EFFECTIVENESS OF EXPLICIT GUIDANCE AND PRACTICES ON ABSTRACTION (EGPA): FOCUS ON COMPUTATIONAL TASKS IN A STEM-INTEGRATIVE ROBOTIC EDUCATION PROGRAM FOR FIFTH GRADE STUDENTS

by

YINGXIAO QIAN

(Under the Direction of Ikseon Choi)

ABSTRACT

In parallel to the increasing emphasis on STEM literacy computational thinking has gained more attention in K-12 education. Scholars have acknowledged abstraction as the keystone of computational thinking. Therefore, to foster K-12 students' computational thinking and STEM literacy, their abstract thinking skills should be enhanced. However, the existing K-12 curriculum may not adequately prepare learners with the abstract thinking skills needed for the STEM workforce. Furthermore, promoting students' abstraction requires understanding its core cognitive processes; otherwise, it becomes a burden for K-12 educators who lack the required knowledge to teach abstraction. Therefore, this study hopes to overcome the gap between the need for future STEM workforce with effective abstract thinking skills and the current curriculum.

This study conceptualizes a unified framework to help K-12 educators understand the three fundamental processes of abstraction—filtering information, locating similarities, and mapping structures—and how they function. Then this study provides a set of design guidelines to enhance K-12 students' abstract thinking skills using a STEM-integrative learning environment. Based on these proposed guidelines, the explicit guidance and practices on abstraction (EGPA) in a STEM-integrative robotics curriculum will be developed to improve K-12 students' abstraction in computational thinking. Finally, the effectiveness of the EGPA in fostering abstraction in computational thinking in the STEM-integrative robotics curriculum will be further explored. Upon the completion of this study, design guidelines and practices for K-12 educators regarding fostering their students' abstraction will be offered.

INDEX WORDS: Abstraction; Computational thinking; STEM education; Explicit guidance and practices on abstraction (EGPA); STEM-integrative robotics curriculum; Effectiveness.

# EFFECTIVENESS OF EXPLICIT GUIDANCE AND PRACTICES ON ABSTRACTION (EGPA): FOCUS ON COMPUTATIONAL TASKS IN A STEM-INTEGRATIVE ROBOTIC EDUCATION PROGRAM FOR FIFTH GRADE STUDENTS

by

YINGXIAO QIAN

B.A., Saint Louis University, 2012

M.Ed., The University of Georgia, 2015

A Dissertation Submitted to the Graduate Faculty of The University of Georgia in Partial Fulfillment of the Requirements for the Degree

DOCTOR OF PHILOSOPHY

ATHENS, GEORGIA

2019

EFFECTIVENESS OF EXPLICIT GUIDANCE AND PRACTICES ON ABSTRACTION (EGPA): FOCUS ON COMPUTATIONAL TASKS IN A STEM-INTEGRATIVE ROBOTIC EDUCATION PROGRAM FOR FIFTH GRADE STUDENTS

by

YINGXIAO QIAN

| | |
|---|---|
| Major Professor: | Ikseon Choi |
| Committee: | Theodore J. Kopcha |
| | John M. Mativo |

Electronic Version Approved:

Ron Walcott
Interim Dean of the Graduate School
The University of Georgia
December 2019

# DEDICATION

This dissertation is dedicated to my beloved family. To my parents, my grandparents, and my husband who always supported me with their endless love. Thanks for their patience, understanding, and unconditional supports for me to complete my doctoral study. I owe you my deepest gratitude. Also, a special thanks to my grandfather who gave me all his love and also encouraged me to chase my dream. I know he must be proud now, and I will always be grateful for the virtue he instilled in me.

ACKNOWLEDGEMENTS

I would like to express my deep gratitude to my advisor and committee chair, Dr. Ikeson Choi, for his support of my doctoral study. His insightful advising guided me through the journey to become a passionate and professional scholar in education. I appreciate the scholarly merits and the rigorousness he had modelled for me.

I would like to express my sincere thanks to my best committee, Drs. TJ Kopcha and John Mativo, for their invaluable wisdom, patience, and support. I feel so lucky and honored to have you with me as my committee members. I would also like to thank Dr. Rob Branch, Dr. Janette Hill, and Dr. Brandy Walker, for their continued encouragement and support with my doctoral study. Without them, I cannot make this dream to come true. I also appreciate Mr. Lee Bane as well as the teachers and the students in the Arts and Innovation Magnet (AIM) Program. "Ms. Karen" will never forget these excellent folks who gave tremendous help to my dissertation research.

My extended appreciation also goes to my friends who has always been around, cheered me up, and helped me overcome challenges. I am so happy that I have known and befriended with so many wonderful people during my doctoral study at UGA. I really appreciate their friendship and accompany these years and look forward to many more.

TABLE OF CONTENTS

Page

ACKNOWLEDGEMENTS ........................................................ V

LIST OF TABLES ........................................................ IX

LIST OF FIGURES ........................................................ XI

CHAPTER

1 INTRODUCTION ........................................................ 1

Background ........................................................ 1

Problem Statement ........................................................ 3

Purpose of the Study ........................................................ 6

Research Questions ........................................................ 6

Terms ........................................................ 8

Significance of the Study ........................................................ 9

2 LITERATURE REVIEW ........................................................ 10

Overview ........................................................ 10

STEM Education ........................................................ 10

Computational Thinking ........................................................ 12

Abstraction ........................................................ 17

Abstraction in Computational Thinking ........................................................ 28

A Conceptual Framework of Abstraction in Computational Thinking ................. 34

Challenges for Students to Develop Abstraction in Computational Thinking ...... 36

Guidelines for Enhancing Abstract Thinking in STEM-Integrative Learning Environments ........................................................ 40

Summary ....................................................................................47
3 METHODOLOGY ....................................................................................49
Overview ....................................................................................49
Research Design ....................................................................................49
Research Sites and Participants ....................................................................................55
Materials and Instruments ....................................................................................57
Data Collection ....................................................................................68
Data Analysis ....................................................................................71
Validity and Reliability ....................................................................................75
Methodological Limitations ....................................................................................76
Ethical Considerations ....................................................................................77
4 RESULTS ....................................................................................78
Results by Research Questions ....................................................................................78
Synthesis of the Findings ....................................................................................113
5 CONCLUSIONS ....................................................................................114
Overview of the Findings ....................................................................................114
Discussion ....................................................................................117
Recommendations and Implications ....................................................................................123
Limitations and Future Research ....................................................................................124
REFERENCES ....................................................................................127
APPENDICES
A Teacher Recruitment Letter ....................................................................................142
B Teacher Consent Form ....................................................................................144

C Parent Recruitment Letter .......................................................................................149

D Parent Consent Form.............................................................................................151

E Student Consent Form...........................................................................................157

F The Abstraction in Computational Thinking Assessment .........................................158

G Student Learning Experiences Questionnaire for the Experimental Group...............164

H Student Learning Experiences Questionnaire for the Control Group ........................172

I Protocol for the Focus Group Interview with the Experimental Group.....................179

J Protocol for Semi-structured Interview with the Teacher..........................................181

K Lesson Plan for the Revised Danger Zone Curriculum with the EGPA ....................183

LIST OF TABLES

Page

Table 1: Features of computational thinking and their definitions from the exiting literature......16

Table 2: The essential cognitive processes in different facets of abstraction ...............................26

Table 3: Marr's Computational Theory and its three levels (Marr, 1982)...................................34

Table 4: Design guidelines for enhancing abstract thinking in STEM-integrative learning environments..........................................................................................................40

Table 5: An overview of the mixed methods research design aligned with each research question . ..........................................................................................................50

Table 6: The overarching research design of the quasi-experimental study.................................53

Table 7: The number of male and female participants in the Control and Experimental Group...56

Table 8: Details about the lesson plan of the revised version of the Danger Zone.......................62

Table 9: The scoring rubrics for the Abstraction in Computational Thinking Assessment...........67

Table 10: The two phases to validate the reliability of inter-raters' abstract thinking scores in the ACT Assessments. ..........................................................................................81

Table 11: The factor analysis results validated the validity of the ACT Assessments. .................82

Table 12: Coefficients for each item if the item was deleted and the overall coefficients. ...........83

Table 13: Means and standard deviations for learning experience satisfaction surveys. ..............84

Table 14: Descriptive statistics on the participants' grade in the pre- and post- tests. ..................86

Table 15: Mixed ANOVA analysis result on the participants' mean score of the ACT assessment. ..........................................................................................................87

Table 16: Mixed ANOVA analysis result on the participants' mean score change in the filtering information activities. ........................................................................................89
Table 17: Mixed ANOVA analysis result on the participants' mean score change in the mapping structures activities..........................................................................................................90
Table 18: Mixed ANOVA analysis result on the participants' mean score change in locating similarities activities ........................................................................................................91
Table 19: Paired samples t-test analysis on the two groups' mean score changes in ACT assessment and its subtests assessing each dimension of abstraction. ...............................93
Table 20: Independent samples t-test analysis on the two groups' mean score changes in ACT assessment and its subtests assessing each dimension of abstraction. ...............................96
Table 21: ANCOVA Results of the ACT Assessment ..............................................................100

LIST OF FIGURES

Page

Figure 1: The order of classification (Lowell, 1977). ....................23

Figure 2: A unified framework of abstraction in computational thinking ....................35

Figure 3: An overview of the research design, data collection, and data analysis procedures ......54

Figure 4: Overall test results of ACT assessment by group about pre- and post- tests ................86

Figure 5: The illustration of the change in the mean score of the ACT assessment for the two groups....................88

Figure 6: The illustration of the change in the mean score of the information filtering activities for the two groups ....................89

Figure 7: The illustration of the change in the mean score of the mapping structures activities for the two groups....................90

Figure 8: The illustration of the change in the mean score of the locating similarities activities for the two groups....................91

Figure 9: Pretest and posttest result of filtering information questions in the ACT assessments completed by the two groups ....................97

Figure 10: Pretest and posttest result of mapping structures in the ACT assessments completed by the two groups....................97

Figure 11: Pretest and posttest result of locating similarities in the ACT assessments completed by the two groups....................98

Figure 12: ANCOVA analysis result of the contrast between the experimental group (group 1) and the control group (group 0) in the posttest result of information filtering in the ACT assessments. ....................100

Figure 13: ANCOVA analysis result of the contrast between the experimental group (group 1) and the control group (group 0) in the posttest result of mapping structures in the ACT assessments. ....................101

Figure 14: ANCOVA analysis result of the contrast between the experimental group (group 1) and the control group (group 0) in the posttest result of locating similarities in the ACT assessments. ....................101

# CHAPTER 1

# INTRODUCTION

## Background

Over the past decade, the expertise of K-12 students in science, technology, engineering, and mathematics (STEM) domains has become a key consideration for the United States. This rapidly growing economy requires schools to prepare a sufficiently well-trained workforce who excel in STEM literacy. STEM literacy is the ability to understand STEM knowledge and apply it innovatively to solve complex problems (Balka, 2011). Zollman (2012) labels the current K-12 students as the "STEM generation," as everyone is expected to be equipped with sufficient STEM expertise. However, this expectation has not yet been met. The Department of Education states that only 16 percent of high school students in the United States are qualified for a STEM-related career, putting the United States significantly behind many other countries. This gap in K-12 students' STEM literacy has become a critical barrier to the growth of the country; the government has thus proposed enhancing K-12 students' STEM literacy as a national priority.

To develop students' STEM literacy, K-12 educators have integrated computational thinking into the STEM classroom. Computational thinking can be understood as a generic problem-solving process that uses computer science concepts to represent complex problems in a manageable and meaningful form and then finds the most efficient solutions using computational tools (Grover & Pea, 2013; Sengupta, Kinnebrew, Basu, Biswas, & Clark, 2013; Wing, 2006). Research indicates that the integration of computational thinking in STEM education enables students to reinforce their understanding of STEM knowledge and integrate this knowledge with computational tools to solve complex problems. For example, Wilensky and Reisman (2006) note that integrating computing practices in high school science classes allows students to better understand advanced scientific concepts. In addition, the integration of computational thinking presents students with the opportunity to use computing devices to solve problems as computer scientists (Weintrop et al., 2016; Wing, 2006). Students with computational thinking are also more capable of using advanced thinking skills, such as logic, abstraction, and parallel thinking, in problem solving (Berland & Wilensky, 2015; DeSchryver & Yadav, 2015; Wilensky, Brady, & Horn, 2014). In summary, K-12 students with computational thinking are more likely to become STEM literate citizens. In particular, as the era of computing has arrived in STEM education, the need for K-12 students to develop computational thinking is more evident (Grover & Pea, 2013; Henderson, Cortina, Hazzan, & Wing, 2007). Students are expected to develop computational thinking so that they can uncover knowledge hidden in vast amounts of data, including either curated or complicated data (Buitrago Flórez et al., 2017).

In order to develop computational thinking, we need to understand abstraction as its underlying component. Abstraction allows students to determine what to focus on or otherwise what to neglect when dealing with complexity, such as complicated datasets and sophisticated computation (Wing, 2008). Computational thinking requires students to represent their solutions "in a form that could be effectively carried out by an information-processing agent" (Wing, 2011, p. 1). To do this, students use abstraction to selectively retain only the key information to ensure that the problem representations can be handled by computing devices. Wing (2006, 2008) proposes that the "nuts and bolts" of computational thinking include defining abstractions, processing multiple layers of abstractions, and identifying the connections among different layers. The ultimate goal of integrating computational thinking in STEM classrooms is to ensure students can identify the appropriate abstraction layer at a specific stage of problem solving and adopt the optimal strategies or tools for that layer of abstraction to tackle the problem (Muller & Haberman, 2008). In sum, fostering K-12 students' abstraction in computational thinking is integral to developing their STEM literacy.

## Problem Statement

To foster K-12 students' computational thinking, it is necessary to realize that what underlies computational thinking is abstraction and its multiple recursive layers (Wing, 2006; 2008). Computational thinking has been prioritized nationwide in K-12 education as a core skill for digital citizenship in the 21st century (Grover & Pea, 2013; Sengupta et al., 2013). Despite the integration of computational thinking in K-12 schooling, promoting students' abstraction is not as widely integrated as desired yet (Van Oers, 2012). Promoting students' abstraction in the classroom is perceived as a burden if educators are not equipped with the required knowledge and pedagogical skills (Van Oers, 2012). However, little empirical research exists to assist educators in understanding and developing students' abstractions in computational thinking. Therefore, it is imperative for educators and scholars to invest more effort in understanding and fostering K-12 students' abstraction in computational thinking.

First, fostering students' abstraction in computational thinking requires an efficient conceptual framework that clarifies the core cognitive processes of abstraction and how it functions in its multiple layers. Lye and Koh (2014) argue that educative experiences in computational practices require cognitive guidance. Grover and Pea (2013) also suggest that computational thinking research should build upon the "cognitive aspects of children and novices learning computational concepts" (p.42). Existing computational thinking research superficially supports abstraction in computational thinking by identifying abstraction as key to the process without addressing the cognitive aspects of how abstraction in computational thinking functions. Without a conceptual framework to understand the cognitive processes involved in abstraction, K-12 educators have difficulty in effectively promoting the required knowledge and skills with their students. Therefore, it is necessary to propose a conceptual framework of abstraction in computational thinking that clarifies the central cognitive process of abstraction and how abstraction functions in multiple recursive layers.

Second, an effective learning environment dedicated to fostering K-12 students' abstraction in computational thinking is demanding. Traditional formal schooling may not be able to fill the gap between the desired and current situation regarding K-12 students' level of abstraction in computational thinking (Van Oers, 2012). Alternatively, Kramer (2003, 2007) advocates developing K-12 students' abstraction by allowing them to practice it instead of formally teaching it. He notes that less than 35% of adolescents acquire abstraction despite it being a prioritized skill in classroom instruction. Providing a real-life context that allows students to practice abstraction might be more likely to help them develop abstract thinking skills than direct instruction. In addition, computational thinking and STEM education are reciprocal. In particular, STEM education provides authentic and meaningful contexts for students to develop computational thinking (Weintrop et al, 2016). It is worth noting that no individual STEM discipline can be meaningfully connected to a real-world context, since the real-world is interdisciplinary (Sengupta et al., 2013). To effectively support the integration of computational thinking into a STEM learning environment, a real-world interdisciplinary context is necessary. For example, Kopcha et al. (2017) design an integrative STEM curriculum to develop K-12 students' computational thinking using robots "to teach and apply concepts by drawing on multiple STEM subjects rather a single one” (p. 32). In other words, a STEM-integrative learning environment may be an alternative to the existing K-12 curriculum in fostering students’ abstraction in computational thinking. This context may also ensure students are able to practice computational thinking components such as abstraction. Given that few implications are available in the existing literature to guide the design of STEM-integrative learning environments, it is important to propose a set of design guidelines with the hope of efficiently supporting the development of K-12 students’ abstraction in computational thinking using STEM-integrative learning environments.

Third, it is important to determine whether the proposed design guidelines for a STEM-integrative robotics curriculum are effective to foster K-12 students’ abstraction in computational thinking before its wider generalization. The researcher of this study will design the explicit guidance and practices on abstraction (EGPA) in a STEM-integrative robotics curriculum to foster abstract thinking skills for K-12 students. The design of the EGPA will be built upon design guidelines proposed by the researcher of this study and will focus on having students practice the three primary cognitive processes of abstraction (e.g., filter information, mapping structures, and locating similarities) in a STEM-integrative robotics curriculum. To further generalize the design guidelines, investigating the effectiveness of the EGPA in developing students’ abstract thinking skills is necessary. In addition, teachers’ and students’ experiences in and perceptions of the EGPA, such as the perceived benefits, challenges, and potential improvement, are fundamental to understand how EGPA works. Therefore, a comprehensive investigation of the effect of the EGPA on fostering K-12 students’ abstraction in computational thinking in a STEM-integrative robotics curriculum is needed.

## Purpose of the Study

The purpose of this study is threefold. First, this research project will propose a unified framework explaining the underlying cognitive processes of abstraction in computational thinking. Second, this research project aims to propose explicit guidance for K-12 educators to develop abstraction in computational thinking in a STEM-integrative robotics curriculum. This study will then design the EGPA based on the proposed guidelines. To further reinforce the generalizability of these design guidelines, it is necessary to investigate whether the EGPA can effectively help foster K-12 students' abstraction in computational thinking. Third, this research will explore the effectiveness of the EGPA in fostering this important thinking skill for K-12 students in a STEM-integrative robotics curriculum. In doing so, this research will hopefully produce empirical evidence for the future effort to establish a unified framework of abstraction and also to improve the design of learning environments to support the development of K-12 students' abstraction in computational thinking.

## Research Questions

The focus of this study is to explore the effectiveness of the EGPA in developing abstraction in computational thinking in a STEM-integrative robotics curriculum. The EGPA is built upon the unified framework and design guidelines proposed in this article by the researcher of this study. Aligned with the focus of this research, this study will investigate the following research questions.

1. What is the effect of the EGPA on the development of fifth graders' abstraction in computational thinking while taking a STEM-integrative robotics curriculum?
    a. What is the change in students' abstraction in computational thinking after completing the EGPA in the STEM integrative robotics curriculum?

b. What is the change in each cognitive dimension of abstraction after completing the EGPA in the STEM integrative robotics curriculum?

c. What is the difference in the level of abstraction between students completing the EGPA and those who did not while taking the STEM-integrative robotics curriculum?

d. What is the difference in the level of each dimension of abstraction between students completing the EGPA and those who did not while taking the STEM-integrative robotics curriculum?

2. What are the students' experiences with the EGPA while taking a STEM-integrative robotics curriculum?

    a. What are students' experiences with the EGPA in a STEM integrative robotics curriculum?

    b. What are students' perceptions of the EGPA in a STEM-integrative robotics curriculum?

3. What are the teachers' experiences of facilitating the EGPA activities in a STEM-integrative robotics curriculum?

    a. What are teachers' experiences of implementing the EGPA in a STEM-integrative robotics curriculum to develop students' abstraction in computational thinking?

    b. What are teachers' perceptions of the EGPA in a STEM-integrative robotics curriculum on developing students' abstraction in computational thinking?

## Terms

### STEM Education

According to Bybee (2010), STEM education “should increase students' understanding of how things work and improve their use of technologies” (p. 996). It is an emerging trend in the current educational landscape that emphasizes developing students’ knowledge and skills regarding science, technology, engineering, and mathematics subjects and also the use of these knowledge and skills to solve real-life problems (Grover & Pea, 2013).

### Computational Thinking

Computational thinking can be seen as a generic problem-solving process that uses computer science concepts to represent complex problems in a manageable and meaningful form and then find the most efficient solutions using computational tools (Grover & Pea, 2013; Sengupta, Kinnebrew, Basu, Biswas, & Clark, 2013; Wing, 2006).

### Abstraction

Abstraction in its nature traces the essence of beings that distinguishes them from other beings (Wing, 2006, 2008). It is a mental process that streamlines the complexity of reality by looking beyond the superficial details and grasping its core.

