and utilized fingers vary greatly from person to person, or are they generally the same?
- What strategies would you take to teach someone crochet?
- Have you ever taught someone crochet? What challenges did you face?

• What are your thoughts on Cro-Create after using it?

• What did you like and what didn't you like about Cro-Create?

## A.3 Sonification, Audio Technology, and HCI Experts Interview Questions

• What is your professional background?

• What led you to be interested in (auditory displays and sonification/music technology/human-computer interaction)?

• Do you teach students?

• In your experience, what do you think is the most difficult concept or idea you have had to teach?

• Have you ever had to teach someone a task that required muscle memory or fine hand gestures?

• Do you have formal training in music?

• Do you think formal training in music would help in developing a sonification?

• In focus group sessions of this study, participants envisioned the system not as a teaching tool, but as a way to complement in-person or distanced social interaction. Did any particular use cases come to mind when I explained the system?

• Would you say that the use case affects the way the sonification should be designed?

• Is it acceptable to conditionally incorporate features in the sonification? (this was only asked of those experienced in sonification)

• Should the number of users be considered when designing the sound?

• In Cro-Create, I classified the gestures and used this information to augment the sound. Should the fact that the dataset was classified by a computer model impact the sound design?

• In crochet, some fingers are more important than others in creating a stitch. Likewise, the crocheter's dominant hand has a greater influence on the outcome than the non-dominant hand. Should this be taken into account when developing the sonification?

# Appendix B

# Technologically-Augmented Dance Study Materials

## B.1 ChatGPT Prompts

*Prompt for Scene 1*

- If I had to make petals of a painting move according to the respiratory rate of a dancer how should I map this respiratory rate to the petals?

*Prompts for Scene 2*

- If I had to make waves move according to a continuous stream of three probabilities representing how close a dancer's movements are to one of three movements, how should I map the three continuous probabilities to the wave movements?

- If I had to make melodious sound according to a continuous stream of three probabilities representing how close a dancer's movements are to one of three movements, how should I map the three continuous probabilities to sound? Please give me details on pitch and tempo.

- What pentatonic, minor, and chromatic scales should I use?

- What octaves should I use for the C major pentatonic scale, the A minor scale, and the chromatic scale from D to A if I will be using them together? What instrument should I use to complement graceful dancing?

*Prompt for Scene 3*

- If I had to make stars in a night sky change according to a continuous stream of data representing a dancer's respiratory rate how should I map this respiratory rate data stream to the stars?

## B.2 Audience Survey

All survey questions were asked of all audience groups unless otherwise noted. All questions were answered on a Likert scale from (1 - "Not at all" to 5 - "Absolutely") unless otherwise noted.

**Performance Related Questions - Visuals** *Throughout the performance, we projected various visuals as the dancer performed. Please answer the following questions based on the performance you just watched.*

- I paid attention to the visuals.
- The projected visuals were pleasing.
- The projected visuals complemented the performance.
- The projected visuals enhanced the performance.
- The projected visuals made sense in the context of the whole performance.

- The projected visuals demonstrated artistic merit.
- The projected visuals were creative.
- The projected visuals seemed meaningful.
- The projected visuals were distracting.
- The projected visuals appeared random.
- I think I would feel the same way about the performance if it didn't have visuals.
- I tried to see if there was a pattern in the visuals.
- I wondered what caused the visuals to change.
- Which of the following do you feel to be the most accurate representation of the performance? (Question asked only to those in the "Tell After" condition) (Likert scale ranged from: 1 - "The visuals mostly seemed to guide the dancer." to 5 - "The dancer mostly seemed to guide the visuals.")
- If I knew exactly what the visuals represented, I think I would enjoy the performance more. (Question asked only to those in the "Tell After" condition)
- I thought about how the visuals were created.
- I wondered why the visuals were chosen.
- I tried to make a connection between what the dancer was doing and the visuals.

