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K-12 Curriculum and Robotics to Address the Workforce Shortage and Advancement of Computing

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Abstract

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Novel contributions for computing and robotics requires a workforce with content mastery. However, current challenges of access, education, and discernment of the problem space, have resulted in a workforce shortage. The purpose of this master's thesis work is to contribute toward mitigating this shortage using two approaches, (1) development of instructional materials and content to teach K-12 students introductory concepts of computing and robotics and (2) a literary overview of human-robot interaction (HRI). The lesson was implemented in K-12 classrooms to measure if students' interest and attitudes toward engineering increased after participating in the lesson. Further, it provides foundational content and low-cost materials for novice K-12 computing educators using a physical robot-arm and coding blocks for students to concretely experience creating programs. Given our preliminary findings, these kinds of K-12 experiences may serve to stimulate students educational paths toward professions in computing and robotics. For HRI, we delineate key factors that constitute effective operation and integration of robots in everyday human environments, namely embodiment, situatedness, morphology, and communication as its absence has created ambiguity in research methodology, results, next steps, and research validity. Lastly, we extend this discussion to the subfield of machine learning.

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Chapter 1

Introduction

The purpose of this master's thesis research is to explore foundational knowledge in computer science and robotics for applications in K-12 engineering education and to provide a comprehensive understanding of foundational concepts of human-robot interaction (HRI) that aid innovation in robotics. This is a critical step in the goal of generating technological advances, meeting workforce demands and diversification, and democratizing the fields of computing and robotics, and its increasingly prominent subfields, e.g. artificial intelligence (AI) and machine learning (ML). Conducting computing and robotics research that produces technological improvement and innovation requires talent that has mastered computational knowledge and statistical learning [2, 3]. Because computing and robotics are being rapidly adapted for various industries, an additional need is that this labor pool needs to have the ability to take on new and arduous problems for different applications. This thesis will provide an overview of computing and robotics K-12 engineering education using research based educational practices and foundational computing curriculum. We will also provide an overview of core robotics concepts and their discernment for effective HRI. Both of these topics are necessary in the pursuit toward mitigating challenges of future technological advances, workforce demands and diversification, and to democratize the fields of computing and robotics.

1.1 Motivation

Within the context of robotics, our research goals involved evaluating and synthesizing the current state of the field to contribute to the larger body of work in HRI. This involved an analysis of past and current literature for clarification and direction of future HRI research by identifying common grounding of terminology – embodiment, situatedness, and morphology –, critical questions that shape and focus the field's investigative goals, and explicit delineation of key robotics concepts to make strides toward effectively integrating robotics in human's day to day lives. These terms form the key elements of robotic design for the construction of robots that effectively operate and interact with people in dynamic and unpredictable environments. Clarification of this terminology and concepts is necessary as its absence has created ambiguity in research methodology, findings, next steps to fill gaps in HRI research, and overall research validity. Providing explicit descriptions of terminology using previously conducted research as justification, equips the HRI community with a comprehensive basis for understanding how and why to construct studies in the HRI field using the recommended findings. As this foundational content is critical to gaining in depth and breadth of knowledge about the robotics field, this contribution served as an introductory book chapter in a collection of works on the technical and social landscape of HRI [4].

Within the context of our investigative works in education, a journal article and conference paper, we sought to implement, distribute, and evaluate a lesson on computational thinking for K-12 students through robotics [5, 6]. This lesson's curriculum is a derivation and extension of research based education practices and foundational computing curriculum [7]. The aim of this work is to help steer educators' efforts in offering computing concepts at K-12 grade levels through access to materials and project-based content that positively impacts students' current engineering identities for future academic and/or career interest in engineering. Developing a lesson on fundamental computational thinking concepts is significant for two reasons: first, higher education has traditionally been the exclusive provider of computer science, making the subject inaccessible to younger audiences and K-12 educators; second, educators are provided with low cost curricular materials for students to interact and concretely experience what it means to program using a robot-arm and a tangible user interface.

As our industries' and our country's economic prosperity has become increasingly dependent on workers with programming skills, policy makers and educators have aligned in valuing the need to introduce K-12 students to computing and robotics.

However, many barriers have made this material difficult for K-12 educators to implement. The subject of computational thinking, or computer science, is not a subject that is accessible through teaching education programs, and it is a skill that has only recently become widely valued in K-12. These factors have obstructed the pace at which K-12 educators have been able to provide this content to their students. Developing an unplugged robotics lesson, "Robots and Sequences," contributes toward mitigating this issue. Moreover, as the various fields of engineering are afflicted with low representation of female students and traditionally underrepresented minority (URM) students, this lesson sought to increase exposure to engineering for students who have traditionally been underexposed to the subject.

More broadly, this introduction is a means of fostering engineering identity development and interest to encourage a more equitably represented population of students to pursue computer science degrees and careers. Further, this trend would result in a more diversified computing and robotics workforce. This sequence of conclusions are based in findings that have identified that underrepresented students are significantly more likely to pursue a computer science degree if they are provided access to this content in K-12 grade levels. Specifically, women are 10 times more likely and Black and Hispanic students are 7 times more likely to pursue a computer science degree [8]. By creating access to a lesson that is comprehensible for a teacher who hasn't previously gained computational knowledge, this research contributes to the larger goal of equipping K-12 educators with the needed content and knowledge resources to deliver these concepts to their students with expertise. Equitable access to computing and robotics education will ensure that the general public has exposure to content that will impact their day to day personal and professional tasks, and offer exposure for future interest toward profession that will remain in high demand [9].

The context of education for this thesis also involves consideration for how ML can be brought to the K-12 education system. AI and ML are subfields of computing and robotics that currently remain absent from the K-12 curriculum. These subfields are major contributing factors to the workforce demand in computing and robotics [Manyika2017]. Given the recent investment in teaching programming in K-12 and considering that existing statistical content is offered at the secondary/high school level, integrating ML content is a conceivable and implementable goal. With ML being a key source to answering open problems across scientific and industrial fields [10], this need will only become an increasingly important demand for our the future workforce to find employment and to be able to make technological contributions [Manyika2017].

1.2 Summary

This thesis will describe how society can leverage the democratization of computing and robotics instruction in K-12 and the discernment of robotics research to address the workforce shortage, diversification, and technological advancements for computing and robotics. Chapter 1 will first describe the current landscape of computing and robotics, delineate what particular challenges have stemmed from this state, and how that has served to motivate our research. Chapter 2 will discuss the first approach we implemented, a foundational lesson of computing introducing students to sequences, debugging, and sensing/decision-making using a robot-arm and tangible user interface for programming. The chapter will provide motivation for the research, review related works, justify the pedagogical design, describe the lesson materials and its step by step process, and lastly provide the results of increasing interest toward engineering. Chapter 3 will discuss the second approach that includes an overview of the field of human-robot interaction, what gaps in research exist, and what the next steps for the field should be to move toward a more comprehensive understanding of how to effectively produce advances in robotics. Chapter 4 will be a discussion chapter to extend the implications of this research within subfields, including AI and ML. Lastly, Chapter 5 will provide a conclusion about the two approaches and their contributions.

Chapter 2

Human-Robot Interaction

The purpose of this thesis is to discuss our research in K-12 engineering education and HRI conceptual discernment to make contributions toward addressing the challenges facing the fields of computing and robotics: the workforce shortage and need for diversification, aiding technological advances and innovation, and democratizing computing and robotics. Our contribution for HRI stems from a book chapter containing a literature review of the field to aid robotics research and innovation that produces effective integration of robotics in social contexts.

This chapter served as introductory content for a reference on HRI theory and applications [4]. The discussion that follows is a delineation of key factors that constitute the effective operation and integration of robots in everyday human environments. This review serves to clarify and focus the work of roboticists and artificial intelligence

(AI) practitioners as its absence has created ambiguity in research methodology, findings, next steps, and overall research validity. With roboticists being an increasingly applied technology for solutions to product development and efficiency, it is imperative to identify the elements needed for successful integration of robotic systems in traditionally human only occupied spaces [9]. This has implications for typically applied spaces of robotics, like construction and manufacturing, but this also offers more effective means of constructing educational materials for K-12 students who need physical evidence of programming for higher engagement when learning computing [11].

Robotics have and will continue to take on an ever more ubiquitous presence in society and industries including transportation, healthcare, education, manufacturing, and customer service [12]. In each of these sectors, the interactions and successful cooperation between humans and robots depend on each party understanding the other's roles and needs. The design choices of roboticists, whether operational or aesthetic, impact the facilitation of interactions between a robot and human [13]. However, the general design of a robot depends on consideration of several factors including its embodiment, presence, morphology, sensing capability, and actuation. Beyond a robot's physical attributes, consideration for the use of the robot, the context of the interaction, and the biases and preconceived notions that individuals and groups have are critical to constructing effective operation. Design factors for the successful integration of robots into everyday human environments also include safety and dependability of a humanoid, as their failures can degrade the quality of an interaction [14], for both present and future exchanges. Knowing that these factors can have drastic effects on the perceptions humans have about robots, it indicates a need for quality robotic design grounded in robust research-based findings to produce adequate interactions between a robot agent and people. Robotic design is a multifaceted problem due to the critical end goal of HRI that robots be intuitively understood by people [15].

The consensus among roboticists is that using human-like form and functionality in robot design should facilitate human-robot interaction, as people are accustomed to interacting with one another [13, 16]. However, what is meant by form can be broad and highly variable as it includes facial features [16], the physical human-like silhouette of a robot, or a combination of the two, making form an often loosely-defined aspect of a robot. Recent design trends in robotics reinforce this notion and align with the evolutionary argument that, because they evolved to interact with one another, resemblance of robotics to humans should make our interactions with robots easier. But merit of this consensus renders skepticism as current research indicates that the spectrum of design choice is vast, complex, and is not limited to form. Embodiment research of artificial cognitive systems has mainly investigated the external features of robotics, but recent research of embodied cognitive science has evolved to include both the external design and the control system to achieve true cognition [17]. The form of a robot, or lack thereof, can have significant consequences for the degree to which people apprehend it and whether a person is willing to engage with it. As such, embodiment, situatedness, and morphology of a robot need to be considered beyond the mere functionality they provide, but also for the perception that these factors provoke during interactions with a robot. Ultimately, the goal is to identify a theory that delineates the robotic attributes that cause people to perceive robots more favorably [18] and consequently be willing to engage in HRI on a long-term and collaborative level.

2.1 Embodiment

The field of embodiment addresses the need to understand how robots effectively interact with people and the environment in which they operate. The definition of embodiment and its effects on HRI are elusive. However, insight into robot embodiment can help robot developers to be aware of the role physical interaction plays in robot behavior and how perceptions of a robot can be affected by its physical instantiation [19]. Several influential ideas have stemmed from studies discussing how embodiment relates to the development of cognition in human beings and how that might inform roboticists' research. This includes the foundational concept that cognition is dependent upon its relationship with interactions between the mind and body, that is, that the mind is inseparable from its physical experiences [20, 21].