### STEM-integrative Curriculum

STEM-integrative curriculum is an innovative curriculum “that uses robots to teach and apply concepts by drawing on multiple STEM subjects rather a single one” (Kopcha et al., 2017, p. 32). In an integrative curriculum, learners are more likely to be engaged in computational thinking to solve an authentic problem and further consolidate their scientific knowledge and thinking skills (Kopcha et al., 2017; Sengupta et al. 2013).

## Significance of the Study

Abstraction has been historically viewed as one of the most advanced thinking skills (e.g., Lowell, 1977; Piaget, 1970). As computational thinking becomes more integral to our functioning in society, abstraction as the fundamental component of computational thinking has also become more widespread (e.g., Colburn & Shute, 2007; Wing, 2006, 2008, 2010). However, research indicates K-12 students might not be able to foster a sufficient level of abstraction without explicit cognitive guidelines (Grover & Pea, 2013; Van Oers, 2012). Without proper instruction available for students, the United States may suffer from the lack of a qualified labor force in the STEM domains and thus not be able to sustain its global superiority in innovation and invention.

This study is significant for the STEM education field since it will enhance the understanding of abstraction in the context of computational thinking by proposing a conceptual framework that clarifies the fundamental cognitive processes of abstraction such as filtering irrelevant information, locating similarities, and mapping structures. In addition, this study is important because it will also offer design guidelines on creating an authentic, problem-oriented STEM-integrative learning environment for educators to foster K-12 students' abstraction in computational thinking. Furthermore, the research will also investigate whether the EGPA developed according to these design guidelines can improve K-12 students' computational thinking in a STEM-integrative robotics curriculum. This finding is also of great significance because it can explore the effectiveness of the proposed guidelines and establish whether the EGPA can be extended to a wider range of contexts for K-12 educators to develop their students' abstraction in computational thinking.

# CHAPTER 2

# LITERATURE REVIEW

## Overview

This chapter will provide a theoretical account of abstraction in computational thinking and thus further propose design guidelines for a STEM-integrative curriculum that is intended to foster K-12 students' abstraction in computational thinking (CT). This chapter will begin with an overview of STEM education and also computational thinking. Then, this chapter will review the history of abstraction and its different dimensions. In addition, this chapter will propose a unified conceptual framework of abstraction in CT by identifying fundamental cognitive processes from its different dimensions. Furthermore, this chapter will discuss the challenges that K-12 students have encountered in developing their abstraction in CT. Finally, this chapter will propose guidelines for a STEM-integrative learning environment to overcome the challenges in developing their abstraction in CT.

## STEM Education

The modern world, characterized by "complex technical and sociotechnical systems," underscores individuals' capabilities of applying the knowledge pragmatically to efficiently identify, absorb, and tackle complex problems (Joyner, Majerich, & Goel, 2013, p. 1043). STEM education is beneficial for preparing students to be better problem solvers, innovators, inventors, self-reliant, and logical thinkers (Jang, 2016), so the nationwide STEM literacy movement has been advocated as one of the standards to evaluate the sustainable competitiveness of the nation. The educational system in the United States thus assumes the hope of preparing a sufficient number of students, teachers, researchers, and practitioners in the fields of STEM in order to meet a national need.

Unfortunately, the U.S Department of Education (2015) stated that U.S. high schools are lagging behind many of other countries with only 16 percent of high school students in the United States are qualified for a STEM-related career. A large majority of K-12 students in the United States are incompetent in the expertise of science, technology, engineering, and math (STEM Education National Science and Technology Council Report, 2013). This gap between the need and the actual number of qualified professions has been perceived as one of the uncontested critical barriers to sustainable growth of the United States (Zollman, 2012). With these concerns, the government proposed a national priority for increasing the competency of K-12 STEM education (National Research Council, 2011).

In particular, computational thinking has been widely recognized as the keystone of STEM expertise with the growing wave of computing (Grover & Pea, 2013). It enables students to address the complex problems in multiple domains and fundamentally influences students' academic performance of STEM (Barr & Stephenson, 2011; Wing, 2006). From a pedagogical perspective, computational thinking deepens students' understanding of STEM knowledge and reinforce their STEM-related expertise (National Research Council, 2011; Wilensky, Brady, & Horn, 2014; Wilensky and Reisman, 2006). For example, Wilensky and Reisman (2006) noted that the integration of computational tools in the high school biology class enables students to generate a deeper understanding of contents and even some "advanced" topics. In addition, students with computational thinking might become better problem solvers excelling at resolving real-world problems, through the use of logic, algorithmic, iterative, recursive, abstract, and parallel thinking (Berland & Wilensky, 2015; Czerkawski & Lyman, 2015; DeSchryver & Yadav, 2015; Wilensky et al, 2014; Wing, 2006). Moreover, teaching computational thinking to students potentially provides them a more prospective view of the scientific field abreast of the time (Wing, 2008). In short, students with computational thinking skills are more likely to become STEM literate citizens and be better prepared for a future career in STEM fields (Weintrop et al., 2015).

The relationship between the computational thinking and STEM education is not single-direction but more reciprocal (Lin, Zhang, Beck, & Olsen, 2009; Weintrop et al, 2015). Besides the aforementioned benefits of computational thinking in students' academic performance in STEM classrooms, STEM education provides authentic and meaningful contexts for students to apply computational thinking and techniques (Weintrop et al, 2015). This reciprocal relationship—using computational practices to reinforce STEM learning and using STEM contexts to enrich computational thinking—lends the ultimate foundation for the proposition of embedding computational thinking in K-12 STEM classrooms (Weintrop et al, 2015). To manipulate this reciprocal relationship between computational thinking and STEM education, this chapter will tap into computational thinking and provide a contextualized definition in the next section.

## Computational Thinking

Computational thinking is considered as a core skill for citizens in the 21st century (Wing, 2006). Many researchers claim this idea is not new but can be dated back to 1960s when Alan Perlis advocated theories about computation and programming among college students (Grover & Pea, 2013; Guzdial, 2008). Then Papert (1980) pioneered computing instruction. He integrated the LOGO programing in the K-12 curriculum to develop children's procedural thinking, which fosters computational thinking from a relatively narrow viewpoint. More recently, Wing (2006; 2008) placed computational thinking in the center of K-12 education and reinvigorated the discussion on how to foster children's computational thinking. To date, there have been multiple versions of definitions of computational thinking (e.g., Wing, 2006; 2008; Know & Ahn, 2014). To foster K-12 students' computational thinking, a comprehensive, operational version in the context of STEM education is required. This section thus reviews different perspectives of computational thinking and provides a contextualized definition of computational thinking in STEM education.

**A Generic Problem Solving Process**

Computational thinking is commonly viewed as a generic problem solving process. Many researchers have investigated features of computational thinking that enable people to understand complex phenomena and solve complex problems (Berland & Wilensky, 2015; Kazimoglu, Kiernan, Bacon & Mackinnon, 2012). For them, computational thinking is an advanced thinking system involving various problem-solving skills. Berland and Wilensky (2015) indicate that computational thinking involves iterative thinking, recursive thinking, abstraction, and decomposition.  Kazimoglu et al. (2012) argue that computational thinking encompasses a set of skills such as building algorithms, debugging, simulating, and socializing. In addition, the International Society of Technology in Education (ISTE) and Computer Science Teachers Association (CSTA) offered a more operational definition of computational thinking with a wider scope of cognitive processes (ISTE & CSTA, 2011):

> (a) Formulating problems in a way that enables us to use a computer and other tools to help solve them; (b) Logically organizing and analyzing data; (c) Representing data through abstractions, such as, models and simulations; (d) Automating solutions through

> algorithmic thinking (i.e., a series of ordered steps); (e) Identifying, analyzing, and implementing possible solutions with the goal of achieving the most efficient and effective combination of steps and resources; and (f) Generalizing and transferring this problem-solving process to a wide variety of problems (p. 1).

However, none of the existing definitions address all features or cognitive processes of computational thinking. The National Research Council (NRC, 2010) thus claims that computational thinking is not a static collection of relevant cognitive processes, but rather that its scope grows in pace with the development of new knowledge and technology.

**The Application of Computer/Technology**

As indicated above, although researchers tend to expand the scope of influences of computational thinking by defining it as a generic problem solving process, many other researchers specify the application of technology as another prominent feature of computational thinking, since the use of technology, such as computers, is ubiquitous nowadays. For example, Wing (2006) broadly defines computational thinking as a process that “involves solving problems, designing systems, and understanding human behavior, by drawing on the concepts fundamental to computer science” (p. 33). Computational thinking requires learners to understand and solve a problem in the same way as computer scientists do, but it is not just a synonym for programming (Grover & Pea, 2013). Wing (2011) defines computational thinking as the “thought processes involved in formulating problems and their solutions so that the solutions could be represented in a form that could be effectively carried out by an information-processing agent” (p. 1). Israel, Pearson, Tapia, Wherfel, and Reese (2015) also understands computational thinking as a process of “using computers to model ideas and develop programs that enhance those programs” (p. 2). In addition, Deschryver and Yadav (2015) provide a more comprehensive definition describing computational thinking as a set of problem-solving skills and strategies in “data-mediated, technology-rich learning and work environments” (p. 415). Know and Ahn (2014) summarize computational thinking as a mental process wherein students undergo analytic and procedural thinking and apply computing toolkits to unravel complex problems in various fields.

Therefore, this paper also underlines the role of technology in computational thinking and understand computational thinking as a specific problem solving process with roots in computer science that highlights the utilization of computers. Computer or technology offers scaffolds for people to effectively solve more complex problems. This could be a unique angle to differentiate computational thinking from a general problem-solving model.

**Leaning on Abstractions**

While scholars describe computational thinking from various perspectives, many of them have confirmed the importance of abstraction in computational thinking (e.g. Czerkawski & Lyman, 2015; Grover & Pea, 2013; Sengupta et al., 2013; Wing, 2006). The use of a computer is common in solving complex problems, but its prerequisite is to represent the complex problem in a precise way that computers can process (NRC, 1999; 2010). That is, computational thinking must precede programming a computer. Wing (2006) portrayed the nuts and bolts of computational thinking as a recursive process of identifying the connections among multiple layers of abstraction and then selecting and processing the most appropriate layers.

In addition, this paper summarizes different components of computational thinking in the literature (see Table 1) and find that abstraction influences each component of computational thinking. For example, abstraction is key to debugging by allowing software developers to focus on relevant details when fixing a specific question in a complex system, without being distracted by unrelated redundancy (Bates & Wileden, 1983). In addition, abstraction underlies generalization because it is a process of "defining patterns, (and) generalizing from specific instances" (Wing, 2011, p.1). In short, abstraction enables people to simplify a complex problem into representations that people can use computer/technology to solve and further generalize the solutions. Based on the aforementioned viewpoints, researchers maintain that abstraction is an essential cognitive skill required for developing computational thinking (e.g., Grover & Pea, 2013; Wing, 2006, 2008).

**Table 1**

*Features of computational thinking and their definitions from the exiting literature.*

| Feature(s) | Definition(s) | Reference(s) |
|---|---|---|
| Logical thinking | "CT refers to solving problems with logical thinking through using various computational models. This includes applying problem decomposition to identify problems and/or generating alternative representations of them. At this level students distinguish between problems and decide whether these problems can or cannot be solved computationally. Furthermore, students are able to evaluate a problem and specify appropriate criteria in order to develop applicable abstractions." | Kazimoglu et al. (2012); Kim, Kim, & Kim (2013); Wing (2006) |
| Procedural thinking | Procedural thinking includes "representing, developing, testing, and debugging procedures, and an effective procedure is a detailed step-by-step set of instructions that can be mechanically interpreted and carried out by a specified agent, such as a computer or automated equipment." | NRC (2010) |
| Abstraction | Abstraction involves extracting common features from specific examples and hiding unnecessary information to simplify complexity | Bennett & Müller (2010); Kramer (2007); Son, Smith, & Goldstone (2011) |
| Problem decomposition | Problem decomposition is a process of breaking a complicated problem into smaller and more tractable pieces that are easier to deal with (e.g., modularizing) | Grover & Pea (2013); NRC (2010); Wing (2011) |

| | | |
|---|---|---|
| Algorithms thinking | Algorithms thinking "involves the construction of step-by-step procedures for solving a particular problem. Selection of appropriate algorithmic techniques is a crucial part of thinking computationally as this develops abstractions robust enough that they can be reused to solve similar problems." | Grover & Pea (2013); Kazimoglu et al. (2012); Snalune (2015) |
| Iterative thinking | Computational thinking is an iterative process based on three stages: 1) problem formulation, 2) solution expression, and 3) solution execution & evaluation. | Grover & Pea (2013); Kazimoglu et al. (2012) |
| Debugging | Debugging is viewed as a process of creating models of actual behavior from the activity of a system and comparing these models to the models of expected behavior of implementers and users of the system. Through these comparisons, debugging tool users attempt to identify sources of errors in the system. | Bates & Wileden (1983); Grover & Pea (2013); Kazimoglu et al. (2012) |
| Generalization | Generalization involves formulating a generic solution or representation that can be applied to solve problems in various contexts. | Sengupta et al. (2013); Snalune (2015); Wing (2006) |

Therefore, this paper defines computational thinking as a problem-solving process that leans on abstractions to develop generalized representations of a complex task for computers or other computing technologies to process and further generate optimized solutions. Computational thinking is a consciously analytical and logical mental process that involves modeling a problem precisely, conceptualizing and solving the given problem at multiple abstraction levels, iteratively debugging solutions, and then formalizing a general solution which could be used in various contexts.

## Abstraction

Understanding the cognitive foundation of abstraction is crucial to designing effective learning environments that promote abstraction in CT. This section starts with a historical review of abstraction and then reveals different dimensions of abstraction. In the end, this chapter will identify the key cognitive processes of abstraction.

**The Historical Aspect of Abstraction**

Current research indicates that abstraction is a fundamental component of computational thinking that enables people to deal with complexity (Grover & Pea, 2013; Sengupta et al., 2013; Wing, 2006; 2011). Understanding the nature of abstraction in general is crucial for design learning environment to promoting individual abstraction and computational thinking. However, abstraction, as the most important component of computational thinking, is still disputed (Van Oers, 2012). It may be difficult for many educators to understand the important role of abstraction plays in computational practices and other fields. In fact, abstraction has been perennially respected as one of the highest levels of thinking that fosters students' problem-solving skills (Piaget, 1970). This section thus features an historical review of research related to abstraction so as to provide a holistic view of this important aspect of computational thinking (Sengupta et al., 2013).

As a philosophical concept, abstraction can be traced back to the time of Plato (427-347 BCE) when he began to distinguish *Forms* (e.g., justice, beauty, and other abstract concepts) from *particulars* in the sensible world (Sengupta et al., 2013). For Plato (380BC), *forms* are the universals shared by all the *particulars*. For example, Colburn and Shute (2007) describe justice as "an immutable Platonic form" (p.171) shared by all just acts, but a particular just act is an imitated justice that is only true to people who see or feel it. Zeki (2000) note that Plato insists ideal forms are eternal universals originating in human intellect, and thus they enable the forming of knowledge, but particulars are temporary representations of the entities or phenomena that might fade in the memory (e.g., the allegory of the cave). For instance, we recognize the color of green despite chromatic aberrations because we have an ideal form of "green" in our brain. For various green colors in our daily life, they are temporary representations of "green" as a particular. Moreover, history indicates that Plato started teaching geometry to develop his students' abstract thinking. (Carson & Rowlands, 2007). For example, the forms of geometrical patterns (e.g., triangle, circle) are the essence of all concrete objects. These geometrical patterns are more abstract than the physical reality. People with knowledge of geometry are thus more likely to use abstraction to symbolize reality and capture the essence of scientific phenomena (Rowlands, 2010; Carson & Rowlands, 2007).

Subsequently, abstraction garners more attention as a cognitive concept of how human minds process abstract and concrete information (Sengupta, et al., 2013). Christoff and Keramatian (2007) note that Locke (1632-1704) started the discussion on the dichotomy of abstract and concrete ideas by defining abstraction as the mental process of leaving out particular differences to form a general idea. Locke believed that abstraction is of considerable importance to human knowledge. He advocated that people focus more on similarities and ignore unnecessary information (e.g., time, place) to form abstract general ideas that are applicable to similar cases. However, Berkeley's proposition contradicts Locke's thoughts about abstract general ideas. Christoff and Keramatian (2007) summarize Berkeley's definition of abstraction as a process of shifting attention, in which selective attention to different properties determines how people overlook irrelevant information and simplify complexities.

More recently, abstraction gained respect as one of the highest levels of thinking when Piaget (1970) indicated that only individuals reaching the highest stage of cognitive development can manipulate abstraction. Piaget (1970) proposed the theory of cognitive development to explain how individual learners process different types of information at various ages. The theory identifies four distinctive stages of cognitive development based on individual growth: the sensorimotor phase (0-2), the preoperational phase (2-7), the concrete operational phase (7-11), and the formal operational phase (12 and up). Only individuals at this highest stage possess the ability to learn and understand abstract concepts (Piaget, 1970). Afterward, a number of researchers posited abstract rationality as the endpoint of cognitive development (Van Oers, 2012; Wertsch & Sohmer, 1995). Abstract rationality is the most advanced thinking associated with de-contextualization and generalization (Derry, 2008). Individuals who acquire abstract thinking skills are thus assumed to have capabilities of identifying general principles while solve a complex situation rather than relying on the specific details of the context (Wertsch & Sohmer, 1995).

Additionally, in a constructive-empirical view, abstraction is defined as a higher-order thinking skill that cognitively exerts classification and generalization on the basis of similarities abstracted from analogical instances (Piaget, 1970; Ozmantar, 2005, Yang, 2013). As one of the highest forms of thinking, abstraction plays an important role in conceptual understanding (Bennett & Muller, 2010), problem solving (Bennett & Muller, 2010; Gelman & Kalish, 2006), and decision making (Breuning, 2003). Ojose (2008) states that abstraction enables individuals to utilize hypothetico-deductive reasoning to predict consequences of their actions and generalize solutions. Through applying abstractions, learners are able to extract relevant information like variables and potential causes of a given circumstance. They are also capable of retrieving similar experiences to resolve complexity and eventually generalize solutions that are closely attached to the de-contextualized operation (Joyce, 1977; Ojose, 2008). Additionally, Ojose (2008) notes that students at the formal operational stage are able to connect abstract concepts to real-life situations and thus outperform others in real-world problem solving.

## Dimensions of Abstraction

Abstraction, as a central cognitive concept, is defined in many ways within various disciplines, providing a comprehensive theoretical base of abstraction. This section reviews various dimensions of abstraction to understand the cognitive foundation of abstraction.

### Classification

Abstraction as classification refers to a cognitive process of grouping similar objects or concepts into homogeneous categories to reduce the complexity (Barsalou, 2003; Lowell, 1977). Therefore, an essential process of classification is to locate similarities among objects/concepts. People who excel in classification identify common essential characteristics among objects/concepts and thus demonstrate a better ability to understand abstract concepts (Chi, Feltovich, & Glaser, 1981). For instance, when students group *pines* and *cypresses* into the same category based on their fundamental commonalities (i.e., needles and cones), they are more likely to comprehend the abstract concept *conifer*.

Lowell (1977) proposes a reverse-pyramid hierarchical model of classification where the levels become more abstract with a tendency to increase inclusiveness from the base to the top (see Figure 1). Level I, attribute identification, is the most fundamental level of abstraction (Lowell, 1977). At this level, people can correctly differentiate objects/events without verbally naming the attributes based on the information they perceive. For example, students can select *galena* and *pyrite* from several similar but different objects without verbalization. At Level II, attribute recognition, people can verbally assign attributes (e.g., color, luster) to their proper symbolic representations. Object recognition is the third level in which people are able to form a name of the events or objects (e.g., *galena* and *pyrite*) based on several gathered attributes. At Level IV, class recognition, people begin to "dispense with specific names and deal with generalized representations of specific names" (Lowell, 1977, p.231). Thus, objects/events with common features (e.g., *galena* and *pyrite*) are grouped into the same class (e.g., *metallic*). Finally, Level V (one-class recognition) and Level VI (two-class recognition) are two of the highest levels of abstraction with greater generality than at any other levels. For example, students at Level V classify *mineral* (versus *living product*) as a more abstract concept including both *metallic* and *non-metallic*. *Natural phenomena* (both *mineral* and *living product*) is detected at Level VI as the most abstract concept with the most generalized representations. In summary, classification helps people grasp the key information and identify essential commonality to understand abstract concepts (Chi, Feltovich, & Glaser, 1981). For instance, students can better comprehend the abstract concept *conifer* if they can group *pines* and *cypresses* by their fundamental commonalities (i.e., needles and cones). To do so, people need to identify the most fundamental attributes from perceived information and extract the common features to form a hierarchy of generalized representations of objects/events.