**Performance Related Questions - Sound** *In part 2, when we showed the wave visuals, there were some sounds that you heard during the performance. Please answer the following questions about this audio you heard.*

- I didn't pay attention to the sound in part 2.
- The sound in part 2 was pleasant.
- The sound in part 2 complemented the performance.
- The sound in part 2 enhanced the performance.
- The sound in part 2 fit with the other sounds in the performance.
- The sound in part 2 demonstrated artistic merit.
- The sound in part 2 was creative.
- The sound in part 2 was meaningful.
- The sound in part 2 was distracting.
- The sound in part 2 seemed random.
- I think I would feel the same way about the performance if it didn't have sound in part 2.
- I tried to see if there was a pattern in sound in part 2.
- I was curious about why the sound in part 2 changed. (Question asked only to those in the "Tell After" condition)
- Which of the following do you believe to be the most accurate representation of part 2 of the performance specifically? (Question asked only to those in the "Tell After" condition) (Likert scale ranged from: 1 - "The sound mostly seemed to guide the dancer." to 5 - "The dancer mostly seemed to guide the sound.")

- If I knew exactly why the sounds were chosen, I think I would enjoy the performance more. (Question asked only to those in the "Tell After" condition)

- I thought about how the sound in part 2 was created.

- I wondered why the sound in part 2 was chosen.

- I tried to make a connection between what the dancer was doing and the sound in part 2.

- I noticed a mapping between the dancer's movements and the sound in part 2. (Question asked only to those in the "Tell After" condition) (Response choices were "Yes," "No," "I don't recall.")

- Can you briefly describe what you think the mapping between the dancer's movements and the sound in part 2 might be? (Question asked only to those in the "Tell After" condition) (Answers were written responses)

## B.3 Focus Group

*Questions related to impressions* <u>*before*</u> *the performance*

[FOR THOSE WHO WERE TOLD ABOUT TECHNOLOGY AFTER THE PERFORMANCE]

- Before the performance started, what were you expecting the performance to be like considering it was advertised as a "technologically-augmented dance performance?"

- How did you think technology would be included in the performance?

[FOR THOSE WHO WERE TOLD ABOUT TECHNOLOGY BEFORE THE PERFORMANCE]

- What were your expectations of the performance after we told you how technology was integrated?

*Questions related to impressions during the performance*

[FOR THOSE WHO WERE TOLD ABOUT TECHNOLOGY BEFORE THE PERFORMANCE]

- Were you watching out for the aspects of the performance we told you were going to be technologically-augmented?
- What did you think about the projected visuals and sound during the performance?

[FOR ALL PARTICIPANTS]

- What did you think about the projected visuals and sound during the performance?

*Questions related to impressions after the performance*

[FOR THOSE WHO WERE TOLD ABOUT TECHNOLOGY BEFORE AND WERE IN THE AI VERSION AUDIENCE]

- Is there anything you expected to see when we told you we would use AI in the performance, but we didn't implement? What caused you to have that expectation?

[FOR THOSE WHO WERE TOLD ABOUT TECHNOLOGY AFTER THE PERFORMANCE]

- Did your impressions of the projected visuals and sound change after we explained how they were created?

- How did you feel about the entire performance after we explained that portions of the performance were created using [TECHNOLOGY]? Why did you feel this way?

[FOR THOSE WHO WERE TOLD ABOUT TECHNOLOGY BEFORE THE PERFORMANCE]

- Did the performance meet your expectations of a technologically-augmented dance performance? Why or why not?

[FOR ALL PARTICIPANTS]

- How do you feel about technology in art?

- Have you heard about artificial intelligence (AI) before today? Did you know that AI can create images and music?

- Do you see any downsides or concerns about using AI in art in general?

- Do you think images and music made by AI can be considered art? Why?

- Do you think AI is different from other technologies people have been using to create art and music, like Photoshop, Procreate, or GarageBand? How so?

- Do you think art made without technology (i.e., physical painting on a canvas or playing a song on a traditional music instrument) differs in creative or monetary value from art created with traditional digital artmaking technologies like Photoshop, Procreate, or GarageBand? How so?

- What do you think the purpose of art is?
- Can AI-made art serve the same purpose as human-made art? Can you expand on that?
- Do you think AI-made art can hold the same monetary value as human-made art? Why do you think that?
- Do you have any suggestions on how we can make the performance better?