The simplest definition of embodiment is the traditional biological definition of an organism with a bodily or material representation. However, embodiment has more recently evolved into a term that is applicable to computational machines and their place within the world. Pfeifer and Scheier [19] define it as follows:

Embodiment: "A term used to refer to the fact that intelligence cannot merely exist in the form of an abstract algorithm but requires a physical instantiation, a body. In artificial systems, the term refers to the fact that a particular agent is realized as a physical robot or as a simulated agent" (p. 649).

Encompassing both physical and virtual agents and connecting the body and mind are key reasons why this definition has become a integral part of the embodiment literature.

This perspective aligns with psychological research which states that human cognition evolved from dense and immediate sensorimotor interactions with the environment, thus understanding the mind requires evaluating its relationship to the physical interaction with the world [22]. Extending this idea, Brooks [23] early on noted that 'Intelligence is determined by the dynamics of interaction with the world' (p. 6). Similarly, Riegler [24] stated, 'A system is embodied if it has gained competence within the environment in which it has developed' (p. 347). Thus, it is not plainly the physical instantiation that defines embodiment of an artificial system, but what a system gains from interacting with its surroundings. Encompassing what is necessary, but not necessarily sufficient, has also become a major part of the embodiment discussion. Duffy and Joue [25] have offered a more comprehensive interpretation of the term:

- The ability to coordinate its actuator and sensor modalities to interactively explore its environment;
- Goal-oriented behavior on micro and macro levels;
- Bi-directional interaction between the agent and its environment;
- Bi-directional communication between the agent and other agents in the environment; and
- An understanding of the physics of the environment, e.g. gravitational effect and friction, to reduce internal environment representation loading by inferences" (p. 6)

Investigative discourse has led to the determination that there is a spectrum of weak to strong embodiment [25]. Duffy and Joue [25] argued that weak embodiment is operationalized when a robot's body is situated in an environment, but remains "a static abstraction of the world and not in the dynamic world itself" (p. 6). Meaning, the agent lacks integration with its environment. Integration is how strong embodiment, on the other hand, is achieved; as stated above, higher-degrees of embodiment promote "learning and adaptation." Additionally, there exists a distinction in perspective of those who view machines whose abilities include intelligence as mechanisms manipulated by their environments, versus AI cognition that develops through the interactions with its environment [26]. It is then important not to overlook embodiment descriptions of systems who react and learn from their environments as this added complexity is a non-trivial task of robotic design.

One early driving argument from two prominent sources Maturana and Varela [27] and von Uexküll [28] disputed that machines could ever resemble living organisms. The researchers argued that living entities are made up of components which continuously interact, regenerate, and evolve, while man made machines do not. Rather, the components comprising a machine are constructed independently of it and those components do not regenerate or evolve as parts of the system. Based on this notion, it seems obtaining robotic embodied cognition is unattainable.

Nevertheless, the field of embodied cognition has flourished. And though the above argument is uncontested, it seems that the level of life-like characteristics the aforementioned theorists, Maturana and Varela [27] and von Uexküll [28], described is not what most modern development of robotics and experimental research currently seeks to achieve. Instead, a robot's ability to function, interact, and react to their surroundings would currently suffice, as that in itself is an ambitious goal within the community's current understanding of artificial intelligent cognition. Therefore, some degree of embodied cognition is attainable and valid within biological and psychological fields, though not to the degree that living organisms experience.

Theoretical discussions, like the one above, have served to clarify how roboticists now define the field of embodied cognition [29]. More explicit understanding of its implementation has also been identified through experimental research of *functional* differences, such as the form a manipulator should take, which can range between a simple grabber to a more complex form that resembles that of a human hand [30]. Empirical work comparing robots to virtual agents, for example, has indicated social effects. Bartneck et al. [31] concluded that robotic embodiment has no more effect on people's emotions than that of a virtual agent, while animacy was correlated with perceived intelligence. Conversely, other empirical work has found the presence of a physical body has an effect on the interactions between a person and a robot [32]. This indicates the need for varied and more extensive research where social and functional differences between embodied and non-embodied agents are distinguished. Further, it is important to justify the benefits of a robot beyond the likely added cost of employing a robot system over a virtual agent for a given task. This is especially true for robotics with assistive applications [12], where the added cost of a robot platform should be justified by a larger client benefit [33]. Likewise, it has been demonstrated that embodiment has a positive effect on patient motivation [34] and task compliance [35]. Moreover, in-person interactions between a human and a robot have a greater effect on weight loss that using a non-embodied agent [36]. Specifically, a functional exploration of robot embodiment should examine the effect embodiment has on the perceived role of a robot [33], the trust one places in a robot [37], the perceived animacy or emotional capability of a robot [38], or the perceived intelligence of a robot [39]. The above studies indicate a need to discern how embodiment relates to different contexts. In the next section, we will disaggregate the embodiment of an agent from its situatedness to understand how the environment influences HRI.

2.2 Situatedness

In recent years, the robotics field has seen a surge in research in the area of situatedness, or situated AI, due to the need to understand how robots can be integrated into the variety of everyday human tasks. The concept of situatedness contributes greater complexity to the embodiment field as it is not only the physical space a robot occupies that influences interactions between humans and robots, but the context of those interactions also plays a role. Situatedness describes the context or environment in which a robot operates. Context refers to the location where a robot is placed (a hospital, an automobile manufacturing plant, a person's home), who the robot interacts with in the environment (a worker, an employee from a different department, a patient, a patient's family). More specifically, how the robot navigates verbal and physical interactions are dependent on its purpose. Situatedness is a concept derived from the field of human cognition. Lindblom [40] explained the need to examine the context of an AI for the following reason, "while a cognitive process is being carried out, perceptual information continues to come in that affects the environment in task-relevant way" (p. 626).

This statement indicates that it is not sufficient to design AI that operates in isolation from their environment as the location can change, the audience can change, or the nature of the interaction can change, and thus alter the intended action of the system. Rickheit and Wachsmuth [41] defined this robot's ability as robustness; an attribute that facilitates integrated meaning. They explained this notion from the perspective of a human being, where humans are not hindered by incomplete or garbled information due to their inherent robustness. That is, people can counterbalance disorder by relating information from multiple sources to generate integrated meaning, such as sense-making through language with the use of observational information and vice-versa. For robots to then reach at least adequate performance in everyday human spaces, it requires that roboticists account for the situatedness of their robot's design through some degree of robustness that will allow navigation in dynamic settings. A focus on situated interaction could examine the use of relative communication as in gestures [42] or deictic pronouns [43]. The use of deictic pronouns has had an effect on interaction quality [22]. Thus, taking into consideration the variability that exists depending on context, it has become increasingly critical to understand how this variability influences robotic design.

The benefit of developing situated AI is the facilitation of human-machine interactions to resemble those of human-human interactions [44]. This means that the goal of AI design is to enable a robot with the capacity to interact with a human in a manner that is perceived as familiar to a person, as in an interaction with another person. Language is one critical component of these interactions. Within a given environment, the meaning of language and the possible actions that can be carried out is limited because the context of an environment steers the meaning that can be extracted [41].

For instance, the actions a robot would need to carry out in using a “stapler” in a body shop would be very different from those in a hospital as the two “staplers” are significantly different in shape and application. Because robots are not currently able to distinguish between context, Rickheit and Wachsmuth [41] recommend designing robotics that are more specialized in the immediate future. Instead of placing the focus on a “universal” robot, the focus should shift to the deliberate development of a robot’s specific intended functions. In this case, the situatedness of a robot would drive its design and also change the meaning of the actions it takes in service of its goals. The dependency that a robot has on its environment is one reason why robot design should be specialized to a particular task [45], but it should do so while maintaining adaptability to the uncertainty of those environments [46].

One strategy proposed for the flourishing of research and design of situated AI is using an interdisciplinary approach. An interdisciplinary approach involves taking on different research perspectives and using research findings as springboards for current gaps in a field’s understanding. Turning to a study of organisms, Bechtel [47] states, “Biological mechanisms are always situated and dependent on their environments as well as in a critical sense distinct from them” [47]. This statement indicates that the mind and body need not be disassociated to achieve distinction in an environment. Moreover, despite the study being an analysis of organisms to understand the advantages in segregating component activities for modularity, the author advocates a mechanistic perspective, as roboticists use. Using an interdisciplinary perspective aided the conclusion and underscoring that organismic systems are integrated, not isolated, from their environment and should be understood as such. As the above study shows, an interdisciplinary approach may help steer research in unexpected and innovative directions that promote new research perspectives, for HRI that means new robotic design. In the discussion below we delve further into the topic of design and describe some of the design considerations that have been suggested and others that have been implemented to engage robots in real-world operations. This will help serve as a basis for future research directions of robotic design.

2.2.1 Design Choices for Situatedness

Similar to interactions between humans, a person forms hypotheses about the capability and actions of a robot during the initial exchanges of an interaction [33]. Pitsch [48] proposes roboticists equip robotic systems to make explicit their abilities for interaction during the early stages of an exchange with a person, thus establishing the necessary conditions to accomplish effective human-robot interactions. Conversely, the mismatch between observed and actual robot capabilities can create interaction challenges [49]. A design strategy that depends on human competencies of sense-making and adaptability would also benefit the system in a highly variable and unpredictable environment [48]. Though humans have the ability to make sense of their surroundings and infer greater understanding about a system's functional capacity, in comparison to a robotic system, this idea may not be viable in contexts with vulnerable populations, including hospitals or working with children. Thus, taking into consideration the common variables in the situated space where a robot will operate is imperative prior to implementing its design.

Suchman [50] proposes a different approach, stating that human-machine interaction is "less a project of simulating human communication than of engineering alternatives to interaction's situated properties" (p. 185). Rather than taking a design perspective of imitating human-to-human interactions with literal substitutions carried out by the robot, robotics design should engage in engineering alternatives to how humans accomplish particular goals, as the system is different and accesses different processes to achieve a goal. For example, based on current expectations of humans in assembly worker positions, Rickheit and Wachsmuth [41] list the following functions as necessary for a robotic system to effectively operate alongside other workers in that environment. They include:

- perceiving audio, visual, and cognitive processes;
- speaking; and
- planning for execution of movement towards objects, e.g., object avoidance.

Researchers note that a robot worker, like a human worker, must be able to carry out the same functions as both individuals and members of a human-robot team. Given these objectives, design features that have been shown to generate effective interactions, based on the capacity of the robot, should be applied, rather than attempting to design a system that imitates the human worker. Therefore, studying the most effective operation for a robot, given the task goal, is the more appropriate technique in design as roboticists can then determine what components are necessary for the system and which are superfluous. A person may use their arms to carry a box, for example, but a robot might use a platform in the middle of its body or one attached to its "feet." This also highlights the need to consider operations and executions that might be available to a robot, but are not for humans, as these operations may enhance the integration of a robot within existing working groups and provide added benefits to human workers.