**Generalization**

Abstraction as generalization describes an inductive process of capturing similarities among objects or concepts to form a generalized representation that can be used to solve analogous problems (Barsalou, 2003; Gentner & Lowenstein, 2002). Generalization, similar to classification, also lies in the cognitive processes of filtering irrelevant information and locating similarities among objects/concepts. For instance, physicists retrieve the fundamental information from and extract common features among various phenomena to generate a formula (e.g., time × speed = distance) or a principle (e.g., the Law of Conservation of Energy) that might help people resolve an unlimited number of problems. Bennett and Müller (2010) also indicate that people with better abstract thinking skills are more likely to form a generalized representation of prior knowledge and then use it to deal with a different but similar circumstance. On the other hand, generalization differs from classification since it allows people to produce a generalized representation (e.g., formula, principles) based on finite examples to solve infinite analogical problems (Barsalou, 2003). In other words, classification highlights the actions of locating similarities among finite samples and of properly categorizing each sample. Bennett and Müller (2010) also indicate that people with better abstract thinking skills are more likely to form a generalized representation of prior knowledge and then use it to deal with a different but similar circumstance.

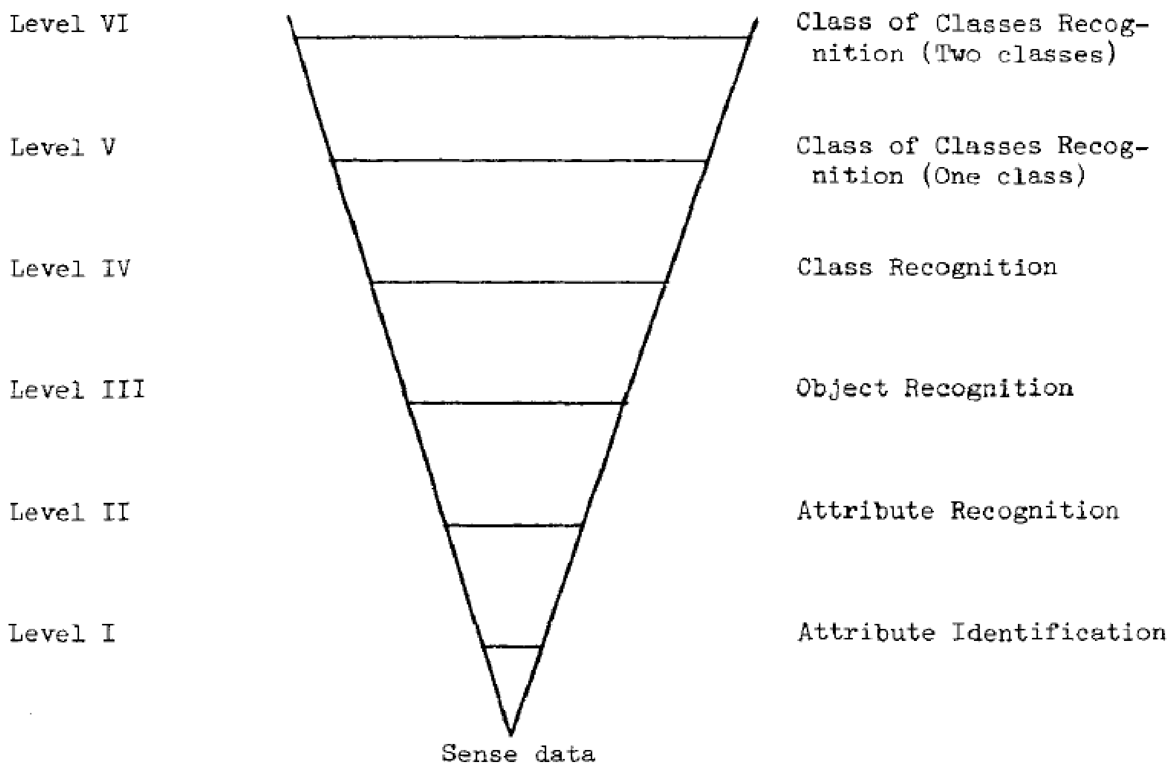



*Figure 1.* The order of classification (Lowell, 1977).

### Simplification

In some ways, abstraction is simplification (Son, Smith, & Goldstone, 2008). Abstraction in this sense places an emphasis on removing irrelevant information to form a more explicit representation of complex problems. Simplification is also the shortcut for abstraction to produce greater generality (Son et al., 2008; Thai, Son, & Goldstone, 2016). By overlooking irrelevant information, simplification "supports learning by getting at the heart of this problem: The few features that are presented are all relevant" (Thai et al., 2016, p.304). For example, computer scientists often simplify a compound problem by chunking irrelevant information into an operational core entity, the black-box (Muller & Haberman, 2008). In doing so, they only attend to the functions of the black-box but overlook the unnecessary details inside it. Computer scientists can thus focus on the core of the problem and then iteratively apply the black-box method to resolve the rest of the compound situation. It should be noted that simplification requires learners to efficiently represent the problem and understand the goal because it determines how people shift their attention consciously to remove unnecessary information (Schwenk, 1984).

### Decomposition

Decomposition, as a facet of abstraction, describes a process of breaking down a complex problem into multiple subparts and mapping a hierarchical structure to represent the problem (Ho, 2001). Decomposition is an important strategy for people to tackle the complexity of ill-structured problems (Simon, 1996). It allows people to form an appropriate problem representation so that they can match it with their prior knowledge to solve the problem (Jonassen, 1997). People decompose a complex problem into a spectrum of subproblems until they can easily develop an explicit solution to them. In addition, sub-problems are formed upon different levels of abstraction. Specifically, sub-problems with higher levels of abstraction are geared toward the overarching structure, but those less abstracted ones are inclined to deal with superficial details (Ho, 2001; Muller, Ginat, & Haberman, 2007). Decomposition also expects people to understand the relationships among each subpart so that they can facilitate the synthesis of solutions to each sub-problem and resolve the complex problem (Liikkanen & Perttula, 2009). For example, architects accomplish a new building design task by splitting it into several parts and then synthesizing each subpart solution as an overarching plan (Rowe, 1987).

**Pattern Recognition**.

Abstraction as pattern recognition denotes the ability to identify patterns and match them with similar patterns in the memory to tackle analogical problems (Gobet, 1997; Muller & Haberman, 2008). A pattern is a generic schema that mainly addresses common features shared among a collection of de-contextualized problems (Gobet & Simon, 1996; Muller & Haberman, 2008). Generally, pattern recognition begins with identifying the consequential cues from the perceived information to generate relevant patterns (Pal & Pal, 2001). Once a pattern is formed, people start to retrieve similar patterns from their long-term memory to formulate potential solutions (Bilalic, McLeod, & Gobet, 2009, Chase & Simon, 1973). In face of complicated problems involving more than one task, people tend to process pattern recognition for each task that they identify by decomposition (Muller & Haberman, 2008). With pattern recognition, people can resolve complex problems even with vague or incomplete information (Patel, Groen, & Arocha, 1990). Therefore, the accretion of domain-specific patterns is necessary for novices to grow into experts in a domain (Bilalic et al., 2009). In addition, pattern recognition is required for experts to quickly make correct decisions in a time-constraint context as it empowers people to resolve the complexity by generalizing a denominator shared among multiple instances (Gobet

& Simon, 1996; Jain & Duin, 2004). In summary, pattern recognition plays an important role in scientific disciplines. Many advanced tasks such as computing DNA sequences, predicting national economics, and debugging programming require professionals to master this type of abstraction.

### Underlying Processes of Abstraction

Each perspective above provides a unique lens to understand abstraction, but each definition uses its own specific terminology to entail different cognitive skills. The lack of a unified understanding of abstraction may bring about additional barriers to fostering abstraction for K-12 students. To overcome this gap, this section presents the fundamental cognitive processes of abstraction in the dimensions above (see Table 2).

**Table 2**

*The essential cognitive processes in different facets of abstraction.*

| **Processes** | **Facets of Abstraction** | | | | | |
|---|---|---|---|---|---|---|
| | Classification | Generalization | Simplification | Pattern Recognition | Decomposition | AB in CT |
| Filtering information | ✔ | ✔ | ✔ | ✔ | ✔ | ✔ |
| Locating similarities | ✔ | ✔ | | ✔ | ✔ | ✔ |
| Mapping the structure | ✔ | | | | ✔ | ✔ |

The first fundamental process consistent in these dimensions is *filtering information,* a cognitive process of ignoring unnecessary information and of focusing only on the relevant information. Filtering information is included in various dimensions of abstraction. For instance, individuals overlook irrelevant information to increase the accuracy of classification (Limshuebchuey, Duangsoithong, & Windeatt, 2015). Generalization also highlights information reduction as a necessary step to formulate a generalized principle (Barsalou, 2003). Therefore, filtering information is integral to identifying the relevant information and thus to understanding the essence of a complex situation. Furthermore, explicitly defining the goal of a given complexity helps people filter information (Limshuebchuey et al., 2015). People with an explicit goal can capture relevant information and then selectively attend to essential features. For example, architects keep only the key information (e.g., location, scale) when sketching the construction plan in a bird's eye view map. Otherwise, irrelevant details might make the map less explicit, or oppositely, excessive abstraction might leave out key details.

The second common process is *locating similarities*, a process of detecting the commonalities between objects or events to form a generalized representation (Barsalou, 2003). This generalized representation can be used to retrieve a proper schema for resolving the complexity or be reused to solve analogous problems. Locating similarities is pervasive in these dimensions above, especially in generalization (Bennett & Müller, 2010; Gentner & Lowenstein, 2002) and pattern recognition (Bilalic et al., 2009). In generalization, locating similarities allows people to form a generalized representation that adaptively responds to similar but different situations (Bennett & Müller, 2010; Gentner & Lowenstein, 2002). In pattern recognition, people locate similarities to abstract common features from objects or events that can be matched with proper schemas stored in the memory. Locating similarities is also a key cognitive process for scientific achievements in various domains. For instance, physicists extract a general principle (e.g., the Law of Conservation of Energy) after recognizing the decontextualized commonalities among various phenomena. Then this principle can be the basis for the physicists to resolve unlimited analogous problems (e.g., inventing steam engines and applying thermometers) in the future.

The third common process is *mapping out a structure of given problems*, which refers to the process of presenting a global overview of problem structure and properly representing the relationships between the core problem and associated sub-problems (Muller & Haberman, 2008). For example, decomposition includes the process of breaking a complex problem into smaller pieces and modeling a hierarchy of interrelated sub-problems (Ho, 2001). Mapping out the problem structure is also essential for decomposition when people synthesize the solution to each subproblem into a comprehensive solution to the overarching problem (Liikkanen & Perttula, 2009). In word, an explicit problem structure is important for people to tackle the complicate tasks in scientific domains. For example, designing a spaceship can be mapped into a structured task involving several sub-tasks such as the engine design, a crew module design, a flight control design, and other component designs. By mapping out the structure, engineers can tackle each subtask sequentially and then make sure these components collectively function as expected.

In summary, abstraction can be achieved through these three cognitive processes, including filtering information, locating similarities, and mapping out the problem structure. Abstraction in its nature traces the essence of beings that distinguishes them from other beings. It is a mental process that streamlines the complexity of reality by looking beyond the superficial details and grasping its core. The ways of abstracting the essence may vary among different individuals and in different domains, but in general, these three processes underlie how abstraction works.

## Abstraction in Computational Thinking

Abstraction is widely acknowledged as the essence of computational thinking in the form of generalized computational representations that can be applied in multiple contexts (Grover &

Pea, 2013; Sengupta et al., 2013; Wing, 2006). Different from traditional notions, abstraction in computing practices is more advanced and unique because of the recursive work in multiple layers of abstractions (e.g., the "global" or "local" view in Wing, 2008, 2010). In computing practices, programmers revolve around multiple levels of abstractions to simplify and resolve the complexity. For instance, software developers tend to use a "global" view (i.e., the higher level of abstraction) of the system to clarify the overarching goal of the software without considerations of underlying systems for the goal (Schmidt, 2006). Furthermore, when writing codes for a specific function, they would transfer to a "local" view (i.e., the lower level of abstraction) to interpret a situation in a more detailed perspective (Hazzan & Kramer, 2007). Therefore, traveling among multiple levels of abstraction becomes a crucial mental process in computing practices. With this capacity, people can accomplish a complicate task in the light of contextualized intentions, without understanding all details in the environment (Muller & Haberman, 2008; Schmidt, 2006; Wing, 2006, 2008). This section will focus on abstraction in CT and discuss its significance provided with two examples in STEM fields, mathematics and computer science.

**Abstraction in Mathematics**

Abstraction in mathematics is a process of developing a mental representation of a mathematical object (Mitchelmore & White, 2012; Yang, 2013). Mitchelmore and White (2012) summarize three common forms of abstraction in math, including empirical abstraction, horizontal mathematization, and vertical mathematization.

In mathematics, the basic level of abstraction is empirical abstraction. Empirical abstraction is the process of obtaining knowledge from the properties of physical objects by extracting and generalizing common features (Beth & Piaget, 1966; Dubinsky, 2002). Many elementary mathematical concepts including numbers and shapes are formed through empirical abstraction. Specifically, empirical abstraction allows learners to extract the underlying similarities among mathematical objects or processes that characterize them and thereby form an understanding of those mathematical concepts (Mitchelmore & White, 2012; Skemp, 1986).

The second level of abstraction in mathematics is horizontal mathematization wherein learners generate mathematical tools (e.g., models) by abstraction to solve real-world problems (Treffers, 1987; Verschaffel & Greer, 2014). The foremost step for learners is to draw out the underlying essence of the real-world situation and model it in the context of mathematics (Drijvers, 2000). Then learners represent the problem with mathematical objects and ignore irrelevant information in order to develop a mathematical tool (Mitchelmore & White, 2012). For Mitchelmore and White (2012), horizontal mathematization is an integral form of abstraction for mathematic learning because it encourages learners to apply mathematics in a non-mathematic context without any consideration of its concrete applications.

At the other end of the spectrum is vertical mathematization (Treffers 1987). Vertical mathematization is a process of forming a higher level of abstraction to efficiently solve mathematical problems with no clues from common experience (Mitchelmore & White, 2012). In this process, learners might totally reorganize their conceptions of mathematics to reach a higher level of abstraction (Tall, 1991). Empirical abstraction and horizontal mathematization are inadequate to represent some mathematical symbols (e.g., $a_0$, $a_1$, or $a_{1/2}$ in Mitchelmore & White, 2012) as they are not common in the real-life experience of learners, so learners are required to restructure their mathematical knowledge framework to represent these symbols at a higher level of abstraction. In addition, vertical mathematization can be iteratively repeated to form a hierarchy of abstraction (Mitchelmore & White, 2012). For example, the hierarchy that ascends from graphs to coordinate planes, then to a 3-dimensional space, and finally to an n-dimensional space is accomplished through vertical mathematization (Mitchelmore & White, 2012).

**Abstraction in Computer Science**

In computing practices, these three core processes also underlie how abstraction functions. Computer science is referred to as a "science of abstraction" where people model the problem in an abstract representation so that programmed devices or techniques can be applied to solve it (Aho & Ullman, 1995). Muller and Haberman (2008) indicate two primary types of abstraction in computer science, data abstraction that "involves separating the logical properties of data from the implementation details" (p. 188) and procedural abstraction that consists of setting apart the action properties from the details regarding the implementation. These two types of abstraction allow people to solve problems like computer scientists. Liskov and Guttag (2001) describe two ways to enable these two types of abstraction, abstraction by parameterization and abstraction by specification, which are also enabled by these three cognitive processes.

Abstraction by parameterization represents the computing components by formal parameters to hide irrelevant identities and detect the essence of the problem. In particular, filtering information and locating similarities are the two main processes underlying the parameterization. Liskov and Guttag (2001) use the example of the lambda expression [λ x, y: int. (x*x + y*y)] as a parameter for the body of computation (x*x + y*y). To do so, learners have to recognize the most consequential information of the computation, which is the underlying principle of the computation instead of the letters in the body of the computation. In addition, learners can use the lambda expression as an abstract form of different bodies of computations (e.g., a*a + b*b, c*c + d*d) when locating the similarities among those computations. In this way, people can use parameters to describe infinite computations in a rather simple way. This type of abstraction is a major pathway for the formulation of a generalizable program, but it is not sufficient to simplify computing procedures (Nicholson, Good, & Howland, 2009).

In contrast, abstraction by specification represents intricate computing procedures by specifying their expected function, especially when the problem involves multiple procedures (Liskov & Guttag, 2001). Through specification, people can focus on the core procedure in problem solving instead of addressing the irrelevant details (Liskov & Guttag, 2001). In this process, filtering information, locating similarities, and mapping structures all play a key role. The use of the “black box” in computing practices is a good specialization example. To resolve compound problems, computer scientists use the “black box” to specify the intended functions of these hidden internal details so that they can simply focus on the input and output end, disregarding solutions to numerous sub-problems (Muller & Haberman, 2008). To use the “black box,” computer scientists need develop an explicit problem representation to understand the main problem and its hierarchical structure. Moreover, they need filter irrelevant information and then put irrelevant details into a functional entity. To clarify the function of the “black box,” computer scientists need locate similarities between different components and then represent the complicated procedures using the function of the entity. In all, specification enables computers to process the real-world complexity by its manageable representation (Nicholson et al., 2009), but doing so requires the three fundamental cognitive processes of abstraction.

On the other hand, Liskov and Guttag’s (2001) clarify the *what* and *how* people can achieve abstraction by parameterization and by specification, but according to Marr (1982), “the most abstract is the level of what the device does and *why*” (p.22). Marr proposes three different levels of abstraction with a focus on the *what* and *why* of abstraction (Shagrir, 2010). Specifically, Marr insists that the computational level is the most abstract level (see Table 3).

People up to this level focus on tackling underling problems and constraints in a certain situation (Marr, 1982). Marr uses the example of cash registers to explain that *what* is being computed is an abstract principle (i.e., theory of addition) mapped from the concrete information in practice (i.e., the price of each item) with a specific goal (i.e., a correct final bill). Another part of this abstract level is to justify why the computation is appropriate for the goal. Marr (1982) indicates that a series of constraints afforded by the context uniquely define the resulting operation. In the case of cash registers, such constraints as "the rules for zero" deem that the theory of addition is the appropriate rule for the computation. The second level is representation and algorithm, which describes how a device represents the input and output and operates algorithms to enable computing (Marr, 1982). For cash registers, Arabic numerals are common representations of the input and the output since both ends use numbers. Accordingly, the usual rules of addition (e.g., carrying one digit if the sum exceeds nine) are the algorithms that ensure that the theory of addition proceeds properly. Generally, a selected algorithm aligns with the defined representations, but choosing the unique representation and algorithms from a wide array of options requires further consideration of the hardware that will physically embody the algorithms (Marr, 1982). The lowest and the most detailed level of abstraction is the hardware implementation that focuses on the implementation of algorithms and solutions (Marr, 1982). One algorithm might be carried out by various types of hardware, but people have to correctly select a proper one to ensure the algorithms are physically enabled.

Following Marr (1982), I speculate that abstraction in CT functions upon the recursive move among three *vertical* layers, one each of which abstraction also *horizontally* proceeds three processes, 1) filtering information, 2) locating similarities, and 3) mapping the structure. For example, software developers use a "global" view of abstraction to clarify the overarching goal and associated constraints to develop a new software (Schmidt, 2006) and transfer to a more detailed "local" view when writing codes for a specific function (Hazzan & Kramer, 2007). The author insists that the ultimate purpose of abstraction is to simplify the reality into its most fundamentally distinguishable essence to be processed by computing devices (e.g., computers) at a specific level.

**Table 3**

*Marr's Computational Theory and its three levels (Marr, 1982).*

| Computational Theory | Representation and Algorithm | Hardware Implementation |
|---|---|---|
| What is the goal of the computation?<br>Why is it appropriate?<br>What is the logic of the strategy by which it can be carried out? | How can this computational theory be implemented?<br>What is the representation for the input and output?<br>What is the algorithm for the transformation? | How can the representation and algorithm be realized physically? |

## A Conceptual Framework of Abstraction in Computational Thinking

This paper proposes that a unified model of abstraction in CT should consist of the *what*, *how*, and *why* of abstraction to describe its process. Building on this notion, this paper conceptualizes a framework wherein abstraction in CT proceeds in both horizontal and vertical directions once the cognitive system perceives the information from the reality (see Figure 2).

On the vertical level, this paper adapts Marr (1982)'s three levels of abstraction in information processing, including computational level, algorithm, and implementation. The most abstract level is the computational level which specifies "the goal of the computation" and "the logic of the strategy by which it can be carried out" (Marr, 1982, p.22). The second level is the representation and algorithm level wherein learners form a representation of the input and output and choose an appropriate algorithm that accomplishes the computation (Marr, 1982). Then, the lowest level is the implementation level wherein learners select the proper hardware that enables the algorithm to function for the purpose of solving the problem. Learners need to decide the proper layer of abstraction to work on according to the constraints of the reality. Whenever necessary, learners have to move back and forth around these layers of abstraction to deal with complexity.