## B.4 Interview Questions

- What goals did you want to reach with the performance?
- What was your inspiration for the performance?
- What is your understanding of the capabilities of technology?
- What do you think technology's role in art should be?
- Do you know about generative artificial intelligence (GenAI)? What are your impressions of it?
- Have you worked with technology in your practice before?
- What was it like working with technology in your practice? If so, what was it like?
- What were your expectations of GenAI while you were working with the technologist?
- How was the choreography of the performance developed?
- Did the technology impact the development of the choreography?

- How did it physically feel to work with the sensors during the performance?
- What were your impressions of the audience?
- What was it like to communicate with the technologist?
- How did you feel and what did you think when you experienced unexpected results with the technology?
- What do you feel dominated the process of developing the performance (i.e., you working around technology or technology working around you)? Explain.
- What do you feel dominated the performance itself (i.e., you were the main focus of the performance or technology was the main focus of the performance)? Explain.
- What is the extent to which you think technologists should learn more about an art form before working with artists?

# Appendix C

# Embodied Learning Study Materials

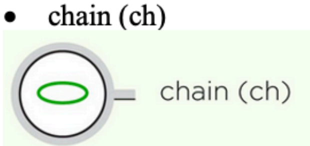
## C.1 Lesson Plans for Learning Crochet with Textual and Verbal Instructions

**Crochet Learning with Text**

**Session 1**

- slip stitch (ss)


- chain (ch)




- single crochet (sc)


Some notation:

- You can follow a crochet pattern using a visual or a textual pattern.
    - Textual patterns use abbreviations for stitches. These are universal with the minor differences (slip stitch can be abbreviated ss or sl st, for example), and the maker of the pattern will often provide a stitch glossary to reduce potential confusion.
    - Visual patterns convey just as much information as textual patterns and the denotation is similarly standardized.
- Any sequence of stitches in parentheses should be replicated the number of times designated immediately after it.
    - (ss sc) x5 means do a slip stitch then single crochet five times.
- An individual stitch that should be repeated can be written using the abbreviation of the stitch followed by the number of times it should be repeated.
    - sc 5 means single crochet five times.

Three little tests:

Can you explain what these do?

1. ss sc ss

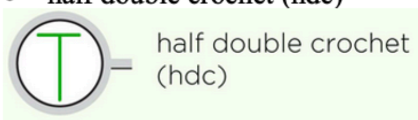
2. ss (ss ch ch) x3

3. ss ch ss (sc 5 ch) x3

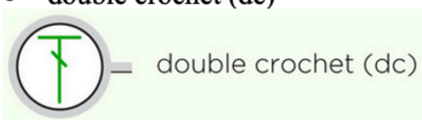
Figure C.1: Page 1 of the lesson plan

**Session 2**

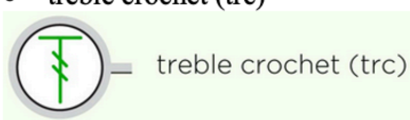
- half double crochet (hdc)




- double crochet (dc)




- treble crochet (trc)




<u>Some notation:</u>

- Sometimes patterns will include natural language mixed with stitch abbreviations. Here is an example:
    - sc in every other stitch
- If a pattern can be made in different sizes, the number of stitches required will be listed one after another in parentheses and separated by commas.
    - A particular sweater can be made in sizes XS, S, M, L, XL. The stitch count would be denoted (#, #, #, #, #) in a pattern.
    - sc (44, 47, 50, 53, 57)
    - You would single crochet (sc) 47 stitches if you wanted to make a size small.

<u>Three little tests:</u>
Can you explain what these do?

- ch 10
  sc 3 dc 3 sc 3
  trc 9

- This pattern comes in sizes (XS, S, M, L, XL)
  ch (20, 23, 25, 27, 30)
  hdc 2 (sc) x(16, 19, 21, 23, 26)

- ch 30
  hdc 4 (sc dc) x10 (sc hdc sc) x9

Figure C.2: Page 2 of the lesson plan

**Session 3**
Review with flashcards.
Explain these patterns to me.

ch 20
hdc 3 (sc 4 dc 3) x2 dc 2

This pattern comes in sizes (S, M, L)
ch (50, 60, 70)
hdc x(4, 5, 6) (sc dc) x(19, 21, 23)

Write your own pattern and explain it to me step by step.