Rickheit and Wachsmuth [41] also highlight one critical component that necessitates a robot's high degree of adaptability, being able to work around people and as members of human-robot teams. These tasks include action executions such as grabbing and placing, but they more specifically involve maneuvering those actions around people and working collaboratively and in close proximity with people. This objective prompts an essential question, how can robots integrate into a social environment? Social environments necessitate that a robot be able to communicate with different kinds of people in a manner that accurately conveys to humans what the robot means. This faculty has been previously tested and shown to provoke difficulty of interaction when the robot is not equipped to manage unpredictable behavior. One study found that when a person interacted with a robot who provided information about a museum venue, the person perceived the robot's pointing gesture as 'misplaced' [50]. The misunderstanding with the robot was due to the robot trying to communicate direction when the person had not expected a physical action from the robot in that moment. Other issues exposed during this same study included the robot's inability to detect confusion by the human following the 'misplaced' response, which further depreciated the quality of the interaction between the human and robot [50].

To surmount the challenges of engaging robots in highly variable and unpredictable environments, design methods need further research within diverse settings. Moreover, taking into consideration the need to realize collaborative tasks and robot specific tasks (tasks that are uncommon to humans), the embodiment and situatedness of a robot should not only be reflected in its design and actuation capabilities. Instead, embodiment and situatedness should be embedded in the sensing and planning capabilities of the robot. In this way, communication can be facilitated to be implicit in nature, using features of the environment and the task to communicate intent and action [51], not explicit, as in communication through an interface which is more computer-like than human-like and non-interactive in nature [52]. The robotics field now widely agrees that it is necessary to equip robots with the ability to navigate their environment, so that they are able to carry out their intended tasks. Without the capacity to navigate and adapt to the diverse factors that will disturb a robot's path, practical functionality will remain unrealistic for day-to-day applications in real-world or uncontrolled spaces. This engineering, however, is not a small undertaking as it requires that a robot have the capacity to instantaneously account for variations in the environment and readjust its trajectory. Therefore, it is necessary to expand the empirical research that measures and isolates the design elements for navigating particular environments to provoke effective HRI.

2.3 Morphology

Morphology is a key factor of robotic design as the expectations people have when interacting with a system and influences the ease with which the robot carries out tasks [53]. A robot's morphology, or form, in both physical and virtual environments, is generally assigned using biologic inspiration and general guidelines, rather than research-based methods that have been shown to improve HRI [54]. Biologic inspiration of shape is generally of two designs, anthropomorphic and zoomorphic. Anthropomorphic forms (human-like) include humanoids and androids while zoomorphic forms (animal-like) include quadrupedal and hexapod robots. More narrowly, design considerations include characteristics like facial features, limb(s), height, mass, and abilities like carrying a payload, manipulating objects, and dynamically reconfiguring any of the aforementioned characteristics based on task needs. Decisions about robot morphology have only become more critical in robotic design as the embodiment argument that a machine's intelligence and physical instantiation are necessary and sufficient to co-develop for successful HRI has gained widespread support. However, currently only limited research exploring how and why morphology and intelligence should be co-optimized exists [30].

2.3.1 Anthropomorphism

The most dominant of the morphological areas is in anthropomorphic design. Anthropomorphism is the study of human-like characteristics applied to non-human objects [18]. The implementation of features that resemble humans in robotic design is due to the anthropomorphic literature's identification of positive effects on HRI [55]. For example, Złotowski et al. [18] study provided evidence that an emotionally expressive robot (using gestures and complementary sounds) is perceived as more anthropomorphic or human-like than one that is not emotionally expressive. Anthropomorphic features are distinguished from tendencies as features encompass the robot's form, while tendencies are concerned with how the features are perceived by humans [56]. Anthropomorphism may be a meaningful approach of design for effective HRI, but it is difficult to understand its current effect as anthropomorphic properties are often too distinct to allow for valid comparison between studies [55]. Specifically, the complexity and high design variability of anthropomorphic robots does not lend itself well to experimental comparison and challenges the degree to which it can be applied for effective HRI.

Despite the challenge of high design variability in anthropomorphic literature, some recent research has taken place to compare components. Mavrogiannis et al. [15] compared four robotic arms with a fifth normalized human arm to determine the human likeness of design with the assumption that the most similar design to a human arm is ideal. This study was also significant in its development of methodology, which the authors argue can serve future study's comparisons of similarity between their robotic arms and the ideal, or human, robotic arm. However, it is important to consider that this idealization based in biology may not be the best comparison. Instead, the comparison should be made with a system whose goal is comparable to that of the intended objectives of the compared arm. Similarly, Liarokapis et al. [57] proposed an open-source, easily reproducible, hand design with the aim that it have an efficient grasp for various applications. Although these studies and studies like them contribute to the understanding of how roboticists can more effectively construct robotic arms and hands, these studies have not addressed the effectiveness of designs in facilitating HRI.

One important consideration of anthropomorphic robotic design, therefore, is the degree to which a robot should take on human-like features to accomplish effective HRI. One prevailing reason is that robotic design should involve form dictated by function [56] for the purpose of making evident the robot's capacity for interaction and avoiding misinterpretations of its abilities. Furthermore, Duffy [56] argues that this ongoing approach to research of anthropomorphic design should lead to the identification of an ideal set of features that strike a balance between people's expectations and the machine's capabilities. For example, the aforementioned study of emotionally expressive robots also tested the influence of intelligence (responding correctly to a question in a quiz game), which had no effect on anthropomorphism [18]. The authors suggest that intelligence may not play as significant a factor in anthropomorphism as people might expect robots to possess intelligent qualities. However, the assessment used in this study may have been the limiting factor as the approach to measure humans' perceptions of robot intelligence was based on correct answers, rather than an ability to reason and craft judicious responses.

More generally, a need exists for HRI to investigate how the anthropomorphic design choices made by roboticists influence HRI, as the aim of HRI is that robotics be intuitively understood by people [15]. To accomplish a more comprehensive understanding of anthropomorphism, that is, a theory that delineates the robotic attributes that cause people to perceive robots more favorably based on their visual similarity with humans, this need must be addressed [18]. A significant limiting factor for anthropomorphic robot design choices lies in the lack of understanding of people's current perceptions and biases about robotics. This scarcity in research should be addressed in conjunction with the set of ideal attributes to achieve an in-depth understanding and effective implementation of HRI.

2.4 Conclusion

This thesis research seeks to contribute toward driving technological advances and innovation in computing and robotics, including the advancement of robotic learning systems. Additionally, this thesis seeks to contribute to the efforts of diversifying and reducing the workforce shortage and in democratizing access of computing and robotics. Throughout this chapter we have discussed the purpose of and the research that supports the need to integrate embodiment, situatedness, and morphology, especially anthropomorphism, in robotic design. Specifically, we understand that within the embodiment field there exists a need to discern the degree to which embodied cognition is attainable, the degree to which social and functional differences between embodied and non-embodied agents are distinguished, and how embodiment influences HRI in different contexts. We also identified the widely accepted idea that the dynamic nature of everyday interactions means it is necessary to equip intelligent systems with the ability to adapt and revise action based on the variability within an environment, namely that an intelligent system account for its situatedness. Without this capacity, navigating and adapting to unexpected and diverse factors that disturb a robot's path will limit its practical functionality and make robotic learning systems an unrealistic tool for day-to-day applications, limiting their advancement.

To facilitate HRI, robotic systems should make explicit their abilities for interaction during the early stages of an exchange with a person; using this approach can help establish the necessary conditions to accomplish more effective HRI [48]. This is especially necessary as prior research has found that human perceptions of what a robot's capabilities are can be mismatched when simply informed by observation, thus creating challenges between the human and robot that compromise the goal of the interaction [50]. More specifically, it is recommended that communication be achieved through facilitation factors considered to be implicit in nature and utilize features of the environment and the task to communicate intent and action [51]. For example, this might have implications for instructional robotics. If an instructional agent can communicate to learners what it is able to do with them to meet learning objectives, then students may be able to more effectively use and collaborate with the agent.

Lastly, anthropomorphic robotic design has been identified as a more effective approach to facilitating HRI [18]. But, as is the case for both embodiment and situatedness, the specific anthropomorphic properties that provoke increased effectiveness of HRI have not be identified due to the high degree of variability that exists for robot design [55]. Without a more robust literature base to discern the most effective forms of robotics within commonplace applications, it will be difficult to know if the applied robotic forms achieve the most compelling HRI. This discussion has served to delineate the key factors that constitute the effective operation and integration of robots in everyday human environments. The review offers clarity and focus for roboticists and AI practitioners of terminology and concepts needed to reduce ambiguity in research methodology, findings, next steps, and overall research validity. This knowledge also serves to determine the fundamental knowledge of robotics to introduce the future workforce to computing and robotics in K-12 grade levels and to decipher the necessary elements needed to advance these fields. Further, with subfields like ML being an increasingly applied tool for developing solutions and answering open scientific problems, it is imperative that these elements be identified for successful integration of learning systems in human-robot collaborative spaces.

2.5 Future Directions and Open Problems

Based on the above findings, it is evident that a comprehensive understanding of the distinctive design features that optimize HRI remains a pronounced need in the field of robotics. Because robots are inherently situated, in that they "occupy particular and specific real-world contexts" [58], making those design determinations is non-trivial. Robotic cognition is dependent upon material instantiation and on social and environmental interactions [58]. A comprehensive understanding then requires extensive investigation where varying degrees of embodiment, situatedness, and morphology are implemented. Moreover, this research should involve the investigation of both the disassociation and the interaction of embodied, situated, and morphological attributes. More broadly, there exists a need to expand empirical research that measures and isolates the design elements for navigation of particular environments.

The robotic research community also notes the need for future studies to involve highly controlled factors, such as comparing the same robot in several different environments and for different kinds of interactions. As more explicitly comparable investigations are conducted, roboticists will gain an understanding of the design elements that should be present based on the specific contexts in which their robot will operate and for the various tasks the robot will perform. Further, to steer the robotics field in a direction that helps determine the effects of embodiment and situatedness on robotic cognition, Spivey et al. [59] proposes future research involve the construction of "computational models that implement sensorimotor grounding as intrinsic to cognitive processes" (p. 1). The authors argue that a theory that isolates the various influences of the different kinds of embodiment will bring clarity to the work of roboticists. Lastly, future studies should involve the testing of robots in environments that reflect realistic use in order to simulate experiences with uncontrolled variables as they reflect the kinds of challenges the robot will encounter in real-world HRI.

Lastly, as we now understand that robots are more effective in human spaces when they are embodied, situated, anthropomorphic, expressive, and communicative, it would behoove the robotics and educational community to consider how these factors contribute to a more engaging learning environment for students. Because we know that students are more engaged with learning computing in K-12 grades when there exists concrete evidence for what they are programming, it may also be beneficial to identify to what degree embodied, situated, anthropomorphic, expressive, and communicative agents are needed to facilitate learning. Questions like, are students more interested in learning computing when their robot agent is anthropomorphized, are students more willing to struggle with difficult content when their agent is more expressive, and do students gain more of an interest in computing, robotics, or engineering when instructional robotic agents are situated and/or embodied?