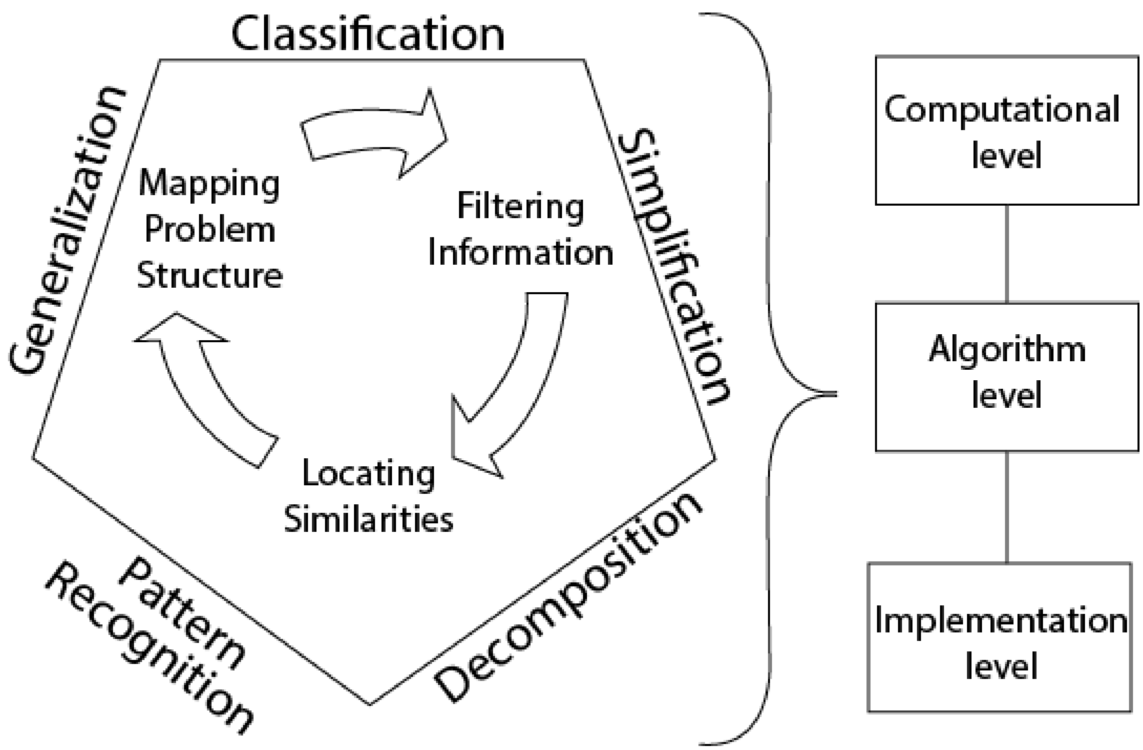



*Figure 2.* A unified framework of abstraction in computational thinking.

On the horizontal level, abstraction allows learners to form a manageable and meaningful representation of compound problems based on three primary cognitive processes. Specifically, filtering information is to intentionally ignore irrelevant information for a more explicit understanding of the problem. Filtering information allows learners to extract information that is the most relevant to the overarching goal of the problem. Following the identified goal, learners can decompose the compound problem into more smaller subparts so that they formulate the solution to each sub-problem. Once the structure is mapped, learners can undertake pattern recognition recursively so that they can locate similarities between the newly identified patterns with existing patterns in their stored memory to suggest potential solutions. Furthermore, learners need recompose the solutions to each subproblem to develop a synthesized comprehensive solution to the main problem. Subsequently, learners might also repeatedly apply the process of locating similarities to form a de-contextualized form of the solutions that can be generalized to various situations. It is worth noting that when undergoing the horizontal aspects of abstraction, learners need also address the vertical movement among multiple layers of abstraction to ensure that they can produce the appropriate representation of the problem for computing devices to process.

## Challenges for Students to Develop Abstraction in Computational Thinking

Abstraction is a complex and sometimes difficult cognitive task. Ojose (2008) notes that K-12 teachers assume their students can always think logically and abstractly, yet this is often not the case (Susac, Bubic, Vrbanc, & Planinic, 2014). In addition, abstraction in CT requires learners to move flexibly among multiple layers of abstraction (Wing, 2008), which might result in additional challenges for students. Understanding the challenges that students face in each cognitive process is critical to foster abstraction in CT. This section will thus discuss challenges students meet in each process.

### Challenges in Filtering Information

Students struggling with filtering information might have difficulty in accurately understanding and representing complex problems. Chi et al. (1981) argue that problem solving starts with analyzing the problem, but experts and novices rely on different evidences to understand the problem. Experts can undertake the qualitative analysis of the given information and activate the stored schema in the memory to retrieve the principle underlying the problem; however, novices filter the information based on the superficial features (Chi et al., 1981). For example, when given a physics problem, novices tend to focus on the irrelevant objects (e.g., cars on the slope) but experts might attempt to find the relevant principle (e.g., friction). Novices' relatively inferior manner often causes that they retain excessive details or remove crucial information. The capacity of individual cognitive systems is limited, so the failure in overlooking irrelevant details might lead to inefficient information processing that further affects the recall of appropriate schemas (Driscoll, 2014). On the other hand, the loss of crucial information decreases the accuracy of problem representation and novices are thus misguided to make an incorrect decision (Bucci, Long, & Weide, 2001). In summary, novices' difficulty in information filtering results from their inability to understand the task. To overcome this challenge, it is necessary to help students articulate their understanding of the problem and identify the explicit goal.

**Challenges in Locating Similarities**

The challenges in locating similarities might result from novices' inability to detect the appropriate level of similarities among multiple instances (Gentner & Toupin,1986; Reeves & Weisberg, 1994). Gentner and Toupin (1986) indicate similarities are categorized in three levels, "mere-appearance matches", "literal similarity" and "analogies". Only detecting the analogies can allow learners to locate the fundamental similarity shared among multiple instances and further form generalized representations to attain abstraction (Gentner & Hoyos, 2017). An example of analogies is to compare the atom to the solar system merely by the fundamental similarities between them (Sahin & Akman, 2009). Mere-appearance matches indicate two instances are similar in terms of their superficial attributes (Gentner & Toupin, 1986). An example of mere-appearance matches is to represent the earth using a blue sphere object with their similarity in the color and the shape. In addition, the literally similar instances might overlap in both superficial attributes and structural properties (Gentner & Toupin, 1986). For instance, the solar system is literally similar to the fifth graders' solar system model since they are similar both in the shape and the structure (Sahin & Akman, 2009). However, the two levels of similarities (e.g., "mere-appearance matches" and "literal similarity") are not sufficient for people to locate the fundamental similarities among multiple objects/events, which requires people to discover the "analogies" (Reeves & Weisberg, 1994). Furthermore, experts generalize a more inclusive solution or principle underlying various situations (e.g., laws of physics) based on the identified proper similarities, while novices' solutions are limited by commonalities on the surface among analogous problems (e.g., friction, center of mass, or a specific mechanism such as a spring or an inclined plane). Therefore, the failure to detect fundamental similarities restricts novices' ability to generalize with sufficient inclusiveness.

**Challenges in Mapping Structures**

Students' challenges in mapping structures are mainly due to their inability to 1) decompose a complex problem into tractable subparts or 2) identify the structural relationship binding these subparts (Liikkanen & Perttula, 2009; Muller & Haberman, 2008). Problem decomposition includes a dual-model view (i.e., explicit and implicit) for people to break down problems and form a hierarchy of subproblems (Ho, 2001). Experts tend to use explicit strategies to analyze the functional structure at the beginning of the problem decomposition and thus generate more effective and explicit structures than novices using implicit strategies (Ho, 2001; Liikkanen & Perttula, 2009). In addition, inefficient structure identification might challenge novices in detecting structural connections among different subparts without assistance; thus, they have difficulty in forming a coherent structure underlying the situation (Liikkanen & Perttula, 2009). On the other hand, the challenges in decomposing problems can also result from that novices' problem schemas are limited and based on superficial commonalities, which decrease their capability to accurately represent problems (Chi et al., 1981; Jonassen, 1997). Therefore, decomposition requires students to develop a global view of structured problem representations. To overcome the challenge, supporting novices to explicitly model the problem structure is necessary.

**Challenges in Moving Around Multiple Layers**

The ability to define and work on abstraction at the proper level is central to CT (Wing, 2008). However, most college students only work on lower layers of abstraction (e.g., algorithm or implementation level) in resolving complex computer science problems (Hazzan, 2003). Armoni (2013) observes that only addressing these lower layers of abstraction in computing problems is detrimental for students to understand, internalize, and apply abstraction and thus prevents them from getting the required practice to foster abstraction. Similarly, Perrenet and Kaasenbrood (2006) report that many college students have difficulty attaining a higher level in their proposed PGK Hierarchy of abstraction. The majority of these students work at Level 2 (program) and 3 (object) rather than Level 1 (execution) and 4 (problem). That is, most college students are still unable to detect the essence of a problem from a global view, making it impossible for them to tackle complexity (Armoni, 2013). On the other hand, Perrenet and Kaasenbrood (2006) find that college students' levels of abstraction improve as their time engaged in relevant practices gradually increases. This finding lays a fundamental basis for fostering abstraction in CT via deliberate training.

### Guidelines for Enhancing Abstract Thinking in STEM-Integrative Learning Environments

This section provides guidelines on designing a STEM-integrative learning environment to develop K-12 students' abstraction in CT. Empirical evidence indicates that formal schooling is not sufficient to foster students' abstraction (Kramer, 2007). Instead, Kramer (2003) advocates developing K-12 students' abstraction by allowing them to practice it. This paper thus proposes a STEM-integrative learning environment to provide a rich and real-life context for learners to effectively practice abstraction in CT (Kopcha et al., 2017; Sengupta et al., 2013). Corresponding to the above challenges, this paper offers relevant design recommendations with cognitive guidelines for educators to develop students' abstraction in CT. Specifically, a problem-oriented STEM-integrated curriculum wherein students are asked to assemble and program robots for earthquake rescue is proposed along with design recommendations (see Table 4).

**Table 4**

*Design guidelines for enhancing abstract thinking in STEM-integrative learning environments.*

| **Challenges** | **Guidelines** | | | | |
|---|---|---|---|---|---|
| | Prompt filtering information with authentic problems requiring multiple-level abstraction. | Support mapping structures using visual representation tools | Assist in clarifying the understanding of complex problems. | Strengthen generalized representations by providing similar but different problems. | Encourage self-explaining during the abstract thinking process. |
| Challenges in Filtering Information | ✔ | | ✔ | | ✔ |
| Challenges in Locating Similarities | | | ✔ | ✔ | ✔ |
| Challenges in Mapping Structures | ✔ | ✔ | ✔ | | |
| Challenges in Moving Around Multiple Layers | ✔ | ✔ | | | |

**Guideline 1: Prompt Filtering Information with Authentic Problems Requiring Multiple-Level Abstraction**

This paper proposes a problem-oriented environment for learners to develop abstraction in CT by practicing its core cognitive processes since abstraction in CT is essentially a problem-solving toolkit (Yadav, Gretter, Good, & McLean, 2017). Particularly, this paper recommends that the problem should 1) include rich but irrelevant information; 2) require multiple layers of abstraction.

First, the problem-oriented environment should ensure that the essence of a problem is not readily revealed and that students have to filter irrelevant information to grasp its essence. Otherwise, learners are less likely to exert abstraction in CT if only relevant information is given. In addition, embedding question prompts is recommended to help learners effectively filter information. Novices unintentionally remove crucial information or overlook some necessary details (Schwenk, 1985). Without effective instructional support, students can fail to foster abstraction because of their struggle in filtering information (Bucci et al., 2001; Son et al., 2008).

Second, this paper proposes the problem-oriented environment should allow learners to practice recursive movements among multiple layers of abstraction in CT. The ultimate goal for fostering abstraction in CT is to ensure that students can identify the correct abstraction layer at a specific stage and adopt the most appropriate strategies or tools for that layer of abstraction (Muller & Haberman, 2008). Therefore, educators should intentionally design problems where students are engaged in multiple layers of abstraction. In addition, Armoni (2013) stresses the importance of helping students distinguish different layers of abstraction (i.e., execution, program, object, and problem, see more in Armoni, 2013) and recommends providing consistent and precise instruction for students to avoid blurring the distinction among the different layers.

**Example.**

During the first class, an authentic situation is presented to students in which they are asked to create a robot to rescue people after an earthquake. A detailed introduction with rich information about the situation is provided, but much irrelevant information is also included, such as the geographical location (e.g., latitude and altitude), how and why the earthquake happened, the measure of the earthquake, and materials of robots (e.g., density, weight, shape, size). Furthermore, sample question prompts are provided including "What is the most important information you should focus on?" and "What is the irrelevant information you should remove?". In addition, the given scenario should refer to Marr's three levels of computational theory (i.e., computational, algorithm, and implementation), allowing students to attend to each level of abstraction and to recursively move among these levels. For example, the scenario should guide students to detect the overarching goal of this mission (i.e., computational level), to understand how to align the algorithm with the goal (i.e., algorithm level), and to manipulate the device to physically implement the solution (i.e., implementation level).

### Guideline 2: Support Mapping Structures Using Visual Representation Tools

Visual representation denotes the technique that helps individuals visually demonstrate the relationships between concepts or ideas in the forms of pictures, diagrams, flow charts, and concept maps (Fiorella & Mayer, 2016). When resolving complex problems, individuals tend to apply abstraction to map out the structure of the problem and also recursively move around multiple layers of abstractions. Under these circumstances, visual representation is much more valuable than verbal representations (Hibbing & Rankin-Erickson, 2003; Leopold & Leutner, 2012).

Primarily, this section focuses on two overarching forms of visual representation, learning by mapping and drawing. Learning by mapping generally depicts the process of visualizing the hierarchically structured relationship of relevant information (Anderson, 1984). This strategy allows individuals to “select relevant information to use as the nodes, to organize them into a coherent structure as specified in the links, and to integrate the incoming material with relevant prior knowledge by determining the overall structure of the material” (Fiorella & Mayer, 2016, p.722). In addition, learning by drawing mainly describes the process of representing the relevant information by an artifact drawn by hand or computer application (Leutner & Schmeck, 2014). Similarly, translating the textual signal into the analogous pictorial representation also enables students to efficiently select the relevant information and form a more coherently structured mental representation (Fiorella & Mayer, 2016).

In summary, the outcome of visual representation helps students explicitly formulate the spatial organization of relevant information and break it down into smaller coherent pieces. STEM educators can thus integrate visual representation tools in the curriculum to help novice students resolve the challenge in mapping structures. With the aid of the tools, students might improve their competence of problem decomposition and structure identification. For students unfamiliar with these tools, pre-learning instructions is needed (Fiorella & Mayer, 2016).

**Example.**

In this earthquake rescuing scenario, instructors can provide a brief instruction on how to use the mapping tools (e.g., *Bubbl.us* or *Popplet*) before students start to break down the rescuing tasks. Once aware of how to use concept maps, students are asked to translate their ideas into the visualized maps. To do this, students need select the key information and tap into the underlying structure of the problem. Then they can use nodes and links to visualize their ideas of the main problem, sub-problems, and the structural relationship among these subproblems in the maps.

### Guideline 3: Assist in Clarifying the Understanding of Complex Problems

This paper recommends that the curriculum should provide enough time, space, and instructional scaffolds for students to articulate their understanding of a complex situation (e.g., what are the main problem and sub-problems? what is the goal of problem-solving?). The understanding of a problem determines whether students can grasp the essence of the complexity and coherently represent it (Bucci et al., 2001; Liikkanen & Perttula, 2009; Son et al., 2008). For example, Son et al. (2008) note that without a well-articulated understanding of a situation, students might not be aware of what information is useful or what structural relationship underlies the problem, which, in other words, accounts for students' frustration in filtering information and mapping structures. Therefore, allocating enough time and space for students to clarify their understanding of the problem is necessary. In addition, instructional scaffolds on articulating students' understanding of a problem are needed. Unlike experts, novices rely on appropriate scaffolds to articulate the structural representation of a complex situation. For example, this paper recommends providing question prompts for students to represent problems more accurately. Relevant question prompts encourage students to intentionally make sense of the problem and to identify the relevant information and underlying structures of a problem (Ge & Land, 2003). Ge and Land (2003) indicate participants exposed to question prompts for problem representations are more likely to explicitly represent the problem than those who are not. For example, sample prompts include "what is the main problem" (Ge & Land, 2003) and "what if the problem or problematic situation itself changed" (Choi, Land, & Turgeon, 2005).

**Example.**

After presenting the authentic situation to students, instructors could intentionally organize a 15-minute class activity for students to articulate their understanding of the earthquake rescuing mission based on the available information. Specifically, students can write down their understanding of the problem in bullets on the whiteboard. During this activity, instructors can also provide question prompts for students to understand the mission. For example, sample prompts include “what is the mission of the robot” and “what do you need to accomplish the mission”.

### Guideline 4: Strengthen Generalized Representations by Providing Similar but Different Problems

This paper recommends allowing students to learn by analogy as a way to help them develop generalized representation. Analogy refers to the process of comparing relational structures between *target* and *base* domains on the basis of fundamental similarity (Gentner, 1983). For example, in the statement “the electron *revolves around* the nucleus is like the planets *revolve around* the sun”, the “electron *revolves around the nucleus*” is the target domain while “the planets *revolve around* the sun” is the base domain. By analogy, students are able to detect the fundamental relationship between two domains and rely on relevant *base* knowledge stored in the memory to make sense of the *target* domain (Duit, 1991).

Specifically, students are asked to compare and contrast analogical problems which are similar but different. Research indicates that when being taught in multiple analogical contexts, students can develop a higher level of abstraction and form more generalized representations to be used to solve similar problems (Gick & Holyoak, 1983; Schank, 1999; Schwartz, Chase, Oppezzo, & Chin, 2011). The convergence of these two analogous domains also enables students to form a more generalized, inclusive schema. Furthermore, analogical abstraction facilitates the process of relational retrieval of existing patterns in the long-term memory and also relational transfer to future similar cases (Gentner, Loewenstein, Thompson, & Forbus, 2009). Therefore, the proper use of analogy might help enhance students' abstraction.

**Example.**

After the earthquake rescuing scenario ends, instructors might consider providing one or two other analogical authentic scenarios for students to reinforce their ability to formulate generalized representations. Students will have to apply generalized algorithms and principles in the STEM field to solve these two contrasting problems. The additional scenarios should be based on different contexts but should rely on the same principle (e.g., selecting the optimized route) and similar algorithms to represent the problem. For example, instructors can ask students to assemble and program robotics in a simulated scenario of completing the geological exploration tasks on Mars with the constraint of limited fuels. In addition, proper instructional support or question prompts are needed to help students recognize the analogy and detect the underlying principles rather than the superficial features of these contrasting cases.

**Guideline 5: Encourage Self-Explaining during the Abstract Thinking Process**

This paper recommends designing self-explanatory activities for students to undergo a series of abstract thinking processes. Self-explaining, or thinking aloud, is a generative learning strategy that requires students to restate the acquired knowledge to themselves (Chi et al., 1989; Roy & Chi, 2005). To self-explain, students have to "select the most important information from the lesson and restate it in their own words (similar to summarizing), generate inferences to organize the material into a coherent mental model, and integrate the material with their prior knowledge by searching for consistencies and inconsistencies between the newly presented material and their existing mental models" (Fiorella & Mayer, 2016, p.727). This provides students with excellent opportunities to engage in the three cognitive processes.

On the other hand, educators should provide efficient prompts to ensure students can self-explain effectively (Johnson & Mayer, 2010, Rittle-Johnson, Loehr, & Durkin, 2017). According to Renkl (1997), most people have passive and superficial self-explanations, but this type of self-explanation is ineffective. In contrast, Renkl (1997) reports that most successful learners tend to self-explain using principle-based explaining (tying to an underlying domain principle such as Newton's Laws) and anticipative reasoning (predicting the next step using prior knowledge). In particular, the principle-based self-explanation is the most effective, especially when participants can identify the fundamental rule underlying the problem and connect it to a domain principle (Renkl, 1997). To help promote efficient self-explanations, educators can periodically provide content-specific prompts for students (Bisra, Liu, Nesbit, Salimi, & Winne, 2018; Cho & Jonassen, 2012). Further, open-ended questions with fewer cues are more effective prompt formats than multiple-choice or fill-in-the-blank ones (Bisra et al., 2018).

**Example.**

In the proposed scenario, instructors will include prompted self-explanatory activities for students to reinforce their abstraction. For example, when creating the rescuing robot, students are prompted to self-explain the information filtering process and justify why the information they kept is crucial to solve the problem. In addition, students will self-explain how they apply multiple layers of abstraction to solve this problem and also to illustrate the generalized solution to similar but different problems. During this process, the provided prompts should be content-specific and relevant to the core principle underlying the problem.