Figure C.3: Page 3 of the lesson plan

## C.2 Lesson Plans for Learning Crochet with Gestural, Textual, and Verbal Instructions

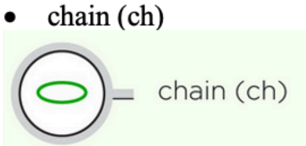
## Crochet Learning with Text and Gestures

**Session 1**

- slip stitch (ss)


**How to slip stitch (crochet)**
https://www.youtube.com/watch?v=8ir3v31G0sg

- chain (ch)




**How to make a foundation chain**
https://www.youtube.com/watch?v=GyMrH4Q8ceM

- single crochet (sc)


**How to crochet single stitches (sc) in the round**
https://www.youtube.com/watch?v=7FcRdxg0aeY

Some notation:

- You can follow a crochet pattern using a visual or a textual pattern.
    - Textual patterns use abbreviations for stitches. These are universal with the minor differences (slip stitch can be abbreviated ss or sl st, for example), and the maker of the pattern will often provide a stitch glossary to reduce potential confusion.
    - Visual patterns convey just as much information as textual patterns and the denotation is similarly standardized.
- Any sequence of stitches in parentheses should be replicated the number of times designated immediately after it.
    - (ss) x5 means do a slip stitch five times.
- An individual stitch that should be repeated can be written using the abbreviation of the stitch followed by the number of times it should be repeated.
    - sc 5 means single crochet five times.

Three little tests:
Can you explain what these do?

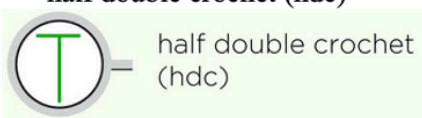
4. ss sc ss

Figure C.4: Page 1 of the lesson plan

5. ss (ss ch ch) x3
6. ss ch ss ((sc) x5 ch) x3

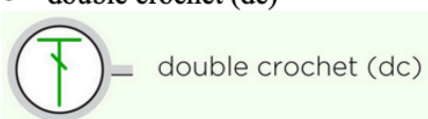
**Session 2**

- half double crochet (hdc)



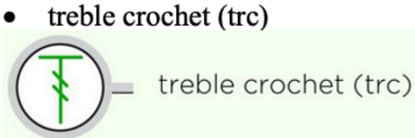

**How to do a half double crochet stitch (hdc)**
https://www.youtube.com/watch?v=f9C1C21MNiM

- double crochet (dc)




**How to do a double crochet stitch (dc) - step-by-step tutorial**
https://www.youtube.com/watch?v=a1whu6Gub1M

- treble crochet (trc)




**How to treble (or triple) crochet (tr)**
https://www.youtube.com/watch?v=3KtzjAAZHVY

Some notation:

- Sometimes patterns will include natural language mixed with stitch abbreviations. Here is an example:
  - sc in every other stitch
- If a pattern can be made in different sizes, the number of stitches required will be listed one after another in parentheses and separated by commas.
  - A particular sweater can be made in sizes XS, S, M, L, XL. The stitch count would be denoted (#, #, #, #, #) in a pattern.
  - sc (44, 47, 50, 53, 57)

Three little tests:
Can you explain what these do?

- ch 10
  sc 3 dc 3 sc 3
  trc 9

Figure C.5: Page 2 of the lesson plan

- This pattern comes in sizes (XS, S, M, L, XL)
  ch (20, 23, 25, 27, 30)
  hdc 2 (sc) x(16, 19, 21, 23, 26)

- ch 30
  hdc 4 (sc dc) x10 (sc hdc sc) x9

**Session 3**
Review with flashcards.
Recreate this pattern:
    ch 10
    sc 3 dc 3 sc 3
Create your own and explain it to me step by step.