Chapter 3

K-12 Computing and Robotics Instructional Materials and Content

The purpose of this master's thesis work is to make contributions toward mitigating the workforce shortage and lack of diversification, to aid the advancement of current technology, and to drive the democratization for the fields of computing and robotics. This chapter serves to outline the approach taken in the development and design of instructional materials and content for a lesson that teaches foundational concepts of computational thinking and robotics to K-12 students. This lesson taught middle school students and measured their interest and attitudes toward engineering, before and after the lesson. We sought to determine if students' interest and attitudes in engineering increased after participating in a computing and robotics lesson. If lessons like these can provide K-12 students with experiences that inform them about what computing and engineering careers might involve, it may be that instruction like this can increase the talent pool for a field currently challenged with an insufficient number of workers. Following is a description of the implemented lesson and its results, as well as a connection to how these early works can contribute to the broader thesis' goals. Lastly, we will discuss future directions for the integration of computing and robotics education, including the addition of machine learning in the K-12 curriculum.

As society has rapidly integrated software and learning systems across public institutions and industries, the economy's workforce development have necessitated a shift. Specifically, the absence of computer science education (CSE) in K-12 grade levels has led to a shortage of skilled Computer Science (CS) college graduates in an area whose workforce is increasingly in demand [60]. Lacking CS education may also be an element that has trickled into issues along the ML training pipeline as the lack of qualified programmers exacerbates the ability to quickly train machine learning practitioners, contributing to the shortage of data scientists in the US [9]. Moreover, the shortage trends in CS and ML are especially prevalent among traditionally underrepresented populations, including females, racial/ethnic minority populations, and low-income students [60]. A study by the National Science Foundation found low participation of women exists across engineering degree levels and fields and, further disconcerting, computer science bachelor degree attainment has seen a ten percent drop in the last two decades for women [61]. Similarly, underrepresented minorities' low engineering degree attainment has remained essentially unmoved for the last two decades, though computer science has seen a gain of almost six percent [60]. Calls for reform from educational stakeholders like the National Science Foundation are leading the conversation to correct the lack of CSE through the "CS for All" campaign [61]. Efforts to onboard CSE in K-12 have also involved collaborations by the National Science Foundation and the College Board to explicitly define core Computer Science Principles (CSP) and to create an Advanced Placement (AP) exam that allows students to earn college and high school graduation credits simultaneously [62]. Although these efforts offer some means of addressing the CS and ML talent shortage problem, they remain insufficient in educating the necessary workforce for the projected rapid integration of software and learning systems.

During the next decade, computing, robotics, and their subfields, e.g. machine learning, are key projected areas of U.S. economic development and labor force growth [9, 63, 64]. This growth places demands on society to equip its future workforce with the necessary knowledge and skills in computer science and engineering (CSE), robotics, and statistical learning. CSE and robotics education are subjects that have traditionally been exclusive to post-secondary institutions and widely inaccessible to K-12 students [65]. This is a critical drawback in the diversification efforts of STEM occupations as computing and robotics fields miss the opportunity to recruit women and traditionally underrepresented groups to the disciplines [][NSF 2015]. These lack of diversification trends are further perpetuated by challenges of access and resources: students' STEM and engineering interest are often set by middle school and because there until recently, there was limited accessibility of computing and robotics instructional materials for public educators [66].

This combination of factors limit the opportunities that students have to interact with CSE and robotics prior to entering higher education or industry. However, given the ubiquity of technology and the identified need to increase access to CSE and robotics, its integration in K-12 curriculum has become a U.S. priority in the last decade. Recent calls for reform from education stakeholders such as the National Science Foundation are leading the conversation to correct the issue through the "CS for All" campaign [67]. This change is also dependent on the research community. Within the complex structure of the K-12 education system, many challenges have and continue to obstruct efforts to integrate CSE. A need exists to establish research-based practices to teach CSE, robotics, and ML and to determine how students best learn and master this material, and to identify how students at different grade levels and stages of cognitive development retain computing concepts [68].

The discussion surrounding workforce shortage for CSE sits within a broader need to sustain workforce development for STEM occupations. The Bureau of Labor Statistics has projected a 17 percent growth rate for STEM jobs between 2012 and 2022 [69]. In 2015, STEM jobs made up about 6.2 percent of U.S. employment, where computing occupations made up about 45 percent and engineering about 19 percent [70]. Given that a large portion of STEM jobs are directly dependent on employees with computational skills, it is evident why this area has become a national educational priority. Moreover, as there is a demand for a skilled STEM workforce, current students more generally require mathematical, scientific, critical thinking, and an ability to effectively communicate technical content across different audiences and formats [69]. Teaching computational thinking while also exposing students to engineering and broader STEM ideas through robotics has far reaching consequences for K-12 pupils.

Robotics is the physical interaction between computing and the real world. As such, a wide range of our professional, industrial, and home environments now, and in the future will involve interactions with machines. Evidence includes the Bureau of Labor Statistics projected growth rate of 7 percent for engineering occupations, including robotics [60]. Exposing students to engineering learning experiences that involve gaining experience with robotic systems has become a growing concern in education. However, robotics lessons and standards remain undefined for K-12 classrooms [71]. Even so, educators and research are leveraging the tool to engage students in STEM experiences and are showing that robotics has is an effective means of engaging and teaching students engineering and computing concepts across K-12 grade levels. For example, students who participated in an intensive week long unit of programming robots in pre-kindergarten and kindergarten using developmentally appropriate tools made significant gains in understanding sequencing [72]. Researchers have also shown middle school girls' experience with robotics to be positive, rewarding, and relevant to their lives [73], indicating the potential for robotics to reduce the underrepresentation of girls in engineering and computer science.

Because poor engagement within introductory computing courses for K-12 students are linked to a lack of physical evidence of programming and because robotic systems are concrete manifestation of code, robotics can be leveraged to address the engagement issue in teaching computational thinking in K-12 grade levels [11]. Using robotics to teach CSE also offers a method for instruction that is more widely applicable to engineering and STEM as robotics is more interdisciplinary and provides instructional materials that can be used for interactive team- and project-based learning [11]. Robotics in the classroom makes a significant contribution to educational reform by teaching computing and engineering together and increasing the technological literacy of students [74].

Seeking to make headway in answering questions of how to teach the content that is atypical for K-12 grade levels. Additionally, we seek to do so without requiring a dependence on costly educational materials or educators with previous CS, engineering, or mathematics backgrounds. As such, we designed a lesson and corresponding instructional materials to teach computing and robotics. Methods for teaching CS have traditionally depended on costly infrastructure, which may be one reason rural and high needs schools are less likely to offer a previously seldom taught subject [67]. This issue is significant as it makes access of professional development materials a challenge for current educators. Given these needs, the priority is to add to research that identifies best educational practices and curricular materials for CSE and robotics in K-12 classrooms. These efforts are part of the long term goal to reduce the paucity of K-12 educational resources and to determine their influence on students' learning of computing and robotics. To successfully address the U.S. skills gap in computing and robotics, innovative education policy needs to promote efforts that improve K-12 students' interest and attitudes. Further, educational policies need to be complemented by effectively trained and supported teachers, research based and low cost instructional materials, and curricula honed to emphasize rigorous studies rather than basic computing literacy.

3.1 Background

Development of this *Robots and Sequences* lesson necessitated the bridging of several theoretical spaces: computational thinking, engineering, robotics, the 5E instructional model, tangible user interfaces, role play, and research based pedagogical practices. Given the effectiveness identified by previous works that independently used these various elements to develop instruction, marrying them together for this lesson was a necessary step in progressing computer science, engineering, and robotics research for K-12. In this section, an overview of the aforementioned subfields and instructional methods and their effectiveness is provided.

3.1.1 Computational Thinking and Engineering

To address the educational needs of one of the fastest growing occupations in the US, researchers and educators have recently constructed guiding principles and defined terminology to provide a common grounding for K-12 CSE curriculum. On a broad level, CSE means students learn to approach problem-solving with the perspective of a computer scientist [75]. The K-12 Computer Science Framework defines computational thinking as "the thought processes involved in expressing solutions as computational steps or algorithms that can be carried out by a computer" [76]. More specifically, the AP Computer Science Principles (CSP), principles for a course and exam that offers high school students credit for mastering basics of computer science, state that CS involves abstraction through models and simulations, algorithms that provide computers with generalizable instructions, creativity through computing, and programming [77]. Thus, teaching computational thinking in K-12 means students learn how to problem solve and create with algorithmic thinking and computing.

3.1.2 5E Instructional Model

The lesson framework for the design of a Robotics and Sequences lesson is based on Bybees' 5Es instructional model, a research-based approach to lesson development involving engagement, exploration, explanation, extension, and evaluation of student learning [78]. This structure offers a tool for integrated instruction; an approach that connects laboratory experience and varied learning activities, including group investigations, discussion, and direct instruction [5]. As such, the 5E instructional model aligns with the intent to use robotics as a means of teaching CSE given that robotic platforms aid in the varied and interactive approaches to learning and teaching [11]. Thus, within this lesson framework students are able to interactively explore sequences, debugging, and sensing/decision-making concepts with hands-on resources by assembling code using unplugged programming blocks and a robot-arm to test their code.

3.1.3 Pedagogy

The aim of the lesson was to introduce three computing concepts to middle school and early high school students, sequencing, debugging, and sensing/decision-making. To accomplish these instructional goals, the lesson was embedded with evidence-based pedagogical practices of active learning, teaming, and multiple opportunities for student talk. Active learning has been shown to increase student performance across STEM disciplines [79] and teaming shows evidence of increased student performance, motivation, and quality of solutions [80]. We integrated student talk using Think-Pair-Share, an activity that gives students time to develop an individual thought-process about a problem, 'think,' time to work with partners to improve and develop their solutions, 'pair,' and time to share and justify their ideas to their classmates, 'share' [81]. Further encouraging, Think-Pair-Share has been shown to increase student engagement and conceptual understanding in CSE specifically [82, 83] and to encourage elaboration of thought processes for difficult concepts [84]. Additionally, HRI education reinforces this lesson plan as recommended practices for teaching HRI content include high degrees of interaction between learners and robots [85].

3.1.4 Tangible User Interfaces

Tangible User Interfaces (TUIs) represent programming commands or actions through text and/or pictures in both computer-based and unplugged formats [86, 87]. TUIs abstract the syntactical aspects of programming, facilitating a focus on learning fundamental computing concepts [88]. They are advantageous for educators in that they are often inexpensive, durable, permit collaboration, and are easily adaptable for different learning environments, rather than restricting learning to a computer monitor [89]. That said, the independence from electrical components means students' TUI programs will not directly control the robot-arm. This may cause a disconnection for students between program generation and robotic manipulation, which we attempt to address through the debugging and sensing exercises.