## Summary

This paper attempts to provide a comprehensive understanding of abstraction by reviewing its historical account and also its different dimensions. Abstraction has historically been one of the most advanced thinking skills and thus been investigated from different perspectives (e.g., Lowell, 1977; Piaget, 1970). By reviewing its various dimensions, this paper identifies three common underlying cognitive processes of abstraction, including filtering information, locating similarity, and mapping structures. When resolving complicated computing problems, these three cognitive processes also have to move recursively around multiple layers of abstraction (Wing, 2006; 2011). In other words, abstraction is important for computational thinking, especially given its significant role in streamline the complexity of the complicated problems. To help K-12 educators foster their students' abstraction in computational thinking, this paper has proposed design guidelines on creating an authentic, problem-oriented STEM-integrative learning environment for educators to foster K-12 students' abstraction in computational thinking. However, to further reinforce the generalizability of these guidelines, it is necessary to investigate whether they are effective to foster students' abstraction in computational thinking. This research thus further designs the explicit guidance and practices on abstraction (EGPA) aligning with these guidelines proposed above. For the next step, this research will integrate the EGPA in a STEM-integrative robotics curriculum, Danger Zone, and then investigate the effectiveness of the EGPA in supporting the development of K-12 students' abstraction in computational thinking (see Chapter 3).

# CHAPTER 3

# METHODOLOGY

## Overview

This chapter describes the methodology of the study. The focus of this study was to investigate the effect of the explicit guidance and practices on abstraction (EGPA) in the STEM-integrative robotics curriculum, *Danger Zone* (Research for the Advancement of Innovative Learning, 2015), on fostering abstraction in computational thinking for fifth graders. Aligned with this focus, a quasi-experimental study using a mixed methods approach was employed. Two teachers and their students voluntarily participated in the study. These two classes were assigned to take the *Danger Zone* curriculum (e.g., control group) or the revised curriculum with the integration of the EGPA (e.g., experimental group) for three weeks. The difference between these two curricula lies in the presence or absence of the EGPA. To investigate the effectiveness of the EGPA on student abstraction in computational thinking, both quantitative data and qualitative data were collected and analyzed accordingly. The remainder of this chapter will describe in detail the research design, research sites, participants, materials and instruments, data collection, data analysis procedures, validity and reliability, and methodological limitations, as well as ethical considerations.

## Research Design

To answer the research questions above, an explanatory sequential mixed methods research design was used for this study (Creswell, 2014; Creswell & Clark, 2017; Greene, 2007).

Specifically, the quantitative data was collected via the abstraction in computational thinking (ACT) instrument (for pretests and posttests) to answer the first research question regarding the effectiveness of the EGPA. For the qualitative source of data, focus group interviews with the selected students and an individual interview with the teacher from the experimental group were conducted (Creswell, 2014; Gikas & Grant, 2013). The qualitative inquiry in this research sought a more comprehensive understanding of the quantitative analysis results and also provided additional insights into participants' experiences with and perceptions of the EGPA while taking the *Danger Zone* STEM-integrative robotics curriculum (Creswell & Clark, 2017; Greene, 2007). An overview of the mixed methods research design aligned with each research question is provided (see Table 5).

**Table 5**

*An overview of the mixed methods research design aligned with each research question.*

| Research Question(s) | Data Collection | Data Analysis |
|---|---|---|
| **1. What is the effect of the EGPA on the development of fifth graders' abstraction in computational thinking while taking a STEM-integrative robotics curriculum?** | **Quantitative** | **Quantitative** |
| 1a. What is the change in students' abstraction in computational thinking after completing the EGPA in the STEM integrative robotics curriculum?<br><br>1b. What is the change in each cognitive dimension of abstraction after completing the EGPA in the STEM integrative robotics curriculum?<br><br>1c. What is the difference in the level of abstraction between students completing the EGPA and those who did not while taking the STEM-integrative robotics curriculum?<br><br>1d. What is the difference in the level of each dimension of abstraction between students completing the EGPA and those who did not while taking the STEM-integrative robotics curriculum? | Abstraction in computational thinking (ACT) assessment;<br><br>Course satisfaction survey | Mixed Analysis of Variance (ANOVA); Independent samples t-test; Paired samples t-test; Analysis of covariance (ANCOVA) |

| | | |
|---|---|---|
| **2. What are the students' experiences with the EGPA while taking a STEM-integrative robotics curriculum?** | **Qualitative** | **Qualitative** |
| 2a. What are students' experiences with the EGPA in a STEM integrative robotics curriculum?<br><br>2b. What are students' perceptions of the EGPA in a STEM-integrative robotics curriculum? | Focus group interviews with three groups of students in experimental group. | Thematic Analysis |
| **3. What are the teachers' experiences of facilitating the EGPA activities in a STEM-integrative robotics curriculum?** | **Qualitative** | **Qualitative** |
| 3a. What are teachers' experiences of implementing the EGPA in a STEM-integrative robotics curriculum to develop students' abstraction in computational thinking?<br><br>3b. What are teachers' perceptions of the EGPA in a STEM-integrative robotics curriculum on developing students' abstraction in computational thinking? | Semi-structured individual interview with the teacher in experimental group. | Thematic Analysis |

**Quasi-Experimental Design**

A quasi-experimental design was used to frame the experiment given the actual classroom setting in this research did not allow for random assignment of participants to different conditions (Cook & Campbell, 1979; Shadish, Cook, & Campbell, 2002). Experimental research usually requires random assignment to ensure its findings can be generalized to a larger population, but for actual school settings, achieving the requirements of random assignment is hard and sometimes even unlikely. As a measure to reduce the threat of selection bias, quasi-experimental design is widely applied in educational research, especially when determining the effectiveness of a new intervention (Shadish et al., 2002).

For this research, the non-equivalent control-group quasi-experimental design was applied (Campbell & Stanley, 2015; Gall, Gall, & Borg, 2007). As an option of the quasi-experimental design, the non-equivalent control-group design is similar to pretest-posttest experiments except for the lack of random assignment (Gall et al., 2007). The non-random assignment results in potential selection bias due to the non-equivalent quasi-experimental design since the two groups are not identical (Tokmak, Incikabi, & Ozgelen, 2013). On the other hand, the non-equivalent control-group design can also control the effects of potential selection bias by allowing the participants in the experimental and control groups to complete pretests and posttests (Cook & Campbell, 1979). Besides the inclusion of pretests, this research recruited a control group with a similar demographic to the experimental group as a measure to minimize the possibility that the difference in posttests resulted from pre-existing gaps in other external factors (see Research Sites and Participants section), such as gender, GPA, and socioeconomic status (Campbell & Stanley, 2015).

In particular, the participants involved in this quasi-experimental design were asked to complete the ACT assessment (O) at the beginning of the experiment (i.e., $O_{pre}$). Then, the participants in the two groups were given three weeks to complete their designated version of the *Danger Zone* curriculum. Participants in the control group interacted with the *Danger Zone* curriculum with no revisions (Research for the Advancement of Innovative Learning, 2015). The *Danger Zone* was originally developed to foster K-12 students' computational thinking in line with the State of Georgia 5th grade curriculum standards. Different from the revised version, this curriculum did not supply specific instructions and activities on abstraction in computational thinking. Upon the completion of the curriculum, both groups completed the ACT assessment (O) again to record their level of abstract thinking skills after taking the curriculum (i.e., $O_{post}$). Specifically, two 5th grade classrooms in a local elementary school were assigned to two different conditions (see Table 6):

- The control group. Students in this group attended a three-week STEM-integrative robotics curriculum, *Danger Zone,* and completed the required $O_{pre}$ and $O_{post}$ assessments before and after interacting with the curriculum.
- The experimental group. Students in this group participated in the new version of *Danger Zone* curriculum with the integration of the EGPA (X) for three weeks, wherein instructions on filtering information, mapping structure, and locating similarities were provided between $O_{pre}$ and $O_{post}$ assessments.

**Table 6**

*The overarching research design of the quasi-experimental study. $O_{pre}$ and $O_{post}$ denote the abstraction in computational thinking (ACT) assessment instrument as pre- and post- tests. X denotes the EGPA in the revised Danger Zone curriculum.*

| **Group** | **Pretest** | **Intervention** | **Posttest** |
|---|---|---|---|
| Control | $O_{pre}$ | | $O_{post}$ |
| Experimental | $O_{pre}$ | X | $O_{post}$ |

The independent variable in this study was the presence or absence of the EGPA in the STEM integrative robotics curriculum for each group. The dependent variables were the participants' level of abstraction and also its three dimensions, including filtering information, locating similarities, and mapping structures. The level of the students' abstract thinking skill and each of these three sub-processes was measured by their responses to the ACT assessment and compared through quantitative analysis to examine whether students improved their abstract thinking skills by engaging with the revised *Danger Zone* curriculum with the EGPA (see Figure 3). Specifically, the quantitative analysis methods used included mixed ANOVA, independent samples t-test, paired samples t-test, and ANCOVA.

### Qualitative Research Design

Qualitative data was collected to investigate participants' and teachers' experience with and perceptions of the EGPA in the *Danger Zone* curriculum. The qualitative data was collected to triangulate findings from the teacher and students in the experimental group immediately following the completion of the revised *Danger Zone* curriculum with the EGPA (Cook & Campbell, 1979; Shadish et al., 2002). The triangulated sources of the qualitative data included semi-structured focus group interviews with three groups of selected participants (each group had four students) from the experimental group and a semi-structured individual interview with the teacher from the experimental group. The thematic analysis (Braun & Clarke, 2006) was applied to process and analyze the qualitative data.

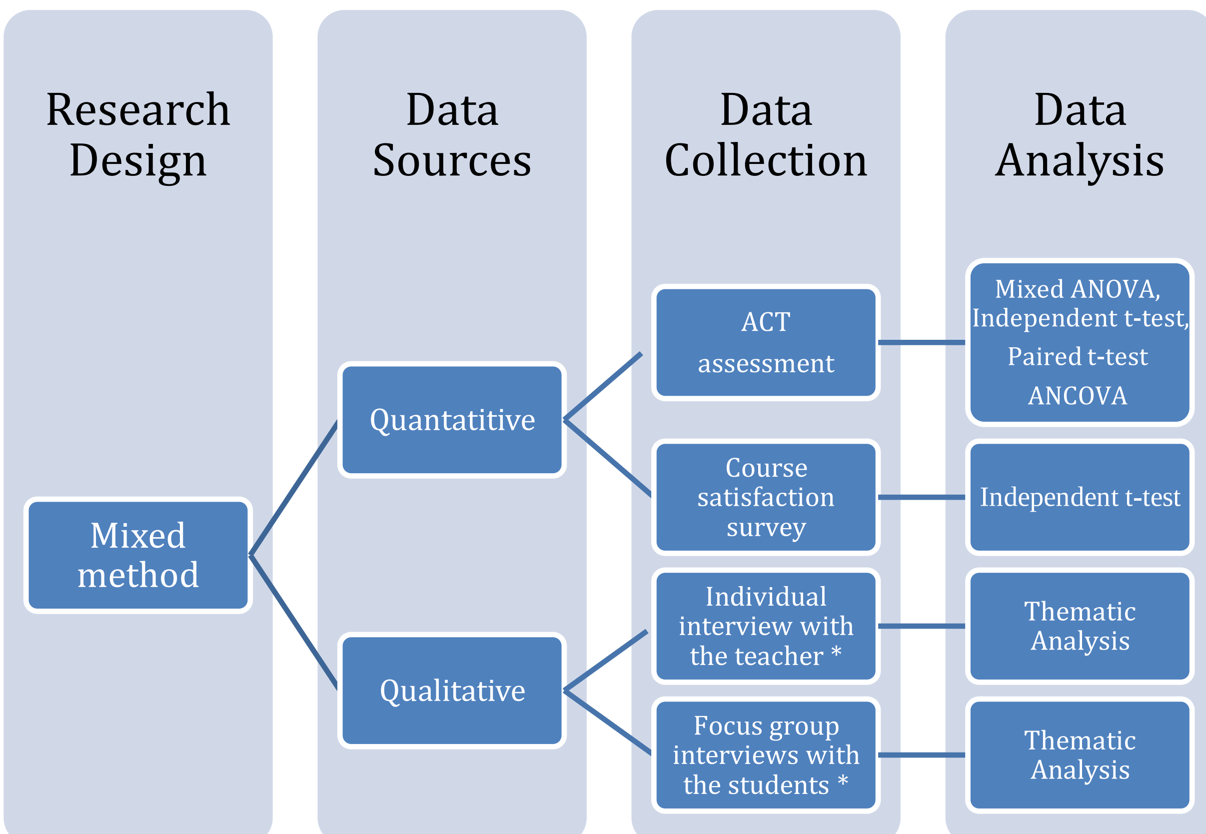



*Figure 3.* An overview of the research design, data collection, and data analysis procedures.
** Note that the students and the teacher involved in the qualitative data collection were only from the experimental group.*

## Research Sites and Participants

The research was conducted in the Arts and Innovation Magnet (AIM) Program sponsored by a local county school system's Center for Innovative Teaching (CFIT) in the southeastern United States. The site selection was based on convenience and availability for the researcher of this study to recruit two similar classrooms for the validity concern with the quasi-experimental design. The researcher contacted the director of the local county school system's CFIT who was in charge of the AIM program to request access. Teachers were recruited through an email forwarded by their curriculum director with the attached teacher recruitment letter (see Appendix A) and consent form (see Appendix B). Only those who had signed the consent form to voluntarily participate in the experiment and returned the signed form to the researcher were considered for this research. In the end, four teachers returned the signed consent form indicating their intention to voluntarily participate.

In particular, two 5th grade female teachers were selected for this research after due considerations of validity for the quasi-experimental design (Campbell & Stanley, 2015). First, the selected teachers had similar teaching profiles relevant to the experiment. They were both responsible for the robotics course in the program. They came from the same school district, holding a teaching certificate authorized by the same state. They also had similar teaching experience in robotics curriculum before participating in this experiment. Second, each of the two 5th grade classrooms had similar student population demographics. Each classroom had a total of 25 students with a similar gender ratio (approximately 1:1, see Table 7). The researcher also compared their milestone grade in mathematics, Lexile, and English language arts. The average score in these three tests differed slightly between the two groups, but the difference was not significant, as informed by the independent samples t-test result ($p > 0.05$). In sum, the two selected classrooms met the requirements of quasi-experimental study.

**Table 7**

*The number of male and female participants in the Control and Experimental Group.*

| Group/Gender | Female | Male | Total |
|---|---|---|---|
| Experimental | 13 | 12 | 25 |
| Control | 12 | 13 | 25 |

Students in each of these two classrooms were recruited via a printed copy of the recruitment letter for parents as well as consent forms for both parents and children. Each participating teacher helped distribute and also collected the recruitment letters and consent forms from the parents (see Appendix C & D) and the consent forms from the students (see Appendix E). In particular, two of the students assigned to the experimental group did not return their consent form for parents and were excluded from this research. In the end, a total of 23 students (i.e., 12 female and 11 male) joined in the experimental group and 25 students (i.e., 12 female and 13 male) participated in the control group. Furthermore, the researchers also collected students' responses to the STEM attitude survey (Faber, Unfried, Wiebe, Corn, Townsend, & Collins, 2013) before the experiment started. The independent samples t-test result confirmed that students in the two groups did not have any significant difference in their attitudes towards mathematics and engineering. This provided supplementary evidence to validate that the selection of the two groups was appropriate for the quasi-experimental design.

The two selected teachers then were invited to attend a training workshop held by the researcher two weeks before the implementation. Each teacher was responsible for their own classroom. The workshop lasted for 60 to 75 minutes mainly focusing on using relevant interventions and relevant support materials. During the workshop, the teacher for the experimental group was given specific instruction on the fundamental knowledge of abstraction and an introduction to the three core cognitive processes of abstract thinking (i.e., filtering information, mapping structures, and locating similarities). Then the researcher of this study went through each lesson of the robotics curriculum with both teachers to ensure they understood the procedures and how to facilitate each activity in class.

## Materials and Instruments

### Intervention

The intervention used in this study was the explicit guidance and practices on abstraction (EGPA) integrated in a STEM-integrative robotics curriculum, *Danger Zone*. The original version of this curriculum was designed in line with the local state standards to help 5th grade students improve computational thinking via solving authentic problems using STEM knowledge from multiple domains rather than a single domain (Kopcha et al., 2017; Research for the Advancement of Innovative Learning, 2015). To accomplish the task in the *Danger Zone,* students needed to incorporate science content knowledge (e.g., volcanoes as constructive or destructive force and the elements associated with active volcanoes such as flowing lava), engineering knowledge and skills (e.g., assembling robots and engineering design processes), programming skills, and mathematical content knowledge (e.g., decimals, multiplications, divisions, algebra word problems, and coordinate algebra). To improve fifth graders' abstract thinking, a series of instructional activities were added to the lesson plan following the five guidelines proposed in Chapter 2. Specifically, the proposed guidelines included 1) prompt filtering information with authentic problems requiring multiple-level abstraction; 2) support mapping structures using visual representation tools; 3) assist in clarifying the understanding of complex problems; 4) strengthen generalized representations by providing similar but different problems; 5) encourage self-explaining during the abstract thinking process. With the integration of the EGPA, the revised *Danger Zone* curriculum consisted of seven lessons, with each lesson centering around specific objectives (see Table 8 for details about the lesson plan of the revised version of the *Danger Zone*). The following paragraphs will introduce in detail how the EGPA aligned with the guidelines and the state standards as well as how the EGPA was integrated in each lesson of the revised *Danger Zone* curriculum.

With the addition of the EGPA, Lesson 1 provided an opportunity for students to determine what information was relevant to problem solving in the provided scenario. The guidelines addressed in this lesson mainly consisted of Guideline 1, 3, and 5. Following Guideline 1 (i.e., prompt filtering information with authentic problems requiring multiple-level abstraction), an authentic scenario was adapted from the United States Geological Survey (USGS) website (https://volcanoes.usgs.gov/vhp/about_volcanoes.html). The overarching task of this scenario was to design a robot to assist scientists to explore dangerous volcano areas and collect samples. To prompt students to filter information, this authentic example, *volcano exploration*, included a large amount of irrelevant contextual information (e.g., how the volcano erupts, the history of the volcano area). In addition, Guideline 3 (i.e., assist in clarifying the understanding of complex problems) recommended providing question prompts for students while they were selecting the important information. Accordingly, question prompts, such as "what is the goal of this task" and "what is the information you must know to accomplish the task?" were included in the filtering information activities for students to clarify their understanding of the problem. Moreover, Guideline 5 (i.e., encourage self-explaining during the abstract thinking process) recommended the inclusion of self-explaining activities. As a consequence, students were asked to restate the rationale of their selection in their own words by responding to the question “why do you need this information?”. In addition, the students were guided through the science content related to volcanoes and the concepts involved in the engineering design process in this lesson.

Starting from Lesson 2, students were taught the key components of robots (e.g., motors) and collaborated with peers to construct robots. This lesson did not involve any EGPA activities. To ensure the consistency between the two curricula, this lesson continued with the same contents as the original version of the *Danger Zone*. Students were presented the knowledge about the central processing unit (CPU) as well as input and output devices. After the lecture, students worked in groups to identify the mechanical components of the robot and then start to build a robot.

In Lesson 3, students were prompted to apply mathematical knowledge to program the robot with *Rogic* (a programming language for robotics similar to *Scratch*). They also interacted with mathematical knowledge and concepts used in the subsequent decomposition activities. Specifically, students were asked to measure the distance that a robot could travel at two different speed settings. Students did not directly interact with the EGPA activities in this lesson, but attending this lesson helped them prepare for the upcoming decomposition task.

In Lesson 4, students were engaged in purposeful programming to plan a route to complete the task. The lesson started with a lecture about the mathematical concept of coordinates and some scientific concepts about volcanos that would help students identify the optimal route for the robot to move. The main activity of the lesson was the decomposition activity wherein students were prompted to decompose the sample collection task for the robot into several different subtasks. The design of the decomposition activity followed three guidelines. First of all, the design followed Guideline 1 (i.e., prompt filtering information with authentic problems requiring multiple-level abstraction) by continuing with the authentic scenario, *volcano exploration*, which required solutions at different levels of abstraction. In addition, the design adhered to Guideline 2 (i.e., support mapping structures using visual representation tools) by presenting students with concept mapping tools (e.g., Bubble.us) to help students delineate the structure of the task. Moreover, the design was consistent with Guideline 3 (i.e., assist in clarifying the understanding of complex problems) by providing students with question prompts such as "what is the subtask?" to reinforce their awareness of the underlying problem structure.

Lesson 5 was designed for students to optimize their solutions and program the robot to accomplish the task. Students continued with the decomposition activity begun in Lesson 4. The purpose of this task was to further decompose the already identified subtasks and figure out how to program the robot with *Rogic* to move along the optimal route. Different from decomposing the task or the problem itself, this part of the decomposition activity mainly focused on breaking down the subtasks into smaller units that could be enacted by lines of *Rogic* codes. The design of this part of the decomposition activity also followed the three aforementioned guidelines (i.e., Guideline 1, 2, & 3) in Lesson 4.