Crochet symbol pictures sourced from :
https://mycrochetpattern.com/beginners/crochet-symbols-and-abbreviations/

Figure C.6: Page 3 of the lesson plan

## C.3 Crochet Test

Gestural Pattern Knowledge Transfer for Algorithmic Languages IRB #24-942

*Your participation in this study is voluntary, you are not required to participate, and you can stop participating at any time without any negative consequences to you.*

***Crochet Test***

1.
sc 3 (trc 3 hdc 3) x9

What is the 12th stitch in the pattern above?

a. sc
b. trc
c. hdc
d. There wouldn't be a 12th stitch.

2.
(S, M, L)
dc x2 (sc 2 hdc 3) x(1, 2, 3)

If I was making a size medium, what would my 11th stitch be?
a. dc
b. sc
c. hdc
d. There wouldn't be an 11th stitch.

3.
How would I write a pattern to alternate single crochet (sc) and double crochet (dc) stitches for sizes small, medium, and large if size small took 30 stitches, size medium took 36 stitches and size large took 42 stitches?
a.

(S, M, L)
(sc) dc x(30, 36, 42)

b.

(S, M, L)
(sc dc) x(15, 18, 21)

c.

(S, M, L)
sc (dc) x(15, 18, 21)

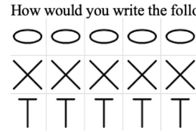
d.

(a) Page 1 of the crochet test

Gestural Pattern Knowledge Transfer for Algorithmic Languages IRB #24-942

(S, M, L)
sc dc x(30, 36, 42)

4.
How would you write the following visual pattern from top to bottom?



a.

ch sc hdc 25

b.

(ch sc hdc) x5

c.

ch 5
sc 5
hdc 5

d.

ch 3
sc 3
hdc 3

5.
How can I crochet a row of 15 single crochet stitches bordered by 2 half double crochet stitches on each side?

a.
hdc hdc (sc) x15 hdc hdc

b.

(b) Page 2 of the crochet test

Figure C.7: Questions 1-5 of the crochet test

Gestural Pattern Knowledge Transfer for Algorithmic Languages IRB #24-942

(hdc (sc) x15 hdc) x2

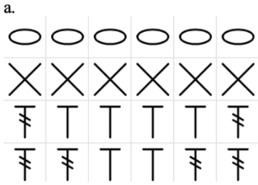
c.
(hdc hdc sc hdc hdc) x15

d.
(hdc) x2 sc (hdc) x2

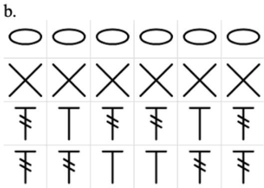
6.
What would the visual pattern be for the textual pattern written below?

ch 6
sc 6
trc (hdc) x4 trc
(trc) x2 (hdc) x2 (trc) x2

a.



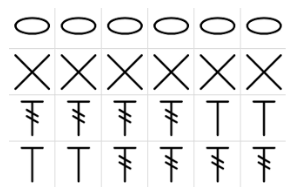
b.



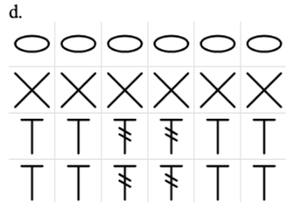
c.

(a) Page 3 of the crochet test

Gestural Pattern Knowledge Transfer for Algorithmic Languages IRB #24-942



d.



7.
How many stitches would this row have?

(sc 2 hdc 5) x2 (sc) x3

a. 12
b. 60
c. 23
d. 17

8.
How many stitches would this row have?

trc 2 ((sc trc) x3 (trc) x2) x2

a. 20
b. 24
c. 9
d. 18

9.
(XS, S, M, L)
trc x(4, 5, 5, 6) (sc hdc dc sc) x(12, 13, 15, 16)

If I was making a size small, what would my 11$^{th}$ stitch be?