3.1.5 Debugging and Sensing/Decision-Making

Teaching debugging is a critical component in the early stages of computing as it is a necessary skill for effective programming. This concept is initially addressed during students' first iteration of code generation, and practiced throughout the remainder of the lesson. We ask students to take on the roles of “programmer” and “robot.”; the “programmer” reads-aloud the assembled set of actions, while the “robot” executes the sequence of actions with their eyes closed to verify the code accomplishes the end goal, prior to testing with their robot-arm. This activity dually serves student’s grasping of debugging and sensing/ decision-making concepts as errors are evident when the robot is not achieving its end goal, and when the “robot” cannot sense the block to know they can pick it up and move it. Further, this activity affirms the connection between programming and robotic control. Students’ taking on the robot’s perspective helps provide intuition for programming robotic operation in general, and addressing the aforementioned disconnection between unplugged program generation and robotic control.

3.1.6 Classroom Implementation

One of the additional goals in the Robots and Sequences lesson was to design instruction that taught engineering in a non-math centric way. Removing the focus on math permits the ease of integration of this lesson in subject areas that are not traditionally considered in computing, e.g. English or Art. This lesson can be paired with similar lessons on technology or robotics as a way of providing students with a tactile experience with theoretical content. Alternatively, this lesson can be paired with discussions on planning for a future profession by allowing students to investigate an area of possible future interest. We recommend using this lesson as an introduction and jumping-off point for students' future learning of computational thinking concepts, including lessons on looping and decision making, as well as in lessons for other fields of engineering.

3.2 Methodology

To address the demonstrated need to integrate computing instruction in K-12 curriculum, we designed a lesson and study to investigate teaching middle and early high school students introductory CSE concepts through robotics. The intent being: to determine if students' interest in engineering and computing increased, and to measure if students learned the fundamental computing concepts of sequencing and sensing after participating in the lesson. Nine one-hour pilot lessons with 148 middle and high school students in both traditional classroom settings and engineering summer camps were conducted. The 148 participants were comprised of 82 students (55 percent) who participated in the lesson at the middle school they attend, and 66 students (45 percent) participated in the lesson through a summer camp at a local university.

According to available 2013-2014 student demographics, the student composition of the two middle schools consisted of 19 percent and 100 percent students receive free-and-reduced lunch; 29 percent and 81 percent are racial/ethnic minorities, 11 percent and 14 percent are students with individualized education plans (students eligible for special education services); and 4 percent and 3 percent are English Language Learners, respectively. The free-and-reduced lunch designation means a students' family has a financial status that is at or below the national poverty line. Demographic information about the summer camp population was not available, but we predicted the SES of students' families to be middle to upper income brackets as a fee of several hundred dollars was required to participate.

3.2.1 Purpose

The one hour 6th-8th grade lesson allows students to engage with robotics as they work through three modules exploring sequences. Sequences are a series of steps followed to complete a task. We focus on the engineering design and revision process (EDP) of creating sequences for robotics actions. This lesson is structured as follows:

- students are given a sequence to execute a simple robotic task,
- students develop a sequence in groups to make a robot perform a specified task,
- students analyze code to find and fix errors that prevent the task from being accomplished, and

to offer students an engineering design experience where they develop, test, and improve sequences for robotics. The lesson structure is a modified form of the Engineering Design Process that reflects the practices of computer scientists and engineers.

Specifically, students create sequences for a specific problem (ask, research, select, and build phases of EDP), present their results for evaluation (communicate and test) and troubleshoot after evaluation to refine their code (redesign).

3.2.2 Lesson Learning Objectives

Students will be able to:

- explain how sequences relate to computing;
- write, read, and interpret sequences that enable a robot to complete a tasks;
- describe the relationship between planned sequences and executed robot actions;
- apply objectives 1 and 2 to design a sequence for a robot;
- define and apply the lesson vocabulary.

3.2.3 Data Collection and Analysis

Student interest and attitudes toward engineering were measured through a 15-question survey given before and after completing the CSE lesson. The survey instrument was developed using the Intersectional Non-Normative Identities in the Cultures of Engineering (InIce) instrument [90] which had been previously validated with over 4,000 first-year university engineering students. Survey items were adapted to meet the expected reading levels of participants in this study. The survey required students to mark their agreement of statements on a 7-point likert scale anchored between "Strongly Disagree" and "Strongly Agree". All statistical testing was done using R [5]. To develop factor scores for interest and attitudes, appropriate questions were aggregated. Socioeconomic status (SES) groups were determined according to each school's SES designation; a measure which places students' economic standing according to the financial standing of the overall student body where they attend [78]. That is, given the large income disparity between the two middle schools and the summer camp populations, we grouped the student population according to SES. The middle school with 100 percent of students that qualify for free-and-reduced lunch was designated low-SES, while the other middle school and the summer camp were designated high-SES.

Both the entire group and the individual groups were checked for normality and constant variance using a q-q plot and a residual plot. All data sets were determined to be non-normal. First, differences in pre- and post-interest and attitudes were checked across the combined population using a Wilcoxon Rank Sum Test (a non-parametric t-test). Differences were also checked along SES groups. Tests that were conclusive for group-differences were checked post-hoc with a boxplot. Significance for all tests was set at the α=0.05 level. The entirety of this study was approved by the local Institutional Review Board (IRB).

3.2.4 Lesson Materials

The robot-arm used for this lesson, the MeArm 3.1, is generated from an open-source MeArm CAD file [1]. A set of magnetic TUIs are generated by laser-cutting basswood **??** and a white board is used for students to collaborate with the code development process. Lastly, a robot environment was created with three concentric half-circles on a sheet of butcher paper and a set of blocks for the pick-and-place tasks 3.3.

3.2.5 5E Lesson Plan and Content

Using Bybee's 5E Instructional Model, our lesson plan guided students through learning of sequences, debugging, and sensing/decision-making through students' construction of code that moves a block from an initial to a final position in the robot's environment.

Engage: The lesson begins by grouping students into pairs or trios and assigning each group a set of lesson materials (See Figure 1 and 2). Students are asked to retrieve their background knowledge about robotics as eliciting previous knowledge during new learning is a key element in increasing student's academic achievement [90]. Then, 2-3 students share their experiences with the class and the class discusses what robots are. We close out the 'engagement' portion of the lesson, by formally defining a robot for students sense- making of their background knowledge. To introduce

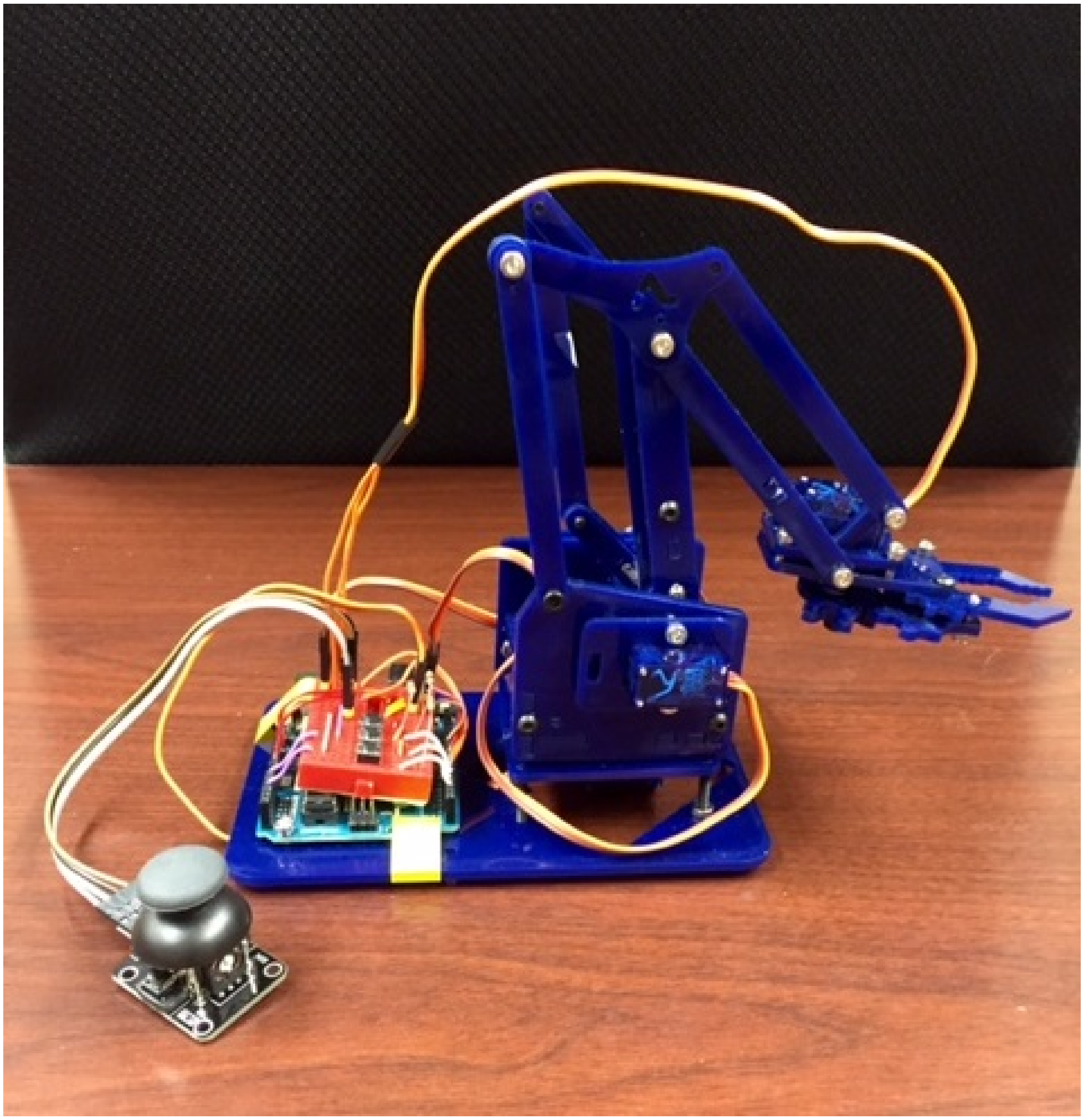

FIGURE 3.1: This instructional robot-arm was constructed by laser cutting plastic material using an open-source CAD file from MeArm [1].