Lesson 6 was a newly added lesson to the *Danger Zone* curriculum, following the proposed guidelines (e.g., Guideline 4 and 5). Specifically, this lesson abided by Guideline 4 (i.e., strengthen generalized representations by providing similar but different problems) by providing students with analogical cases to reinforce their expertise in identifying their fundamental similarities. Another authentic problem-based scenario, *Earthquake Rescue*, was also adapted from the USGS website (https://earthquake.usgs.gov/learn/kids/eqscience.php). Once students accomplished the task of collecting the samples from the volcanic areas using the robot, students continued to work on this analogical scenario in a similar manner: designing a robot able to rescue people and things from the destruction caused by an earthquake. In addition, another self-explaining activity involved in this lesson complied with Guideline 5 (i.e., encourage self-explaining during the abstract thinking process) by creating opportunities for students to describe the similarities they identified between the two cases and justify why these similarities were the most fundamental (e.g., at the level of analogy, Gentner & Hoyos, 2017; Gentner & Toupin, 1986). This lesson followed additional guidelines in selecting and facilitating the analogical case (e.g., volcano exploration v.s. earthquake rescuing). Specifically, for the earthquake rescuing scenario, students also completed a series of tasks on filtering information and decomposition. For example, the analogical scenario of an earthquake rescue was an authentic problem provided with an amount of irrelevant information (i.e., Guideline 1). In addition, students were provided with concept mapping tools (i.e., Guideline 2) and question prompts (i.e., Guideline 3) to clarify the underlying structure of the multiple-level problem. After students completed these main activities, the last lesson (i.e., Lesson 7) of the revised Danger Zone curriculum prompted students to present their projects and also reflect on the learning experience.

**Table 8**

*Details about the lesson plan of the revised version of the Danger Zone.*

| Lesson(s) | Time | Lessons | |
|---|---|---|---|
| | | **Guideline(s)** | **The Lesson Objectives of Revised *Danger Zone* with the EGPA for the Experimental Group** |
| **1<br>Danger Zone** | 2 hours | **Guideline 1: Prompt filtering information with authentic problems requiring multiple-level abstraction.**<br><br>**Guideline 3: Assist in clarifying the understanding of complex problems.**<br><br>**Guideline 5: Encourage self-explaining during the abstract thinking process.** | Analyze the problem scenario ***provided with unnecessary information***; Differentiate necessary and unnecessary information **(Activity: Filtering Information);** identify problem goal. |
| | | | Explore the science content of the task (i.e. volcanoes) |
| | | | Explain the steps in the engineering design process |
| **2<br>Build-a-Bot** | 2 hours | | Construct a robot |
| | | | Identify the mechanical components of the robot under construction |
| | | | Define the role of the central processing unit (CPU) |
| | | | Explain the difference between input and output devices |
| **3:<br>Primary Programming** | 1 hour | | Act out the basic programming commands |
| | | | Practice programming the robot in Rogic |
| | | | Apply the mathematical concepts of decimals to program their robot to follow basic commands |
| | | | Acquire mathematic knowledge and information required for decomposition tasks by ***measuring the distance that a robot can travel at two different speed settings***. |
| **4<br>Purposeful Programming** | 2 hours | | Further examine science content that will impact programming (i.e. specific types of volcanic terrains) |
| | | | Apply the mathematical concepts of coordinate grids to their movement plan. |
| | | **Guideline 1: Prompt filtering information with authentic problems requiring multiple-level abstraction.**<br><br>**Guideline 2: Support mapping structures using visual representation tools**<br><br>**Guideline 3: Assist in clarifying the understanding of complex problems.** | ***Engage in the instructional activities to decompose the complex task*** **(Activity: Task Decomposition).** This activity will help students understand the significance of problem decomposition and learn about how to decompose a program. |

| | | | |
|---|---|---|---|
| **5**<br>**Prime Optimization** | 2 hours | **Guideline 1: Prompt filtering information with authentic problems requiring multiple-level abstraction.**<br><br>**Guideline 2: Support mapping structures using visual representation tools**<br><br>**Guideline 3: Assist in clarifying the understanding of complex problems.** | ***Use visual representation tools to decompose the complex task into smaller pieces*** **(Activity: Task Decomposition).** This is the continuance of problem decomposition activity in Lesson 3 wherein students will be fostered to decompose problem. |
| | | | Apply the mathematical concepts of decimals, measurement, coordinate grids, and variables to their programming. |
| | | | Engage in the engineering design process to program and navigate their robot (e.g., plan, test, evaluate, and revise their programs) in order to complete the task. |
| | | | Determine their best problem solution. |
| **6**<br>**Additional Challenge** | 3 hours | **Guideline 1: Prompt filtering information with authentic problems requiring multiple-level abstraction.**<br><br>**Guideline 3: Assist in clarifying the understanding of complex problems.**<br><br>**Guideline 5: Encourage self-explaining during the abstract thinking process.** | ***Analyze the earthquake rescuing scenario provided with unnecessary information***; Differentiate necessary and unnecessary information **(Activity: Filtering Information)**; identify problem goal. |
| | | **Guideline 1: Prompt filtering information with authentic problems requiring multiple-level abstraction.**<br><br>**Guideline 2: Support mapping structures using visual representation tools**<br><br>**Guideline 3: Assist in clarifying the understanding of complex problems.** | ***Engage in the instructional activities to decompose the complex task*** **(Activity: Task Decomposition).** This problem decomposition activity is analogical to that in the volcano scenario. Students will decompose the problem into several pieces. |
| | | **Guideline 4: Strengthen generalized representations by providing similar but different problems.**<br><br>**Guideline 5: Encourage self-explaining during the abstract thinking process.** | ***Identify underlying commonalities of two scenarios*** (i.e., volcano exploring and earthquake rescuing); and ***attain generalized representations*** (i.e. generalized algorithms, underlying equations) **(Activity: Locating Similarities).** |
| **7**<br>**Reflect and Share** | 1 hour | | Share their results with peers |
| | | | Explain and justify their approach to solving the problem |
| | | | Engage in academic discussions around programming challenges |

## Instruments

The instruments used in this study included the Abstraction in Computational Thinking (ACT) Assessment (see Appendix F), the scoring rubrics for the ACT assessment (see Table 9), and also the student Learning Experience Questionnaire (see Appendix G). The section below will introduce each instrument in detail.

### Abstraction in Computational Thinking Assessment.

In order to assess students' performance on abstraction in computational thinking, a new instrument, called Abstraction in Computational Thinking (ACT), was developed based on the conceptual framework of abstraction in computational thinking proposed by the author (see Chapter 2). This instrument was reviewed by two experts on developing assessment instruments. Their feedback ensured each item in the instrument addressed the relevant dimension of abstract thinking. In addition, two 5th grade teachers were invited to review the textual contents of the instrument to ensure the instrument was readable and comprehensible by their students. Except for several revisions on wording, the two teachers confirmed the textual contents described in the instrument aligned with fifth graders' level of reading and comprehension.

The ACT Assessment included eight open-ended questions that evaluate the respondents' expertise in the three fundamental cognitive processes of abstract thinking (i.e., filtering information, locating similarities, and mapping structures). Authentic contexts were incorporated in the assessment, such as a firefighting rescue scenario. Each process directly corresponded to two or three of these eight questions (e.g., two questions were relevant to filtering information and three questions addressed each of the other two cognitive processes). Specifically, for the process of filtering information, two relevant questions mainly assessed students' abilities to identify the key information and grasp the main goal of a complex situation. For the locating similarity process, three relevant questions primarily evaluated students' capacities of categorizing the problem and tracing the underlying similarity to formulate generalized problem solutions. For the process of mapping structures, three relevant questions were used to rate students' competency in decomposing a complex question into several reasonable subparts to simplify the question. When responding to each question, students were asked to provide justifications for their responses with the hope of providing an accurate assessment of their abstract thinking skills.

**Scoring rubrics for the Abstraction in Computational Thinking Assessment.**

A scoring rubric for the ACT assessment instrument (see Table 9) was used to grade the participant response to each question. This scoring rubric was developed by the researcher of this study based on existing performance metrics used to assess each cognitive process of abstraction (i.e., filtering information, locating similarities, and mapping structures). To develop the rubric, the researcher first defined each cognitive process of abstract thinking based on the conceptual framework in Chapter 2, and then described its expected performance. Sample responses for each question illustrating the different levels of abstract thinking were provided as an example of the expected performance. Each participant response was evaluated using an ordinal value on scales such as 0-1-2-3-4 or 0-2-4, based on the performance description and the specific criteria for each question.

Each participant's response to the questions regarding filtering information and mapping structures was assessed using a five-level ordinal scale (0-1-2-3-4). For example, for the filtering information questions, participants would receive a score of "4" if they demonstrated a clear understanding of the problem and accurately identified all ten key elements of the problem. If they demonstrated sufficient understanding of the problem and recognized seven to nine key components of the problem, they would get a score of “3”. If they hardly understood the problem and detected few key elements, a score “2” (4–6 components) or “1” (1–3 components) was given, depending on the number of identified key items. If no response was received or no key elements were identified, a score of “0” was assigned. In contrast, participant responses to the questions regarding locating similarities were assessed using a three-level ordinal scale (0-2-4). Their responses were graded as follows: 1) a response that located the underlying similarity of the problem would receive 4 points; 2) a response that only identified the superficial similarity would receive 2 points; 3) no response received or a response that recognized no similarity would receive 0 points. The earned points for all three categories of questions were summated as a total score of the participants’ level of abstraction in computational thinking.

Before being used to assess the participant responses to the instrument, the rubric was also reviewed by expert scholars and researchers with rich experience and advanced knowledge of assessment development, as well as the 5th grade teachers who had taught the robotics curriculum. The feedback from both experts and teachers validated the use of the rubric to grade participants’ performance in regards to each dimension of abstraction in computational thinking.

**Table 9**

*The scoring rubrics for the Abstraction in Computational Thinking Assessment.*

| Score | Filtering Information Scoring Criteria | Mapping Structures Scoring Criteria | Locating Similarities Scoring Criteria |
|---|---|---|---|
| 4 | Demonstrates a clear understanding of the problem. Accurately identifies all key elements of the problem (7 elements) | Demonstrates a clear understanding of the problem structure and the relationship of the sub-problem to each other. Accurately identifies all sub-problems identification and appropriately explain their relationship. | Report underlying similarity of the problem or referencing the underlying similarity of problem solution (time*speed=distance, algorithm, flowchart). |
| 3 | Demonstrates a sufficient understanding of the problem. Minor errors may be present in identification of elements. (5-6 elements) | Demonstrates a sufficient understanding of the problem structure and the relationship of the sub-problem to each other. Minor errors may be present in sub-problems identification or explanation of their relationship. | |
| 2 | Demonstrates a minimal understanding of the problem. Some errors are present in identification of elements. (3-4 elements) | Demonstrates a minimal understanding of the problem structure and the relationship of the sub-problem to each other. Some errors are present in sub-problems identification or explanation of their relationship. | Report surface similarity of the problem (i.e. character and/or theme) and/or referencing the surface similarity of problem solution (e.g., using robots and mapping out the grid) |
| 1 | Does not demonstrate an understanding of the key elements of the problem. Several errors are present in the identification of elements. (1-2 elements) | Does not demonstrate an understanding of the problem structure and the relationship of the sub-problem to each other. Several errors are present in the sub-problem identification or explanation of their relationship. | |
| 0 | No answers or no correct answers are offered. | No answers or no single correct answers are offered. | No answers are offered or no similarity is reported. |

**Student Learning Experience Questionnaire.**

This questionnaire (see Appendix H) was used to address learner experience with and perception of the EGPA in the revised *Danger Zone* curriculum on fostering students' abstraction in computational thinking. This questionnaire contained two sections with a total of seven questions: two demographics questions and five open-ended questions. The questionnaire was distributed to the students in the experimental group at the end of the last lesson (only available to the students in the experimental group). To strengthen the validity of the study, this questionnaire was reviewed and validated before implementation by an expert group of three researchers who have rich relevant research experience. Based on the feedback from the expert group, this questionnaire was further revised before implementation. For example, the language used in this questionnaire was revised to align with fifth graders' average level of reading comprehension skills.

## Data Collection

The Institutional Review Board (IRB) approval was obtained prior to the data collection. This study collected two types of data, quantitative and qualitative data, to maximally ensure its rigor (Creswell, 2007). This section will provide a detailed introduction to the procedures of data collection.

### Quantitative Data Collection

Quantitative data was collected via the Abstraction in Computational Thinking (ACT) assessment and students' Learning Experience Questionnaire distributed to all participants in this research.

**Abstraction in Computational Thinking Assessment.**

Students participating in the study (both the experimental and the control group) were asked to complete the ACT assessment instrument before (i.e., pretests) and after (i.e., posttests) engaging in the designated STEM-integrative robotics curriculum. For the pretest, the teachers in both groups assigned an electronic version of the ACT assessment to each student via *Google Classroom* before the instruction started. *Google Classroom* is a free web service developed by Google for schools that aims to simplify creating, distributing and grading assignments in a paperless way (classroom.google.com). Each group had a separate license to access their own *Google Classroom*. After the assessment instrument was assigned, the participants were asked to complete and submit their responses in 40 minutes. The pretest submissions were immediately available to the researcher once the teacher confirmed all students had sent their responses. Upon completion of the pretest, each classroom began their own three-week STEM-integrative robotics curriculum. During the last lesson of the assigned curriculum, the posttest instrument was distributed to all participants electronically using *Google Classroom*. Once all the submissions were recorded, this data was shared with the researcher, and then the researcher organized the dataset for subsequent statistical analysis.

**Student Learning Experience Questionnaire.**

The student Learning Experience Questionnaire was completed by the participants in both groups to inquire about their learning experience with and perception of the different versions of curricula. This questionnaire was distributed to the students via *Google Classroom* at the end of the curriculum. The students were asked to complete the questionnaire in 20 minutes and submit their response within *Google Classroom*. Their responses were recoded and compiled into a spreadsheet for data analysis.

## Qualitative Data Collection

The qualitative data was collected through semi-structured focus-group interviews with participants selected from the experimental group (Gikas & Grant, 2013) and also a semi-structured individual interview with the teacher from the experimental group (Creswell, 2007, 2014).

### Student focus group interview.

Focus group interviews with three groups of students (each group had four students) selected from the experimental group were conducted immediately after the curriculum ended. Three focus group interviews mainly focused on students' experience with the EGPA in the revised *Danger Zone* curriculum and their perceptions of its effects on developing abstraction in computational thinking. A maximum variation strategy was used as a selection standard for purposeful sampling (Gikas & Grant, 2013; Miles & Huberman, 1994). All participants who completed the revised *Danger Zone* curriculum in the experimental group were considered for selection. The maximum variation standard was then implemented based on their pretest scores to ensure the selected participants represented a wide range of levels of abstraction thinking skills (Miles & Huberman, 1994). Three groups of participants were selected for the focus group interviews, each of which lasted for 45 to 60 minutes in a face-to-face setting. A semi-structured protocol (see Appendix I) was used to structure each focus group interview (Gikas & Grant, 2013). Upon the approval of the students and parents, each focus group interview was audio-recorded for subsequent data analysis.

### Teacher interview.

Creswell (2007) insists the interview is a primary method to examine participants' perceptions and experiences. Therefore, this study included an individual interview with the teacher in the experimental group to inquire about teacher experience with the EGPA in the revised *Danger Zone* curriculum and their perception of the efficacy of the EGPA to develop students' abstraction in computational thinking. The interview was conducted in a face-to-face setting for 45 to 60 minutes at the commencement of the curriculum. A semi-structured protocol (see Appendix J) was used for this interview, allowing researchers to probe the most meaningful comments on the effectiveness of the curriculum and attend to any emerging questions regarding further modification of the curriculum (Gikas & Grant, 2013). The interview was also audio-recorded for subsequent transcription and data analysis upon approval of the teacher.

## Data Analysis

### Quantitative Data Analysis

Before conducting any statistical analysis, the research checked the validity and reliability of the main instruments in the study. First of all, the researcher performed a two-step inter-rater reliability to confirm the agreement between two reviewers reached an acceptable level. The quantitative data collected from the ACT Assessment was converted into scores using the above rubric for each participating student. The rubric scores indicated the level of each student's abstraction ability and its three dimensions. Since the judgments of the researcher of this study might be subjective, it was important to invite a secondary rater and confirm agreement between raters on their assessments of the level of participants' responses (Gwet, 2014). To increase the rigor of this study, the researcher invited a scholar with rich research experience in using robotics curriculums to foster students' computational thinking as the secondary reviewer. The inter-rater reliability was calculated to confirm the degree to which different raters agreed in the assessment decision reached an accepted level (Gwet, 2014). After all the participating students submitted their responses to the ACT assessment instrument, the two reviewers randomly selected 20% of the submitted responses and evaluated these responses independently. Cohen's (1960) kappa value was then employed to estimate inter-rater reliability. Once the average inter-rater reliability reached an acceptable level, the researcher of this study graded the remaining assessment instruments. In addition, for two-phase validation, the researcher invited the external reviewer to grade another ten students' submissions of pretests and posttests and compared with the researcher's grading. Cohen's (1960) kappa value was calculated again to validate the inter-rater reliability reached an acceptable level. Second, a factor analysis was conducted to confirm the validity of the ACT assessment (Loewen and Gonulal 2015; Plonsky and Gonulal 2015). Specifically, the principal component analysis was used as the method for factor extraction, abiding by the rule that Kaiser's eigenvalue needed to be larger than 1.0 (Gonulal, 2019). In addition, the Quartimax with Kaiser normalization was selected as the rotation method to determine the correlation between factors and each item on the assessment. Those items with a value of loadings larger than 0.30 were considered as significant in this research. Third, Cronbach's $\alpha$ was calculated to determine the reliability of the Learning Experience Questionnaire. To assess the reliability of each item on the survey, both overall value and the if-item-deleted value for each item were calculated. Following this, the researcher made the decision on which items to keep for the subsequent quantitative analysis.

Then the researcher analyzed student responses to the Learning Experience Questionnaire. The purpose of this analysis was to rule out any external influences from the difference in teachers' facilitation and the participants' satisfaction with the curriculum. The independent samples t-test analysis was conducted to determine whether there were any significant differences in student responses to the course satisfaction questionnaire.

Aligned with the research purpose and the research questions, a mixed analysis of variance (ANOVA) was conducted on student responses to the ACT assessment to determine the effect of time (e.g., pre- and post- tests) and treatment (e.g., experimental and control) on the improvement of abstraction in computational thinking. The mixed ANOVA was used because it could compare the effect of treatment over the duration of the experiment and also examine the interaction between these two variables (Edwards, 1951; von Ende, 2001). Independent samples t-test analysis and paired samples t-test analysis were then conducted as post-hoc analysis to further investigate the effect of the interaction. Specifically, paired samples t-test analysis was administered to understand the mean score change in ACT assessment between the pretest and the posttest. Accordingly, the independent samples t-test analysis was used to compare the difference in posttest scores between two treatment groups so as to further detect the effect of the treatment on the change in student performance.

In addition, considering the limitation of the quasi-experimental design, an ANCOVA analysis was performed to compare whether any significant differences existed in students' abstraction between the two treatment groups. ANCOVA analysis is often used to determine the influence of categorical independent variables on the means of a dependent variable when there are effects of other covariates (Rutherford, 2011). For this research, the pretest score was the covariate. The dependent variable was the total score earned on the posttest (continuous) and the independent variable was the group the students were assigned to (categorical). Using the ANCOVA analysis, this study mitigated the influence of any possible differences that might have already existed before attending the designated curriculums in the level of abstraction in computational thinking between these two groups (Green & Salkind, 2011). In addition, the research needed to test the assumption of homogeneity of regression slopes and ensure it satisfied the condition to use the ANCOVA analysis (Harwell & Serlin, 1988). Specifically, before running the ANCOVA analysis, the research tested this assumption by determining whether the covariates (e.g., pretest score) significantly related to the independent variable (e.g., group) or not (Green & Salkind, 2011).

**Qualitative Data Analysis**

Thematic analysis was conducted in this research to understand the participants' experiences of fostering abstraction in computational thinking via participating in a STEM-integrative robotics curriculum (Braun & Clarke 2006; Clarke & Braun, 2013). Before the analysis, the audio-recorded data of the individual interview with the teacher and the focus group interviews with the students from the experimental group were transcribed by the researcher. Data analysis was then conducted by following Braun and Clarke's (2006) thematic analysis framework.

The very first step was to carefully read each interview repeatedly to ensure the researcher was immersed in the data and to get "familiar with the depth and breadth of the content" (Braun & Clarke, 2006, p.87). While reading each transcript, the researcher took notes of some points that might be relevant to the research question. During phase two, the researcher generated initial codes for each sentence and highlighted the interesting segments relevant to the research questions and generated some proper labels to describe them (Braun & Clarke, 2006). In the following transcript segments, the researcher reused and/or replaced the existing labels to explain them. New labels were created if new perspectives were identified. The next step was to identify preliminary themes by examining the initial codes and grouping similar codes by meaning (Braun & Clarke, 2006). At this stage, the researcher sorted the preliminary codes that had emerged in the transcript into specific categories following the convergence principle and organized the codes into categories. The fourth phase of the data analysis was to review themes (Braun & Clarke, 2006). The codes within each category were then re-examined. During this phase, the researcher re-read the segments associated with each category and considered whether the data was well-aligned with the category. In addition, the preliminary categories were carefully reviewed to make sure they were coherent and distinct from each other. During phases five and six, broader themes with descriptions of their essence were identified and synthesized in order to write a final narrative for each theme including what each theme was and why it was important.