(b) Page 4 of the crochet test

Figure C.8: Questions 5-9 of the crochet test

Gestural Pattern Knowledge Transfer for Algorithmic Languages IRB #24-942

a. trc
b. sc
c. hdc
d. dc

Figure C.9: Page 5 of the crochet test

## C.4 Programming Test

Gestural Pattern Knowledge Transfer for Algorithmic Languages IRB #24-942

*Your participation in this study is voluntary, you are not required to participate, and you can stop participating at any time without any negative consequences to you.*

***Programming and Algorithms Test***

**1.** What will the following algorithm display?

a ← 13

b ← 17

a ← a + 1

c ← a / 7

DISPLAY(c)

DISPLAY(a)

DISPLAY(b)

A. 2 14 17
B. 13 17 5
C. 2 12 2
D. 14 17 2

**2.** What will the following algorithm display?

a ← 13

a ← 17

a ← a + 1

DISPLAY(a)

A. 13
B. 17
C. 18
D. 19

(a) Page 1 of the programming test

Gestural Pattern Knowledge Transfer for Algorithmic Languages IRB #24-942

**3.** What will the following algorithm display?

a ← "Milk"

a ← a + "Cookies Soda"

a ← a + "Chips"

b ← a + "put them in a bag so you know they stay crisp"

DISPLAY(b)

A. Milk
B. Milk Cookies Soda
C. Put them in a bag and they stay crisp
D. Milk Cookies Soda Chips put them in a bag so you know they stay crisp

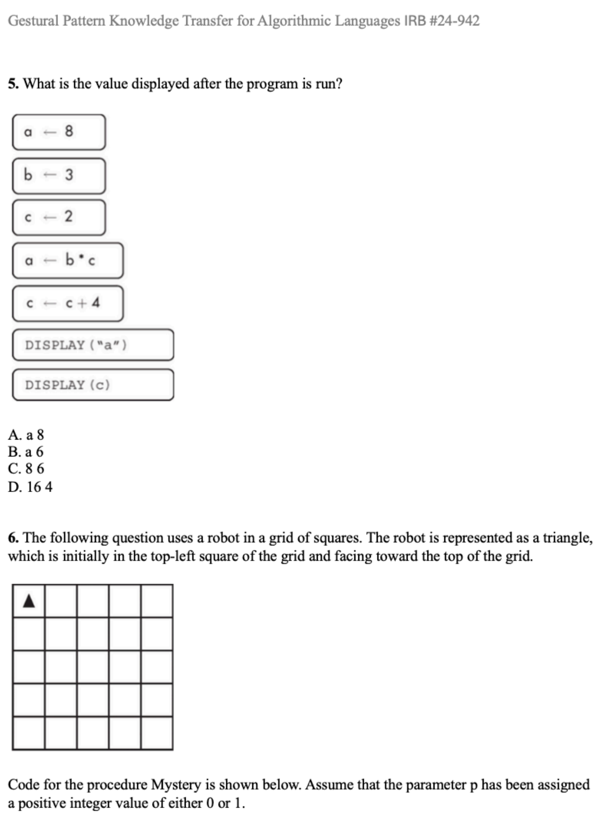
**4.** What is the value displayed after the program is run?

```
a ← 8
b ← 3
c ← 2
a ← b * c
c ← c + 4
DISPLAY ("a")
DISPLAY ("c")
```