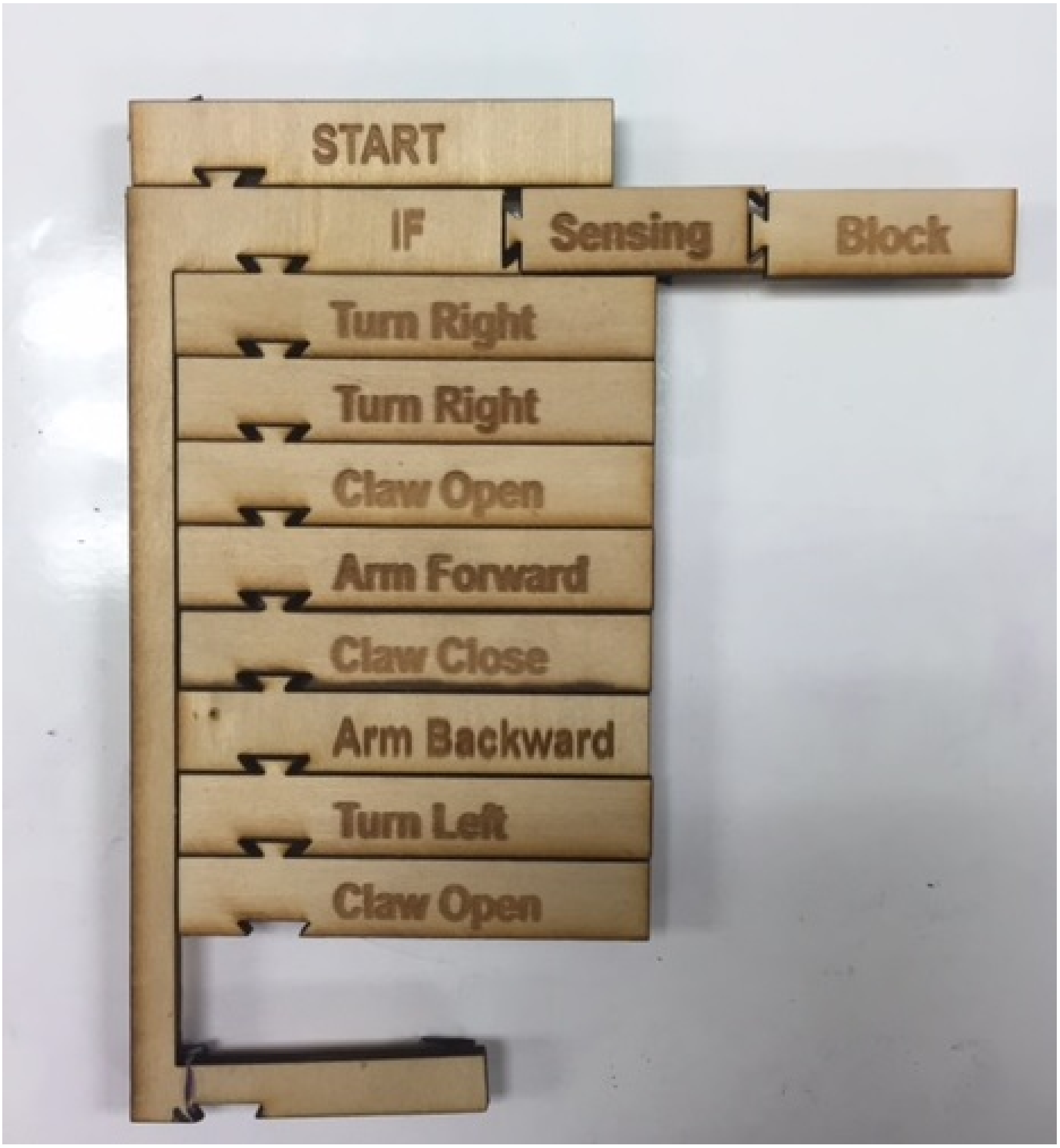

FIGURE 3.2: These basswood pieces had robotic actions etched into them and magnets attached on their back sides to allow students to easily order their sequences of actions on a white-board.

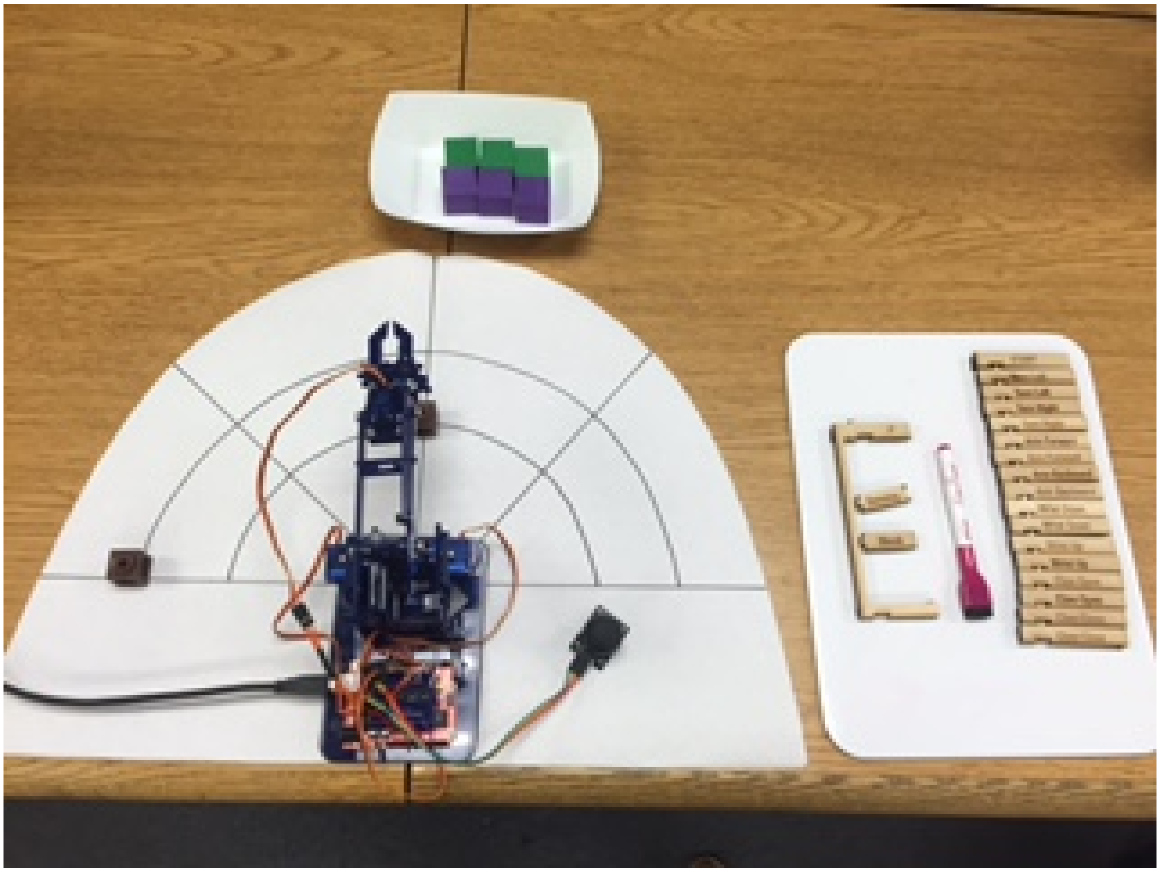

Figure 3.3: This is the robot's environment and starting point for the various pick-and-place tasks for which students are asked to generate a program.

students to the logic of programming, we ask students to consider a relevant sequence of actions that they execute every day, brushing their teeth. We provide example code for teeth brushing to guide student thinking in the direction of how they will construct a complex program for a robot. Questions were then posed to students to reflect on sequencing, "Did the order of the steps matter" and "Can any steps be switched?" Driving this reflection was the Think-Pair-Share activity where students think, describe their thought processes with a partner, and then share their discussions with the class.

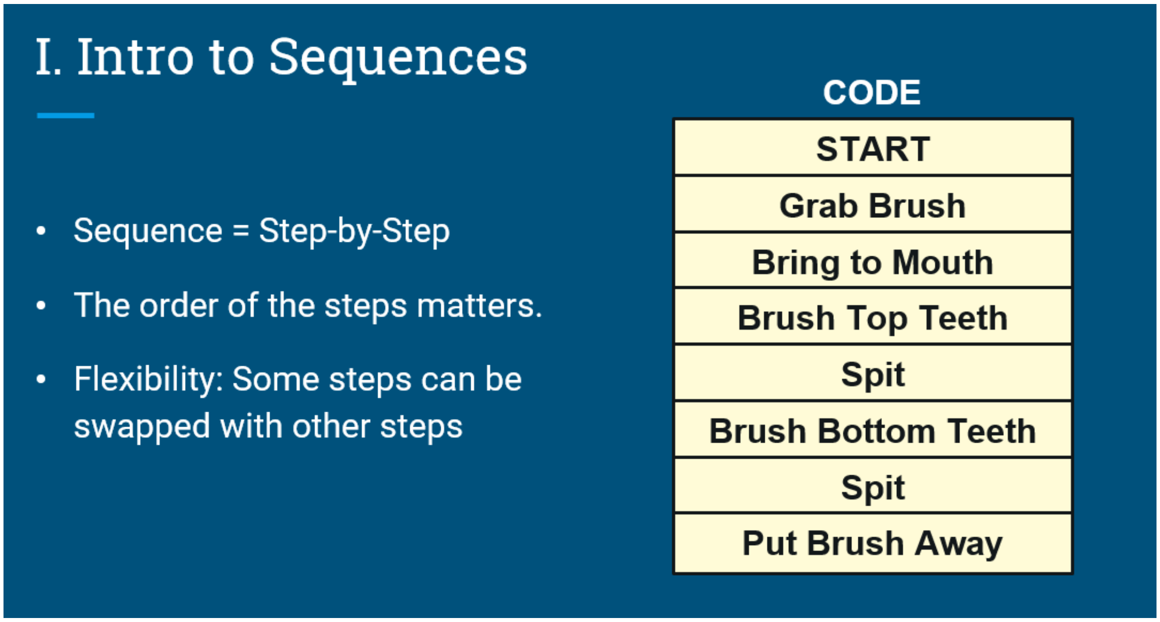

FIGURE 3.4: The sequence given to students when first introducing them to the concept of sequences. This served as a means of creating relevance and stimulating background knowledge for students about sequences they encounter everyday.

Explain/Explore: Next, we provided time for students to investigate, observe, formulate explanations, and clarify questions about their learning [Anderson] through a series of three activities.

- 1. *Sequences to Actions:* First, students watch a video where a robot-arm sorts lemons and limes to demonstrate what they will accomplish with their MeArm. Then, we provide a small sequence of instructions similar to those that they will use in future exercises. We ask students to take on the roles of "programmer" and "robot." In these roles, students execute their provided programs with their own arms, mimicking the same actions their robots will complete. Finally, students verify the code with their MeArm. This lesson activity offers students a means of gaining intuition for control of robotic operations.

- 2. *Designing Sequences:* To extend the depth of this exploration, students execute a second sequence, this time self-constructed, using their magnetic TUIs. The instructor simply provides the initial and goal positions for a block. The students' goal is to program the robot-arm to go to the initial block position, grab the block, and move and place the block in the goal position. 3.5 As with the first program, students will take on the roles of "programmer" and "robot" to debug their program prior to executing it with the MeArm.