## Validity and Reliability

### Quantitative Data Validity

For this study, four actions were taken to increase the validity and the reliability of the quantitative data. First, the study calculated the inter-rater reliability twice to ensure the agreement between different raters on the level of participant responses to the ACT assessment reached an acceptable level (Gwet, 2014). Second, to ensure the validity of the assessment and its scoring rubric, the instrument was reviewed by experts with expertise on developing assessments to ensure the specific items addressed the relevant dimensions of abstract thinking. In addition, 5th grade teachers were invited to review the items of the assessment instrument, as well as the curriculum, to ensure the content was readable and comprehensible by their students. Third, the research conducted a factor analysis to determine the validity of the ACT assessment. Fourth, the research calculated Cronbach's α to confirm the reliability of the Learning Experience Questionnaire.

### Qualitative Data Validity

From the perspective of qualitative research design, the researcher triangulates the data collection methods to guarantee the rigor and reliability of the research (Creswell, 2007). According to Creswell (2007), triangulation was a way to deal with the validity threat of self-report bias and guarantee the rigor and reliability of the research. Therefore, the qualitative data collected from the teacher interview and student focus group interviews was triangulated to present an authentic understanding of students' learning experiences and also allow the researchers to attend to the emerging challenges experienced by teachers and students (Gikas & Grant, 2013). In addition, a member check was used to reinforce the rigor of the research. After the data analysis, the researcher drafted a summary of the findings and sent it to the teachers and students in the experimental group to make sure that the findings reflected their experience and perceptions (Creswell, 2007; Gikas & Grant, 2013). Finally, the researcher of this study included direct quotes when reporting the results so that the audience are able to assess the rigor of this study (Merriam, 2009).

## Methodological Limitations

The first methodological limitation results from the ACT assessment. The rubric for this assessment was not empirically investigated but instead proposed based on the author's conceptual framework on abstraction in computational thinking. To further increase the rigor, additional empirical justification on the rubric may be needed. Moreover, further elaboration on the content of the rubric might be necessary as a limited number of items for assessment might lead to inaccurate results in quantitative analysis (Huberty & Morris, 1989).

In addition, qualitative research was conducted to gain an authentic, in-depth understanding of participants' experiences and perceptions of the intervention. However, all studies have limitations that result from methodologies used, the data collected, and the analysis techniques employed. Similar to other qualitative studies, the main limitation of this study was generalizability (Golafshani, 2003). The qualitative part of this study mainly focused on the experience and how the experience was made sense of by participants themselves. The findings of this study might not extend to wider populations with the same degree of certainty. In addition, the qualitative analysis could not avoid the subjective bias in the interpretation of teachers' and students' perceptions and experiences.

## Ethical Considerations

According to Tracy (2010), ethical considerations include "ethics in participant recruitment, data collection, and relationships with participants, data analysis, and data sharing, and an ethical study is ultimately marked by ethical practices throughout the research process" (p. 847). The UGA IRB policy specifies how participants should be recruited and the ways in which data should be collected. My ethical decisions were naturally guided by the study's IRB specifications to ensure my research did not harm the participating students or teachers. To make sure the interests and rights of all participants involved in my research were safeguarded, I planned through the consequences of each decision and exactly adhered to the laws for research regarding human rights and data protection. First, there was a repeated and explicit emphasis on participation being voluntary and the researcher was consciously non-judgmental of participant practices. Participants' involvement in the research activities was voluntary and they could choose to stop at any time without any penalty. Second, to protect the identity of participants and maintain confidentiality, all identifiable information in the data was replaced by a code which only the approved researchers had access to. Additionally, all information and interview audio files were deleted as soon as possible after completion of data analysis. The results were also reported without any identifiable information.

# CHAPTER 4

# RESULTS

This chapter showcases the results of both quantitative and qualitative data analysis. The chapter starts by reporting the quantitative analysis result of the quasi-experiment, in response to the first research question. In addition, this chapter provides an in-depth analysis of the qualitative data collected during this research in response to the other two research questions, the teachers' and students' experience with and perceptions of the *Danger Zone* robotics curriculum with the addition of the EGPA. A synthesized summary of both types of data analysis results is provided at the end of this chapter.

## Results by Research Questions

### Research Question 1: What is the Effect of the EGPA on the Development of Fifth Graders' Abstraction in Computational Thinking While Taking a STEM-integrative Robotics Curriculum?

This section presents the quantitative result of the quasi-experimental design as a response to the first research question. First, this section validates the Abstraction in Computational Thinking (ACT) assessment and also the Learning Experience Questionnaire by presenting the value of Cohen's Kappa (i.e., for the inter-rater reliability of grading ACT assessment), the result of factor analysis (i.e., for the validity of ACT assessment), and Cronbach's $\alpha$ (i.e., for the reliability of the Learning Experience Questionnaire). Second, this section describes the result of the independent sample t-test analysis on the participants' course satisfaction in the hope of eliminating any external factors such as difference in instructors' facilitation and participants' satisfaction with each curriculum. Third, the results of a series of statistical analyses on the participants' responses to the ACT assessment is reported, including mixed analysis of variance (ANOVA) and its post hoc analyses as well as the analysis of covariance (ANCOVA). Specifically, this section presents the result of the mixed ANOVA on the participants' mean scores in the ACT assessment with time as the within-subject factor and treatment as the between-subject factor. Then the result of the post hoc analyses, including paired samples t-test and independent samples t-test analyses on the participants' mean scores in the ACT assessment, are presented to better understand the interaction between time and treatment. In the end, the ANCOVA result is discussed to contrast the experimental and control groups' abstract thinking and associated dimensions. In particular, the two aforementioned methods of analysis were conducted to answer the research questions. For quasi-experimental research, ANCOVA was a preferred method to determine how categorical independent variables influence the means of a dependent variable when the effects of other covariates were considered (Gall et al., 2003; Rutherford, 2011). However, the mixed ANOVA method could also compare how the treatment over the duration of the experiment impacted the variables with additional considerations of the interaction between these two variables (Edwards, 1951; von Ende, 2001). Given each analysis method has its own pro and cons, this research conducted both methods of analysis to cross-validate the quantitative results.

**Validity and reliability of the instruments.**

*Inter-rater reliability of grading the ACT assessment***.** The researcher calculated the inter-rater reliability between the two reviewers grading the ACT assessment. One of the reviewers was the author who had rich research experience in computational thinking and STEM education. The second reviewer was a STEM education researcher with abundant experience in coordinating research projects on computational thinking and robotics education. To obtain an efficient inter-rater reliability score, the rating procedures were completed in two phases (see Table 10).

During the first phase, the second reviewer was trained to rate the ACT assessment in accordance with the rubrics and, meanwhile, two reviewers negotiated to make minor revisions to the rubrics to make each evaluation criterion more explicit and relevant. After the initial rater-training for the second reviewer, five participants from each group (both control and experimental groups) were randomly selected. That is, a total of ten participants' pre- and post-assessment submissions (10% of the total 96 assessments, including ten copies of pre- and ten copies of post- assessments) were randomly selected and then independently coded by the two reviewers in order to estimate the inter-rater reliability. Upon the completion of independently grading the assessments, Cohen's (1960) kappa value was calculated to validate the grading system of the ACT assessment. The Cohen's kappa value was 0.874 which confirmed an acceptable level of agreement between the two reviewers on rating the ACT assessment. Then the first reviewer (i.e., the researcher) graded all of the remaining assessments (a total of 86 copies of ACT assessments, including 43 pre- and 43 post- assessments) for both groups.

To reinforce the reliability of the first reviewer's rating, another round of inter-rater grading on the ACT assessment was performed. In this phase, the primary investigator randomly selected another ten students' assessments from the remaining submissions respectively in each group. A total of ten students' pre- and post- assessments (23% of the remaining assessments), including ten pre- and ten post- assessments, were graded by the second rater independently.

Cohen’s (1960) kappa value was then calculated again to confirm a high level of inter-rater reliability ($k$ = .902) was obtained (Landis & Koch, 1977).

**Table 10**

*The two phases to validate the reliability of inter-raters’ abstract thinking scores in the ACT Assessments*.

| Phase(s) | Procedure(s) |
|---|---|
| Phase 1 | Step 1: Conducting rater-training on grading of the ACT assessment and negotiating to formatively revise the rubric.<br>Step 2: Randomly sampling 10% of total submissions of ACT assessments<br>Step 3: Each reviewer independently grading the sampled ACT assessments (10%)<br>Step 4: Calculating the Cohen’s Kappa value to compare the agreement on grading between two reviewers. |
| Phase 2 | Step 1: The first reviewer graded all of the remaining copies of ACT assessments.<br>Step 2: Randomly sampling 23% of the sum of the remaining assessments of the ACT assessment.<br>Step 3: Each reviewer grading the sampled copies independently (including ten pre- and ten post- ACT assessments).<br>Step 4: Calculating the Cohen’s Kappa score to compare the agreement between two reviewers. |

*Validity of the ACT assessment.* The factor analysis on the posttest results of the ACT assessment was conducted to determine its construct validity. The principle component analysis on the seven-item ACT assessment yielded a three-factor solution, accounting for 66.05% of the total variance in the data (see Table 11). This value, higher than the average in this field, indicated this three-factor solution was acceptable (Loewen & Gonulal 2015; Plonsky & Gonulal 2015). The three factors were labelled in accordance with the focus of different questions, addressing three fundamental cognitive processes of abstraction. Specifically, the three questions in the decomposition activities were clustered on Factor 1 and thus were validated to assess students’ ability to map the problem structure. The three questions included in the locating similarities activities were confirmed with validity of evaluating students’ expertise in finding the fundamental level of similarities between analogical cases. In addition, the question for the filtering information task was also efficient in comparing students' capabilities in identifying key information. In sum, the construct validity of the ACT assessment was validated to efficiently assess each of the three core cognitive dimensions of abstraction.

**Table 11**

*The factor analysis results validated the validity of the ACT Assessments*.

| Item | Factor loadings | Communality | Eigenvalues | Variance |
|---|---|---|---|---|
| Factor 1: Mapping structures | | | | |
| Q2.1 | 0.760 | 0.715 | 2.487 | 35.531 |
| Q2.2 | 0.778 | 0.697 | | |
| Q2.3 | 0.752 | 0.603 | | |
| Factor 2: Filtering information | | | | |
| Q1 | 0.825 | 0.698 | 1.121 | 16.018 |
| Factor 3: Locating similarities | | | | |
| Q3.1 | 0.768 | 0.644 | 1.015 | 14.502 |
| Q3.2 | 0.374 | 0.686 | | |
| Q3.3 | 0.756 | 0.581 | | |

*Reliability of the Learning Experience Questionnaire*. Cronbach's $\alpha$ was obtained for both the overall survey items and the condition of if-item-deleted to validate the reliability of the Learning Experience Questionnaire (see Table 12). When calculating the value of Cronbach's $\alpha$ when each item was eliminated, the result found the value of Cronbach's $\alpha$ increased when removing Questions 8, 15, 17, & 19. To increase the reliability of the Learning Experience Questionnaire, those four questions were excluded for future analysis. In the end, the results indicated that the overall Cronbach's $\alpha$ was 0.854. Each remaining question had great reliability as the overall Cronbach's $\alpha$ would decrease when removing any of them.

**Table 12**

*Coefficients for each item if the item was deleted and the overall coefficients.*

| | Cronbach's α if Item Deleted | Overall Cronbach's α = .854 |
|---|---|---|
| 2 | .840 | |
| 3 | .852 | |
| 4 | .850 | |
| 5 | .841 | |
| 6 | .852 | |
| 7 | .849 | |
| 9 | .851 | |
| 10 | .844 | |
| 11 | .842 | |
| 12 | .830 | |
| 13 | .867 | |
| 14 | .839 | |
| 16 | .853 | |
| 18 | .847 | |
| 20 | .845 | |
| 21 | .832 | |
| 22 | .846 | |
| 23 | .843 | |
| 24 | .844 | |

**Independent samples t-test analysis on Learning Experience Questionnaire.**

An independent samples t-test analysis on the participants' responses to the Learning Experience Questionnaire was conducted to understand whether any external factors such as the instructors' facilitation and the participants' satisfaction with the curriculum. Although the average level of course satisfaction varied by groups and by questions, the difference between the two groups was not statistically significant (see Table 13). In other words, these aforementioned external factors did not have a significant influence on the results. In addition, the participants in the experimental group expressed a high level of perceived easiness about the EGPA and its subordinated activities, meaning following along with the activities was not a concern for them during the experiment. With this being said, the research was validated to proceed with statistical analysis on the participants' performance on the ACT assessment in order to investigate the effectiveness of the two curricula on fostering the participants' abstraction in computational thinking.

**Table 13**

*Means and standard deviations for learning experience satisfaction surveys.*

| Question(s) | Mean (SD) | | t | df | Sig |
|---|---|---|---|---|---|
| | Control | Experimental | | | |
| 2. I enjoyed the robotic class. | 4.38 (0.77) | 4.48 (0.85) | -0.44 | 45 | 0.66 |
| 3. I understood the class contents well. | 3.58 (0.83) | 3.74 (0.81) | -0.65 | 45 | 0.52 |
| 4. I had enough time to complete all activities | 3.38 (1.31) | 3.52 (1.04) | -0.43 | 43.47 | 0.67 |
| 5. I think I made good relationship between my team members for collaboration. | 4.04 (1.00) | 4.09 (1.28) | -0.14 | 45 | 0.89 |
| 6. While I use robotic equipment in the class, I was able to participate in the class well without any technical problems. | 3.54 (1.35) | 3.74 (1.06) | -0.56 | 43.26 | 0.58 |
| 7. My teacher encouraged students to share their ideas about things we are studying in class. | 4.00 (0.93) | 4.26 (0.54) | -1.18 | 37.19 | 0.25 |
| 9. My teacher wanted us to become better thinkers, not just memorize things. | 4.39 (0.72) | 4.61 (0.50) | -1.19 | 39.10 | 0.24 |
| 10. The activities helped me learn. | 4.42 (0.65) | 4.48 (0.67) | -0.32 | 45 | 0.75 |
| 11. The activities were interesting to me. | 4.17 (0.82) | 4.26 (0.81) | -0.40 | 45 | 0.69 |
| 12. I learned a lot by working with other students. | 4.17 (0.92) | 4.30 (0.88) | -0.53 | 45 | 0.60 |

| | | | | | |
|---|---|---|---|---|---|
| 13. Building the robot was easy. | 3.54 (1.22) | 3.65 (1.23) | -0.31 | 45 | 0.76 |
| 14. Programming the robot was easy. | 2.61 (1.34) | 3.13 (1.18) | -1.40 | 44 | 0.17 |
| 16. I usually look forward to this class. | 4.13 (0.76) | 4.17 (0.78) | -0.19 | 44 | 0.85 |
| 18. Sometimes I get so interested in my work I don't what to stop. | 3.83 (1.09) | 3.87 (0.82) | -0.13 | 45 | 0.90 |
| 20. The reading about volcano was easy. | | 4.43 (0.79) | | | |
| 21. The reading about earthquake was easy. | | 3.70 (1.33) | | | |
| 22. The problem decomposition task was easy. | | 4.65 (0.57) | | | |
| 23. The compare and contrast activities were easy. | | 3.57 (1.41) | | | |
| 24. The topic (Volcano and earthquake) we studied are interesting. | | 4.41 (0.67) | | | |

**Mixed ANOVA analysis on the mean score in the ACT assessment.**

Overall, the participants in both the experimental group and the control group earned a higher score in the posttest than in the pretest. The mean score for the experimental group was 7.96 before attending the *Danger Zone* curriculum with the treatment of the EGPA, compared to 15.91 after the treatment. In contrast, the mean score for the control group in the pretest was 10.80 compared to 11.24 in the posttest after attending the *Danger Zone* curriculum (see Figure 4). The 95% confidence intervals confirmed that the mean scores were reasonably close to the population mean (see Table 14). To decide whether any change in abstract thinking is the result of the interaction between time (the within-subjects factor) and treatment (between-subjects factor), a mixed ANOVA was performed on the mean score that the two groups earned in the ACT assessment.

**Table 14**

*Descriptive statistics on the participants' grade in the pre- and post- tests.*

| Group(s) | Time | Mean | SD | Std. Error | 95% Confidence Interval | |
|---|---|---|---|---|---|---|
| | | | | | Lower Bound | Upper Bound |
| Control | Pre | 10.80 | 3.08 | 0.59 | 9.62 | 11.98 |
| | Post | 11.24 | 2.99 | 0.60 | 10.03 | 12.45 |
| Experimental | Pre | 7.96 | 2.75 | 0.61 | 6.73 | 9.19 |
| | Post | 15.91 | 3.04 | 0.63 | 14.65 | 17.18 |

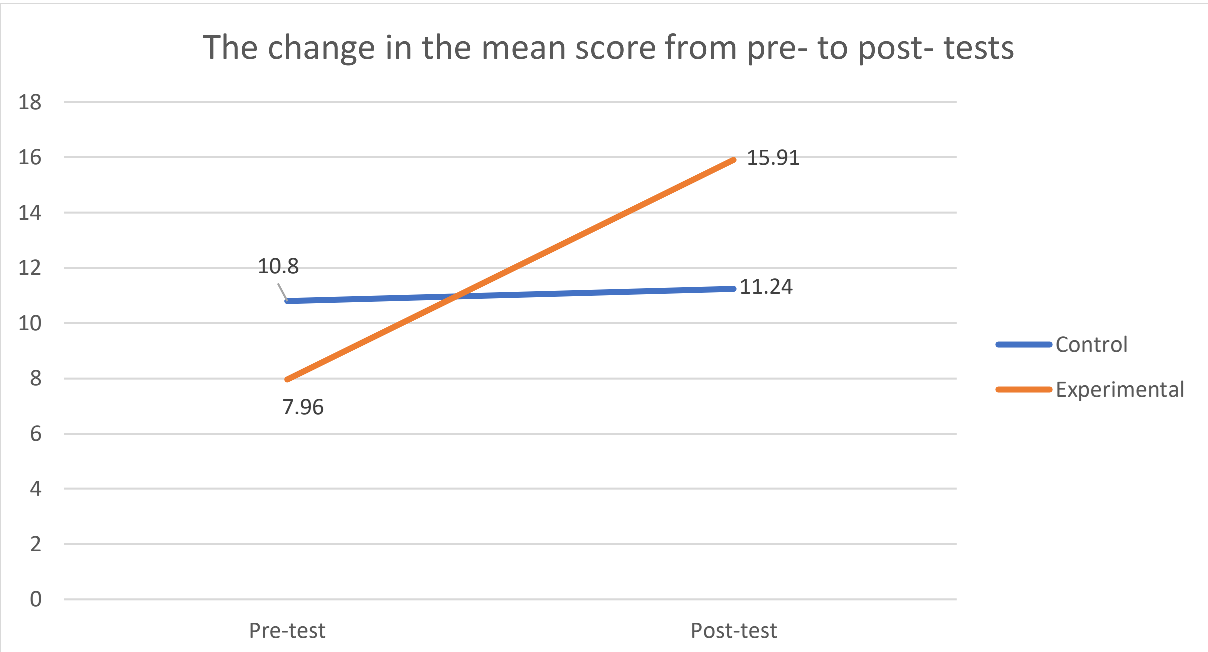



*Figure 4.* Overall test results of ACT assessment by group about pre- and post- tests.

For this mixed ANOVA analysis, the within-subjects factor was the time when the participants completed the ACT assessment (pre-instruction and post-instruction) and the between-subjects factor was whether the participants received the EGPA treatment when attending the *Danger Zone* robotics curriculum (control group and experimental group). Since the repeated measures only involves two levels of independent variables, the Mauchly's Test of Sphericity is not necessary for this analysis (Edwards, 1985; Girden, 1992).

The mixed ANOVA result indicated abstract thinking was significantly influenced by the interaction between time and treatment, F (1, 46) = 79.50, $p < 0.001$, $\eta_p^2 = 0.63$. In addition, the result showed a significant effect of the within-subject factors (i.e., the time) on the increase of the participants' mean scores in the ACT assessment, F (1, 46) = 99.20, $p < 0.001$, $\eta_p^2 = 0.68$ (Table 15 & Figure 5). However, the effect of the between-subject variable (i.e., the treatment) was not significant, F (1, 46) = 1.50, $p > 0.05$, $\eta_p^2 = 0.03$. Considering the interaction between time and treatment was significant, a follow-up test was conducted to better understand how the interaction functioned. Specifically, a separate mixed ANOVA on the time and on the treatment was performed for each dimension of abstraction, namely filtering information, mapping structures, and locating similarities.