A. a 8
B. a c
C. 8 6
D. 16 4

(b) Page 2 of the programming test

Figure C.10: Questions 1-4 of the programming test



Gestural Pattern Knowledge Transfer for Algorithmic Languages IRB #24-942

**5.** What is the value displayed after the program is run?

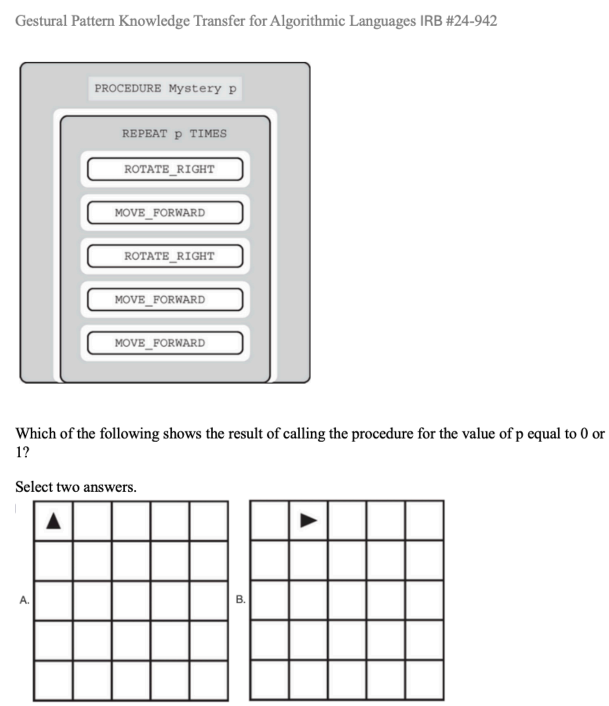
```
a ← 8
b ← 3
c ← 2
a ← b * c
c ← c + 4
DISPLAY ("a")
DISPLAY (c)
```

A. a 8
B. a 6
C. 8 6
D. 16 4

**6.** The following question uses a robot in a grid of squares. The robot is represented as a triangle, which is initially in the top-left square of the grid and facing toward the top of the grid.

Code for the procedure Mystery is shown below. Assume that the parameter p has been assigned a positive integer value of either 0 or 1.

(a) Page 3 of the programming test



Gestural Pattern Knowledge Transfer for Algorithmic Languages IRB #24-942

```
PROCEDURE Mystery p
    REPEAT p TIMES
        ROTATE_RIGHT
        MOVE_FORWARD
        ROTATE_RIGHT
        MOVE_FORWARD
        MOVE_FORWARD
```

Which of the following shows the result of calling the procedure for the value of p equal to 0 or 1?

Select two answers.

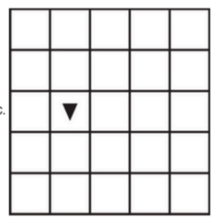
A.

B.

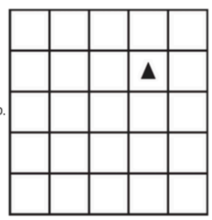
(b) Page 4 of the programming test

Figure C.11: Questions 5-6 of the programming test

C.



D.



**7.** The following code segment is intended to find the maximum.

```
PROCEDURE Mystery list
  max ← list[1]
  FOR EACH item IN list
    IF (MISSING CODE)
      max ← item
RETURN max
```

Which of the following code segments can replace MISSING CODE to make the procedure work as intended?

A. max > item
B. max = item
C. item > max
D. max >= item



**8.** The following code segment is intended to switch the values of x and y (assume x and y have already been initialized).

```
x ← y
y ← x
```

What can be done to make the code segment work as intended?

A. Add "temp ← x" above "x ← y" and replace y ← x with y ← temp
B. Nothing, the code works as intended
C. Add "temp ← x" below "x ← y"
D. Add "temp ← y" above "x ← y"

**9.**

```
PROCEDURE Mystery (number, list)
  x ← 0
  FOR EACH item IN list
    IF (number = item)
      x ← x + 1
RETURN x
```

What is the purpose of the procedure above?

A. To find the amount of items in list
B. To find the amount of items in list that are equal to number
C. To find the amount of items in list that do not equal number
D. Nothing, compile-time error

(a) Page 5 of the programming test

(b) Page 6 of the programming test

Figure C.12: Questions 6-9 of the programming test

## C.5 Semi-Structured Interview

*Questions on beliefs in abilities and success in activities:*

- Did you think you could succeed on the crochet test?

  Why or why not?

  How do you think you did on the test, from 0-100%?

- Did you think you could succeed on the programming/algorithms test?

  Why or why not?

  How do you think you did on the test, from 0-100%?

- Do you think you could get better at crochet?

- Do you think you could get better at programming/algorithms?

*Questions on motivation and interest in activities:*

- Could you see yourself continuing to learn crochet?

  Why or why not?

- Could you see yourself continuing to learn programming/algorithms?

  Why or why not?

*Questions on similarities and differences in activities:*

- What differences did you see in the programming/algorithms test versus the crochet test, besides the subject matter itself?

- What similarities did you see in the programming/algorithms test and the crochet test?