- 3. *Redesigning and Debugging Code:* For the final programming activity, students are again provided with initial and final block positions, as well as a program sequence, but this sequence will contain an error. Multiple solutions exist for students to fix the bug. Debugging a sequence provides students time to reflect and brainstorm possible solutions to an error and to identify the best solution based on their discussion. This process is a key component of computational learning and the engineering design process [91]. Lastly, we ask students to exchange their code with a group, affording each group with an opportunity to verify another team's code and evaluate their solution. After, students are asked to reflect on how missing one step can significantly deviate the end goal and to consider examples of how this happens in their own lives (e.g., you can't put on your shoes before your socks).

*Extend and Evaluate:*Each group is given a worksheet with two blank mats for an initial and a final block position. The groups choose what the two positions are,

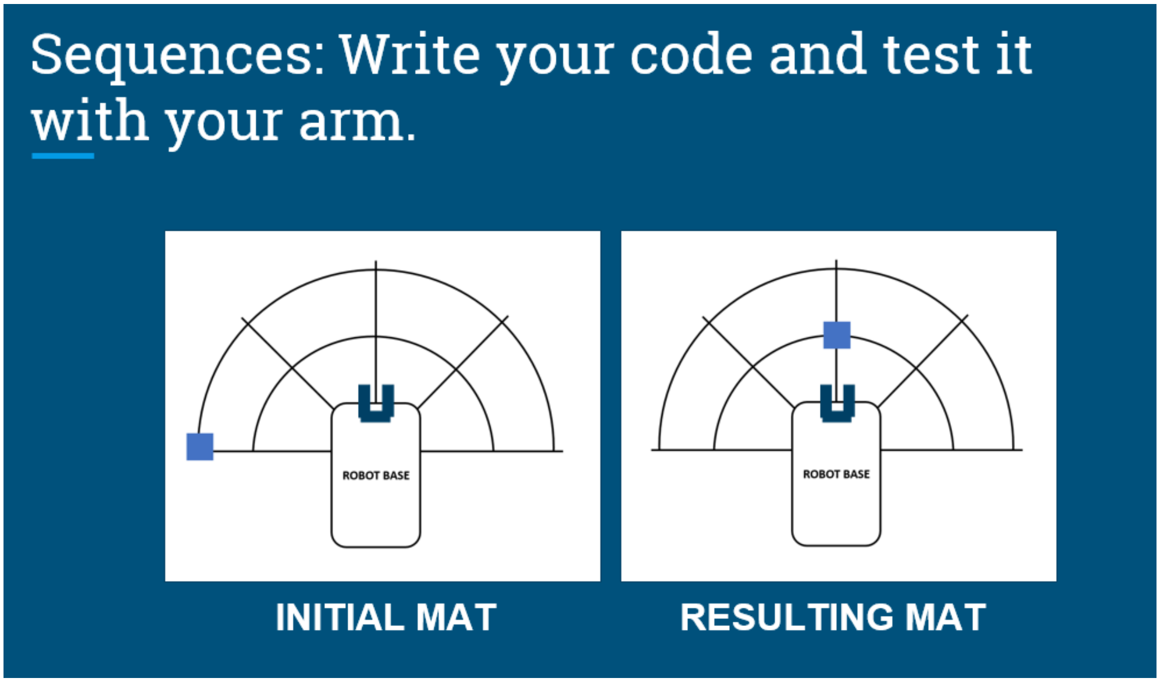

FIGURE 3.5: The figure on the right indicates to students the starting position for their robot and the initial location of the object their robot is trying to grasp and move. This serves as a simple robotic task for students to write their first programs.

draw them on their worksheet, and trade worksheets with a neighboring group. The groups are then asked to produce a sequence of instructions that accomplishes moving a block from the provided initial and final positions. Finally, an assessment with problem-solving questions for students to apply sequencing and debugging skills was created. Conceptual questions are also posed about sequences not explicitly related to computer science.

3.3 Results

A population of n=146 students grades 6-10 participated in our CS and robotics lesson and completed pre- and post-lesson surveys about their interest and attitudes toward engineering. 43 percent of students reported that this was their first experience with an engineering lesson. Students were sorted according to two income groups, low-SES, n=94, and high-SES, n=52. The initial Wilcoxon Rank Sum Test for differences between the entire groups pre- and post-interest (W=9806.5, p=0.22) and attitude (W=9464.5, p=0.10) scores were insignificant, suggesting no difference in interest and attitudes before and after the lesson delivery. Follow-up tests for differences between SES groups also showed no significant differences exist between students total change in pre- and post-interest (W=2044.5, p=0.08) and attitude (W=2247.5, p=0.42) scores. Although these tests were insignificant for differences across SES groups, we also tested for differences between pre-interest scores, post-interest scores, pre-attitude scores, and post-attitude scores, by SES group. Differences were found between pre-interest scores by SES ($W = 3381$, $p < 0.001$), post-interest scores by SES ($W = 3042$, $p = 0.01$), pre-attitudes scores by SES ($W = 3530$, $p < 0.001$), and post-attitudes scores by SES ($W = 3302.5$, $p < 0.001$) Illustrated in Figure 3 and Figure 4, these differences highlight that low SES students had lower pre- and post-interest, and lower pre- and post-attitudes than their high SES peers.

3.4 Conclusion

The above research demonstrates that a need exists to increase our understanding of students' general STEM interest and attitudes, including how to design instruction that positively impacts those attitudes. Data analysis of our middle school populations by income-levels revealed an increase in interest toward engineering for low-SES students. This suggests that students of low-SES and/or are racial/ethnic minority populations have more to gain from access to engineering lessons similar to ours than students who are not. Further, middle school is an integral time for students to be introduced to these topics as it is the time period when a foundation is laid for post-secondary STEM success [92]. Interventions that target student populations with less access to computing and robotics may help shift the decline in students' early-on STEM interest as they matriculate through K-12 grades [66].

As the goal of this thesis research is to make an investigative contribution toward instructional materials and content for K-12 that help toward reducing the workforce shortage and aiding the advancement of computing and robotics technologies, the findings from implementing our *Robotics and Sequences* lesson are favorable. Gaining preliminary evidence as to how K-12 students can be encouraged to gain interest and positive attitudes toward computing, robotics, and engineering offers motive to consider how similar and currently untaught subjects might be taught in K-12 grade levels, e.g. AI and ML.

3.5 Future Work

Gaining a more comprehensive understanding on the findings from this work may be achieved by focusing on particular populations. 45 percent of our sample population included students who participated in this lesson through a high-cost summer camp and thus were self-selected for interest in engineering. Evaluating and comparing schools with large student populations of low-SES and high-SES and/or racial/ethnic minority students may reveal how and why these populations' initial interest and attitudes in engineering shift. Additionally, doing research with a baseline population of students who have not previously participated in engineering lessons may provide an upper bound on possible gains for engineering interest and attitudes. Future work should also involve participants that are more reflective of K-12 students populations to reduce the ceiling effect for interest and attitudes toward engineering. In general, increasing the size and diversity of sample student populations should be considered for works that extend these findings. Lastly, because our survey instrument was for engineering specifically, next steps should involve development of robotics and computing specific measures of interest and attitudes that reflect culturally relevant aspects of computing education.

Chapter 4

Discussion

The purpose of this master's thesis research is to explore computer science and robotics for applications in K-12 human-robot interaction (HRI) and engineering education. These goals are part of an effort to provide a comprehensive understanding of foundational concepts of HRI that aid innovation in robotics and to provide K-12 instructional materials and content for democratization that improves the talent shortage, lack of equitable representation of traditionally underrepresented populations in these fields, and our technological advances. Moving forward with this objective requires decomposition of the problem space. As such, what follows is a discussion of a prominent subfield of computing and robotics, machine learning (ML). This discussion will include a description of the current state of the field, factors that have caused this field to rapidly flourish, typical applications of the tool, challenges, and how advances will benefit society. We've chosen to provide this section as an extension of this thesis' work, and a preview of upcoming work, due to the significant investment and changes being brought on by this subfield [9].

4.1 Machine Learning

Within the context of computer science, the aim of machine learning or statistical inference is to develop intelligent software for process understanding and automation [3]. Equipping a computing machine with a capacity for learning enables the implementation of processes characterized by automated tasks and apprehension that humans can use to apply for decision-making within complex systems. Specifically, Mitchell [93] defined ML as follows, *"A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E."* Where experience E is data, e.g. a robot's x, y position or the number of times the robot successfully completes a task.

Process understanding of intelligent software and automation are already firmly cemented in our social structure. Facial recognition and navigation software are housed on our smartphones, accessing our web browsers or social media means having a filtering of ads, news, and an offering of recommendations for our social networks, music libraries, and watchlists. Further, the capacity that machine learning has for integrating into a very diverse pool of problems is due to one simple idea: pattern recognition. As the applications for predictive capacity are widespread, it is already integrated within the two research spaces of this thesis, robotics and education.

In robotics, machine learning has been applied for decades to equip robots, and autonomous systems in general, with decision-making abilities for planning and navigation [94] and to predict human behavior for planning of these systems within real-world environments that involve human-robot interaction [95]. Although the field of education isn't characterized with a similar longevity of application, it has recently seen a substantial increase in its adoption as more and more educators and education stakeholders identify new ways of leveraging learning analytics [96]. This section will provide a theoretical overview on how pattern recognition is achieved and describe applications, challenges, and the current direction of the field of machine learning, with a focus on robotics and education.

Implementing ML means a model has been generated to represent a set of data for future predictions. An algorithm reviews a set of data, it identifies the patterns in that data (learns the data) and then extracts the most significant parts of those patterns to make predictions when it is later presented with new data; a three-step general process of training, model creation, and model testing. Central to the learning process is the generation of a model, the "problem of inducing general functions from specific training examples" [93]. Generating a model involves using a previously collected set of data to determine the key elements that describe that data, data patterns. In statistical terms, [97] explains that pattern recognition is based on a single fundamental idea, the inductive learning hypothesis, which states that *"Any hypothesis found to approximate the target function well over a sufficiently large set of training examples will also approximate the target function well over other unobserved examples."* [93]. The target function, or general function, serves as the generalizable version of seen data which is later used for similar kinds of data, to make predictions about that unknown future data.

Inherent in pattern recognition is a level of uncertainty about the reliability of the predictions. To account for this uncertainty, ML relies on probabilistic theory to evaluate the inputs, to learn the models that represent them, and to identify best methods that generate reliable decision-making sources [98].

4.1.1 Types of Machine Learning Systems

Machine learning encompasses three types of learning tasks: supervised learning, unsupervised learning, and reinforcement learning. The different methods of building learning systems are based on the kinds of data inputs and outputs that are expected to be used and obtained. Supervised learning means a set of data inputs, either categorical or continuous, are given alongside their corresponding labels or targets for training and the algorithm learns to classify future similar data [3]. Unsupervised learning uses data sets where the labels or targets are not provided. Rather than learning to categorize or predict values, the ML algorithm will output a probability distribution that represents the generation of the dataset, that is, learns the given data structure [3]. For example, if the data inputs are images of farm animals, then the algorithm learns to classify the categorical labels for pig, cow, chicken, and goat, where if the data inputs are continuous prices for a skincare retailer, then the algorithm learns to predict the value of products, e.g. makeup and fragrances in the range of 0-500 dollars. For an unsupervised algorithm, the labels for the different animals would be unknown and learned from patterns in the data, e.g. facial features, height, and color. The assumption being that the latent variables, the features of the data, are contained within the given data and can be extracted to produce the observations [3].

Reinforcement learning is the more distinct of the three methods as it involves an agent being solely dependent on interacting with its environment to receive feedback from the interactions that produce learning [93][Sutton and Barto]. This approach to learning most closely resembles the manner in which humans learn [3]. For example, if an agent autonomously navigates a series of paths, the agent will be given a reward when it follows the goal path, but receive no reward when it navigates other paths, or little reward if a path is a neighbor to that of the goal path. These reward values accumulate to generate the greatest cumulative reward path, or optimal path, making them appropriate to solving by dynamic programming algorithms for optimization problems [93].

4.2 Workforce Development for Machine Learning

The advancement of machine learning methods and technologies is currently obstructed by a major challenges, the lack of workforce development and diversification. The shortage of ML talent has stemmed from the rapid adoption of automation tools across different industries and businesses without the means to train the number of skilled workers needed to meet the demand [9]. Further, the growing role of learning and big data in the private sector is projected to continue creating significant demand for statisticians and data analysts. According to research conducted by the Manyika [9], by 2020 big data analytics could increase annual GDP in retail and manufacturing by 325 billion dollars [99]; a consequence that is predicted to result in a shortage of up to 250,000 data scientists in the US in the next decade [9]. To alleviate this national shortage, companies investing in product analytics are using strategies like hiring foreign-born workers and offering on-the-job training [100]. Further, once hired, challenges exist in accessing the utility of predictive technologies; the MIT Sloan management review has identified a lack of appropriate analytical skills, difficulty in aggregating multiple data sources, and turning analytical insights into business actions as key challenges in developing the workforce needed for company's current and future demands [100].

The growing role of automation offers further consideration to the issue of workforce development as this area is predicted to significantly impact work on a global scale. A survey representing 80 percent of the global workforce estimates about 15 trillion dollars, or half of all jobs, may become automated [9]. Industry pursuit of automation is based on competitive advantage through potential gains in productivity by combining mechanization and learning capabilities that increase process optimization, accuracy, and safety of current efforts [9]. These factors offer a compelling narrative to consider how our education system can help mitigate these challenges to provide future workforce members and industry with highly-skilled employees. That is, the adoption of K-12 statistical learning, programming skill sets, and robotics may aid in developing a future workforce equipped with digital literacy, STEM skills, and statistical and numeracy proficiency needed to meet this demand.

4.3 Benefits to Society

The problems amenable to the field of ML are broad; wherever there is data, a ML algorithm can be implemented to learn and infer [3, 98]. Given this capacity, the integration of ML into our social infrastructure will involve automation of processes across the major institutions and services including education, healthcare, the judicial system, traffic management, manufacturing, and information security. Moreover, these benefits are already evident. Educational services offer personalized learning services [101], oncologists are being assisted in cancer detection [102], and the judicial system has seen a means of racial bias reduction in criminal sentencing [103]. Further encouraging is that these advances are not limited to larger social entities nor do they require state-of-the-art hardware. Instead, ML is becoming a tool for democratized services as it can be housed on a smartphone through machine learning software platforms like Google's Tensorflow. A fitting example of this democratization is Plant Village, a company using image recognition to help rural farmers in African countries monitor plant health and detect and diagnose disease to increase yield [104]. Despite the challenges that ML still needs to overcome, the implications of integrating inference within existing public services and industries means providing more accurate, personalized, and robust technology with equitably distributed access.

4.4 Conclusion

Machine learning has already and will continue to change our social and economic infrastructure and fundamentally alter what it means for people to"work." To achieve an effective transition and to provide access to the career and higher-quality of living benefits that come from leveraging learning systems, the majority of the U.S. population needs access to machine learning and robotics education. As such, the intent of this master thesis research is to contribute to the fields' understanding in developing lesson that teach the necessary skills, computational thinking and robotics, to help mitigate the workforce challenges for the advancement of machine learning technologies.

Chapter 5

Conclusion

The purpose of this master's thesis work is to make contributions toward mitigating the workforce shortage and lack of diversification in computing and robotics; to aid the technological advancement of computing and robotics; and to contribute toward democratizing computing and robotics as these subjects have been inaccessible to traditionally underrepresented populations. This thesis has provided two approaches used to move toward addressing these issues, development of instructional materials and content to teach middle and early high school students' introductory concepts of computing and robotics and a literary review of human-robot interaction (HRI). Specifically, this thesis provided an overview of past research efforts within computer science and robotics, the current states of K-12 computing education and HRI, and findings from our two approaches.

The aim of this work was to help steer educators' efforts in offering computing concepts at K-12 grade levels through access to materials and project-based content that positively impacts students' current engineering identities for future academic and/or career interest in engineering. Further, as we know that interventions that target student populations with less access to computing and robotics may help shift the decline in students' early-on STEM interest while matriculating through K-12 grades, this may serve to reduce the workforce shortage. Moreover, as the fields of engineering has seen lower representation of female students and traditionally underrepresented minority (URM) students within degree programs and industry, this lesson sought to increase the exposure to engineering content for students who might not have previously encountered the subject, to encourage engineering identity development that might spark and foster an interest in the subject for a more diverse population of students. By creating access to a lesson that was comprehensible for a teacher without previous computational knowledge, this research contributed to the larger goal of equipping K-12 educators with the content and knowledge resources needed to deliver this content to their students with expertise. Lastly, the context of education for this thesis also involved an exploration and consideration for how ML can be integrated into the existing K-12 curriculum. ML is currently absent from the K-12 curriculum. Given the need to expand the ML workforce, it is imperative that a long-term investment be made on a national and local level to provide future workforce members with access to foundational education about a field that will be evermore integrated into our personal and professional lives.

Within the context of robotics, the investigative goal was to evaluate and synthesize the current state of the field to contribute to the larger body of work in HRI. Throughout this work we discussed the purpose of and the research that supports the need to integrate embodiment, situatedness, morphology, especially anthropomorphism, and expressiveness in robotic design. Specifically, we understand that within the embodiment field there exists a need to discern the degree to which embodied cognition is attainable, the degree to which social and functional differences between embodied and non-embodied agents are distinguished, and how embodiment influences HRI in different contexts. We also identified the widely accepted idea that the dynamic nature of everyday interactions means it is necessary to equip intelligent systems with the ability to adapt and revise action based on the variability within an environment, namely that an intelligent system account for its situatedness. Without this capacity, navigating and adapting to unexpected and diverse factors that disturb a robot's path will limit its practical functionality and make robotic learning systems an unrealistic tool for day-to-day applications, limiting their advancement.

Computing and robotics have, and will continue to, contribute technologies that offer society improvements in social welfare and an overall higher quality of life for all. Due to this potential, industries and institutions will continue to leverage these technologies to address open social and scientific problems. As software and learning systems expand within our economic infrastructure, it will become increasingly pressing for our society to be equipped with a skilled labor pool. Developing these technologies and making novel contributions necessitates a workforce with mastery of computational knowledge, however these fields are currently challenged with a workforce shortage and a lack of diversification that strains the capacity to meet these goals. Therefore, developing K-12 instructional curriculum for computing using research based pedagogical practices like think-pair-share and role play and developing instructional materials that offer students a concrete experience of what programming is, can help establish interest in K-12 that leads to the pursuit of professions in computing and robotics. Additionally, these investments in general education will offer access to subjects traditionally reserved for higher education and contribute to the democratization and diversification of fields challenged with significant underrepresentation of women and people of color. Lastly, our HRI discussion served to discern the need to integrate embodiment, situatedness, morphology, especially anthropomorphism, expressiveness, and communication in robotic design, to effectively operate and collaborate in social contexts. Together, these factors can move us closer to workforce equity, sufficient numbers of workers interested in these fields, a general public with basic knowledge of current and future technologies, and move us toward technological advances.

Appendix A: Pre and Post Assessments for the Robots and Sequences Lesson

Pre-Assessment for Computer Engineering Through a Human-Robot Interaction Lesson
Spring 2016

1. Have you participated in an engineering lesson(s) before?	Yes	☐	No	☐
2. What is your definition of engineering?				

	Strongly Disagree				Strongly Agree
3. I enjoy learning engineering.	☐	☐	☐	☐	☐
4. I expect to do well in this engineering lesson.	☐	☐	☐	☐	☐
5. I am interested in learning more about engineering.	☐	☐	☐	☐	☐
6. I like to imagine creating new products.	☐	☐	☐	☐	☐
7. If I learn engineering, then I can improve things that people use every day.	☐	☐	☐	☐	☐
8. I am good at building and fixing things.	☐	☐	☐	☐	☐
9. I am interested in what makes machines work.	☐	☐	☐	☐	☐
10. Designing products or structures will be important for my future work.	☐	☐	☐	☐	☐

	Strongly Disagree				Strongly Agree
11. I am curious about how electronics work.	☐	☐	☐	☐	☐
12. I would like to use creativity and innovation in my future work.	☐	☐	☐	☐	☐
13. Knowing how to use math and science together will allow me to invent useful things.	☐	☐	☐	☐	☐
14. I believe I can be successful in a career in engineering.	☐	☐	☐	☐	☐
15. My classmates ask me for help engineering.	☐	☐	☐	☐	☐

Post-Assessment for Computer Engineering Through a Human-Robot Interaction Lesson
Spring 2016

1. Have you participated in an engineering lesson(s) before?	Yes	☐	No	☐
2. What is your definition of engineering?				

	Strongly Disagree				Strongly Agree
3. I enjoy learning engineering.	☐	☐	☐	☐	☐
4. I expect to do well in this engineering lesson.	☐	☐	☐	☐	☐
5. I am interested in learning more about engineering.	☐	☐	☐	☐	☐
6. I like to imagine creating new products.	☐	☐	☐	☐	☐
7. If I learn engineering, then I can improve things that people use every day.	☐	☐	☐	☐	☐
8. I am good at building and fixing things.	☐	☐	☐	☐	☐
9. I am interested in what makes machines work.	☐	☐	☐	☐	☐
10. Designing products or structures will be important for my future work.	☐	☐	☐	☐	☐

	Strongly Disagree				Strongly Agree
11. I am curious about how electronics work.	☐	☐	☐	☐	☐
12. I would like to use creativity and innovation in my future work.	☐	☐	☐	☐	☐
13. Knowing how to use math and science together will allow me to invent useful things.	☐	☐	☐	☐	☐
14. I believe I can be successful in a career in engineering.	☐	☐	☐	☐	☐
15. My classmates ask me for help engineering.	☐	☐	☐	☐	☐

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