**Table 15**

*Mixed ANOVA analysis result on the participants' mean score of the ACT assessment.*

| **Source** | **Type III Sum of Squares** | **df** | **Mean Square** | **F** | **Sig.** | **Partial Eta Squared** |
|---|---|---|---|---|---|---|
| Between Subjects (Treatment) | | | | | | |
| Intercept | 12624.17 | 1 | 12624.17 | 941.13 | .00 | .95 |
| Group | 20.05 | 1 | 20.05 | 1.50 | .23 | .03 |
| Error | 617.03 | 46 | 13.41 | | | |
| Within Subjects (Time) | | | | | | |
| Time | 422.28 | 1 | 422.28 | 99.20 | .00 | .68 |
| Time * Treatment | 338.40 | 1 | 338.40 | 79.50 | .00 | .63 |
| Error (Time) | 195.81 | 46 | 4.26 | | | |

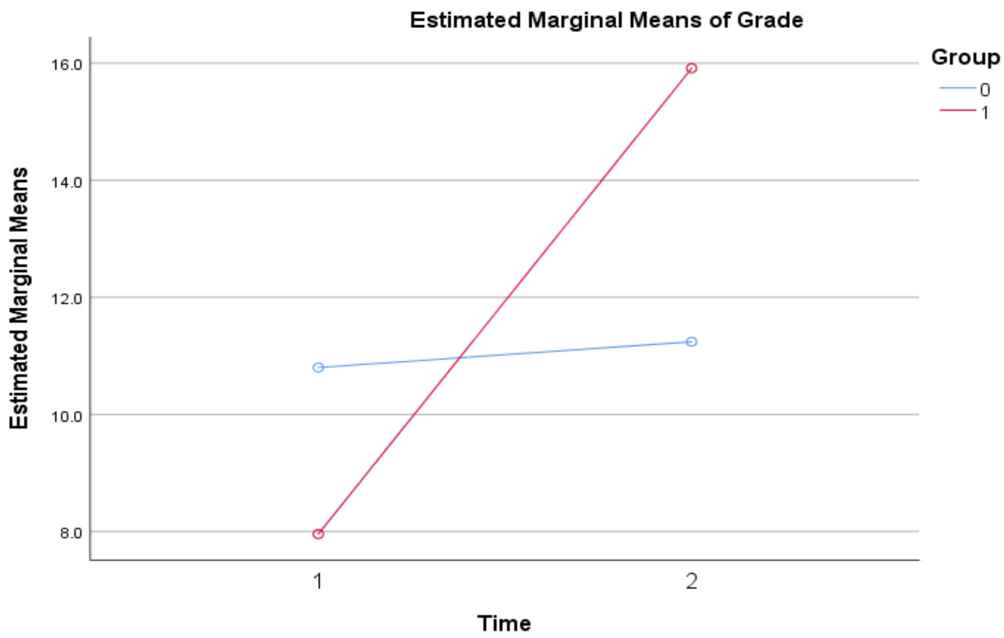



*Figure 5*. The illustration of the change in the mean score of the ACT assessment for the two groups.

Separate mixed ANOVA analyses were conducted to determine whether the interaction between treatment and time had a significant effect on the participants' mean scores in each separate section of the ACT assessment (i.e., Q1, Q2, & Q3). In each analysis, the treatment condition (experimental group and control group) was the between-subjects variable and the time (pre- and post- test) was the within-subjects variable. The mixed ANOVA result indicated that the interaction between treatment and time

1) significantly influenced the change in the participants' level of information filtering (i.e., Q1), F (1, 46) = 46.38, $p < 0.001$, $\eta_p^2 = 0.50$ (Table 16 & Figure 6);

2) significantly influenced the change in the participants' level of mapping structures (i.e., Q2), F (1, 46) = 55.80, $p < 0.01$, $\eta_p^2 = 0.55$ (Table 17 & Figure 7);

3) significantly influenced the change in the participants' level of locating similarities (i.e., Q3), $F(1, 46) = 14.27$, $p < 0.001$, $\eta_p^2 = 0.24$ (Table 18 & Figure 8).

**Table 16**

*Mixed ANOVA analysis result on the participants' mean score change in the filtering information activities.*

| Source | Type III Sum of Squares | df | Mean Square | F | Sig. | Partial Eta Squared |
|---|---|---|---|---|---|---|
| Between Subjects | | | | | | |
| Intercept | 287.90 | 1 | 287.90 | 297.39 | .00 | .87 |
| Group | 4.78 | 1 | 4.78 | 4.93 | .03 | .10 |
| Error | 44.53 | 46 | .97 | | | |
| Within Subjects | | | | | | |
| Time | 23.94 | 1 | 23.94 | 84.72 | .00 | .65 |
| Time * Group | 13.10 | 1 | 13.10 | 46.38 | .00 | .50 |
| Error(Time) | 13.00 | 46 | .28 | | | |

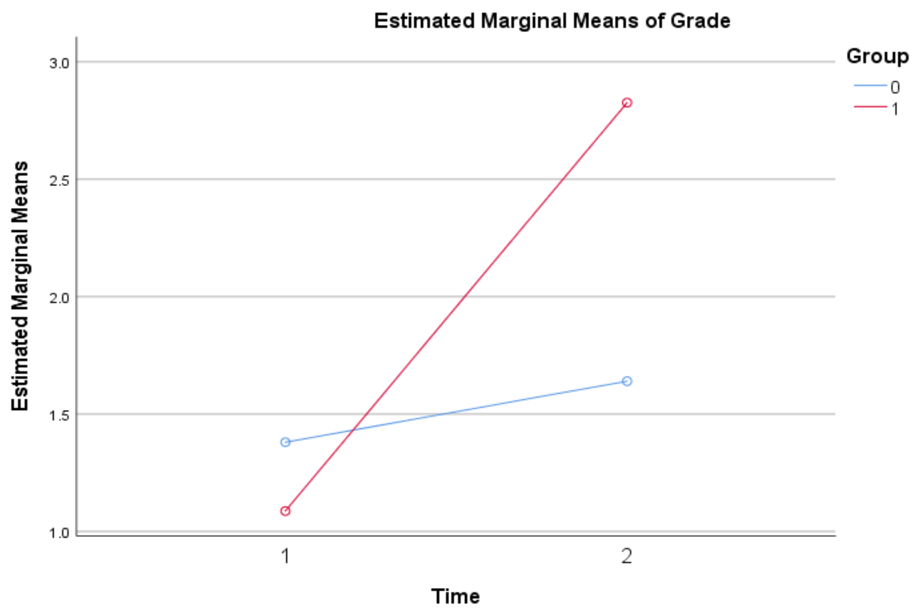



*Figure 6.* The illustration of the change in the mean score of the information filtering activities for the two groups.

**Table 17**

*Mixed ANOVA analysis result on the participants' mean score change in the mapping structures activities.*

| Source | Type III Sum of Squares | df | Mean Square | F | Sig. | Partial Eta Squared |
|---|---|---|---|---|---|---|
| Between Subjects | | | | | | |
| Intercept | 1301.65 | 1 | 1301.65 | 199.00 | .00 | .81 |
| Group | .55 | 1 | .545 | .08 | .77 | .00 |
| Error | 300.89 | 46 | 6.54 | | | |
| Within Subjects | | | | | | |
| Time | 133.39 | 1 | 133.39 | 54.86 | .00 | .54 |
| Time * Group | 135.66 | 1 | 135.66 | 55.80 | .00 | .55 |
| Error(Time) | 111.84 | 46 | 2.43 | | | |

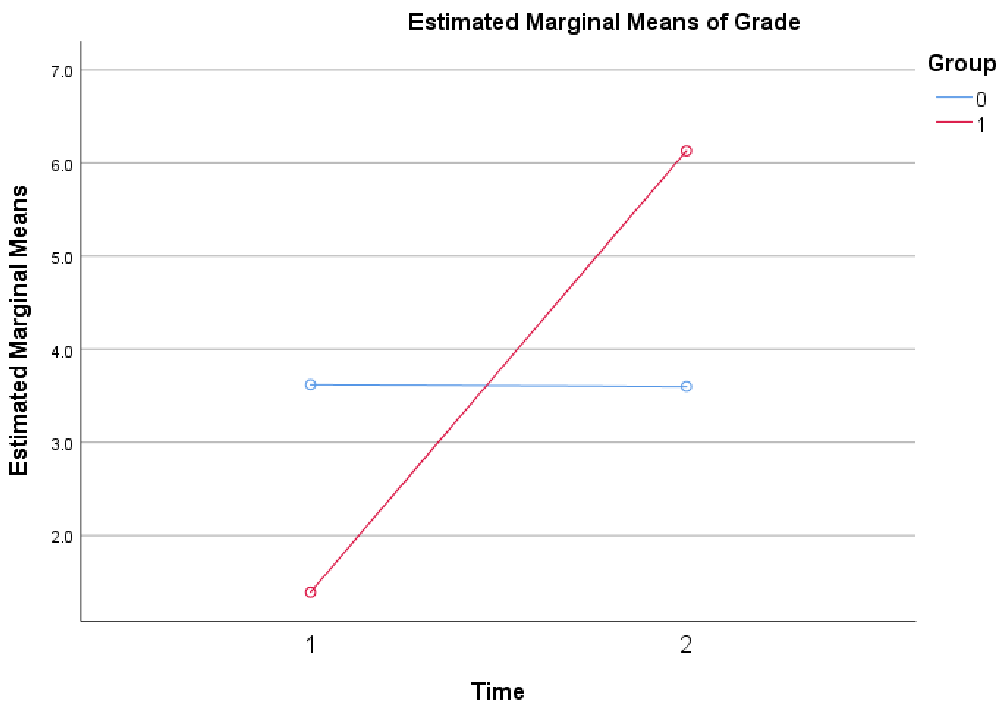



*Figure 7.* The illustration of the change in the mean score of the mapping structures activities for the two groups.

**Table 18**

*Mixed ANOVA analysis result on the participants' mean score change in locating similarities activities.*

| Source | Type III Sum of Squares | df | Mean Square | F | Sig. | Partial Eta Squared |
|---|---|---|---|---|---|---|
| Between Subjects | | | | | | |
| Intercept | 3529.45 | 1 | 3529.45 | 952.19 | .00 | .95 |
| Group | 2.12 | 1 | 2.12 | .57 | .45 | .01 |
| Error | 170.51 | 46 | 3.71 | | | |
| Within Subjects | | | | | | |
| Time | 16.08 | 1 | 16.08 | 22.04 | .00 | .32 |
| Time * Group | 10.41 | 1 | 10.41 | 14.27 | .00 | .24 |
| Error(Time) | 33.55 | 46 | .73 | | | |

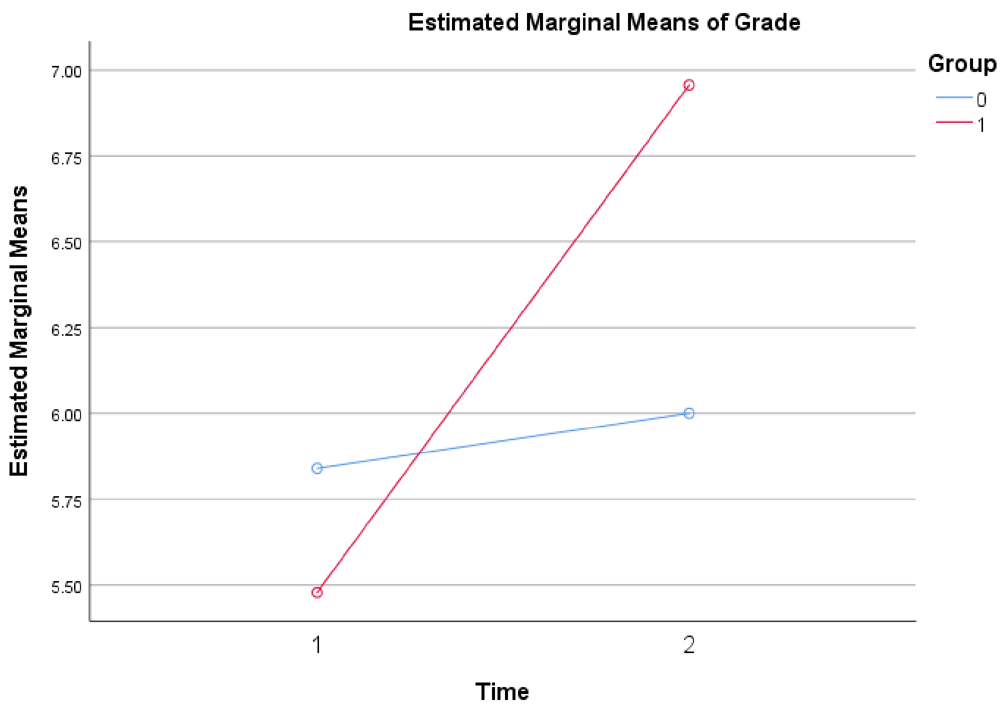



*Figure 8.* The illustration of the change in the mean score of the locating similarities activities for the two groups.

*Summary*. Overall, the mixed ANOVA analyses results indicated that the interaction between the time and treatment had a significant main effect on the participants' abstract thinking and each of its three dimensions. To further investigate how each factor influenced the change in abstraction, a series of paired samples t-test and independent samples t-test analyses were conducted as the post-hoc tests. The following paragraphs will present the results of the post-hoc analyses.

**Paired samples t-test analysis on the mean score in the ACT assessment.**

A paired samples t-test was conducted to determine the effect of the time (i.e., pre- and post- tests) on the change of the participants' mean scores on the ACT assessment as well as each subtest of three dimensions of abstraction from the pretest to the posttest. The result (see Table 19) indicated the experimental group's mean score of abstract thinking and its associated dimensions in the ACT assessment significantly increased after attending the *Danger Zone* robotics curriculum with the integration of the EGPA, while the mean score for the control group marginally increased or even decreased in the posttests. This indicated that the addition of the EGPA to the *Danger Zone* robotics curriculum significantly improved the abstract thinking skills of the participants in the experimental groups. The following paragraphs describe in detail the results for the overall performance as well as the performance regarding each dimension of abstraction in the ACT assessment.

**Table 19**

*Paired samples t-test analysis on the two groups' mean score changes in ACT assessment and its subtests assessing each dimension of abstraction.*

| Processes | Questions | Groups | Pretest M(SD) | Posttest M(SD) | Pair M(SD) | df | t | Sig | Cohen's d |
|---|---|---|---|---|---|---|---|---|---|
| Filtering Information | Q 1 | Control | 1.38 (0.83) | 1.64 (0.70) | -0.26 (0.56) | 24 | -2.32 | 0.03* | -0.46 |
| | | Experiment | 1.09 (0.85) | 2.83 (0.78) | -1.74 (0.92) | 22 | -9.11 | 0.00* | -1.90 |
| Mapping Structures | Q 2 | Control | 3.62 (2.11) | 3.60 (2.02) | 0.02 (1.34) | 24 | 0.08 | 0.94 | 0.01 |
| | | Experiment | 1.39 (1.44) | 6.13 (2.72) | -4.74 (2.86) | 22 | -7.94 | 0.00* | -1.66 |
| | Q 2.1 | Control | 1.04 (0.89) | 0.96 (0.89) | 0.08 (0.95) | 24 | 0.42 | 0.68 | 0.08 |
| | | Experiment | 0.26 (0.62) | 2.41 (0.89) | -2.15 (0.97) | 22 | -10.64 | 0.00* | -2.22 |
| | Q 2.2 | Control | 1.84 (0.99) | 2.00 (1.15) | -0.16 (0.85) | 24 | -0.94 | 0.36 | -0.19 |
| | | Experiment | 0.22 (0.42) | 2.24 (1.40) | -2.02 (1.53) | 22 | -6.35 | 0.00* | -1.33 |
| | Q 2.3 | Control | 0.78 (0.87) | 0.68 (0.69) | 0.10 (1.04) | 24 | 0.48 | 0.64 | 0.10 |
| | | Experiment | 0.91 (0.21) | 1.52 (0.23) | -0.61 (0.84) | 22 | -2.44 | 0.02* | -0.51 |
| Locating Similarities | Q 3 | Control | 5.84 (1.52) | 6.0 (1.58) | -0.16 (0.47) | 24 | -1.69 | 0.10 | -0.34 |
| | | Experiment | 5.48 (1.81) | 6.96 (0.88) | -1.48 (1.68) | 22 | -4.23 | 0.00* | -0.88 |
| | Q 3.1 | Control | 2.12 (0.93) | 2.24 (0.88) | -0.08 (0.40) | 24 | -1.00 | 0.33 | -0.20 |
| | | Experiment | 1.87 (0.82) | 2.48 (0.59) | -0.61 (0.84) | 22 | -3.48 | 0.00* | -0.73 |
| | Q 3.2 | Control | 1.84 (0.47) | 1.92 (0.57) | -0.08 (0.28) | 24 | -1.45 | 0.16 | -0.29 |
| | | Experiment | 2.04 (0.83) | 2.48 (0.51) | -0.44 (0.73) | 22 | -2.87 | 0.01* | -0.60 |
| | Q3.3 | Control | 1.84 (0.47) | 1.84 (0.47) | 0.00 (0.29) | 24 | 0.00 | 1.00 | 0.00 |
| | | Experiment | 1.57 (0.84) | 2.04 (0.56) | -0.48 (0.90) | 22 | -2.55 | 0.02* | -0.53 |
| | **Total** | Control | 10.80 (3.08) | 11.24 (2.99) | -0.44 (1.54) | 24 | -1.43 | 0.17 | -0.27 |
| | | Experiment | 7.96 (2.75) | 15.91 (3.04) | -7.96 (3.90) | 22 | -9.78 | 0.00* | -2.04 |

*Note*: Filtering information are out of 4 points, mapping structures and locating similarities are out of 12 points, overall abstract thinking assessment are out of 28 points.

First, by comparing the change in mean scores of the ACT assessment from the pretest to the posttest, the research found that both the experimental group and the control group had an increase in their overall abstract thinking skills, though the mean score change in the control group was relatively subtle. The result of the paired samples t-test analysis [$t(22) = -9.78$, $p < 0.001$] indicated that the increase in the experimental group's total scores in the ACT assessments was significant, but in contrast, the control group reported a non-significant change in the sum score of the ACT assessments [$t(24) = -1.43$, $p > 0.05$]. In other words, there was a statistically significant improvement in the experimental groups' abstraction after taking the Danger Zone robotics curriculum with the integration of the EGPA, from $7.96 \pm 2.75$ to $15.91 \pm 3.04$ ($p < 0.001$); an improvement of $7.96 \pm 3.90$.

Secondly, for each dimension of abstraction, the experimental group also had an increase from the pretest to the posttest in the mean score on the respective questions of assessing filtering information (Q1), mapping structure (Q2), and locating similarities (Q3). The result of the paired samples t-test analysis revealed that this increase in the experimental group's mean score in information filtering [$t(22) = -9.11$, $p < 0.005$], mapping structure [$t(22) = -7.94$, $p < 0.005$], and locating similarities [$t(22) = -4.23$, $p < 0.005$] was significant. The result also indicated that there was no statistically significant difference between the pretest and the posttest for the control group in their mean score of activities regarding mapping structures [$t(24) =0.08$, $p > 0.05$] and locating similarities [$t(24) =-1.69$, $p > 0.05$], and the mean score of the control group in some questions actually decreased (e.g., Q2, Q2.1) or remained unchanged (e.g., Q3.3). For the filtering information process, the control group had a significant increase in the mean score of associated questions [$t(24) = -2.32$, $p < 0.05$], but the amount of the increase was much smaller than the experimental group in terms of the effect size [the experimental group's value of

Cohen's d (-1.90) was much larger than that of the control group (-0.46)]. This also confirmed the effectiveness of the EGPA in improving the participants' abstraction in computational thinking when integrated in the STEM-integrative robotics curriculum.

**Independent samples t-test analysis on the mean scores in the ACT assessment.**

An independent samples t-test was conducted to understand how the treatment influenced the participants' total grade in the ACT assessment. The results (see Table 20) indicated that the participants in the experimental group (e.g., $15.91 \pm 3.04$) had statistically significantly higher levels of abstract thinking compared to the control group (e.g., $11.24 \pm 2.99$) at the end of the experiment, $t(46) = 5.36$, $p < 0.001$. Furthermore, it is worth noting that on the pretest, the control group (e.g., $10.80 \pm 3.08$) had a statistically significantly higher levels of abstract thinking than the experimental group ($7.96 \pm 2.75$), $t(46) = -3.361$, $p < 0.005$). The result confirmed that the experimental group had a significantly larger increase in the level of abstract thinking after taking the treatment of the EGPA in the *Danger Zone* robotics curriculum. In other words, the addition of the EGPA to the *Danger Zone* curriculum helped the participants foster their abstract thinking.

Furthermore, separate independent t-tests were conducted to compare the difference in performance between the two groups with regards to each dimension of abstraction. At the end of the experiment, the participants in the experimental group earned a statistically significantly higher grade than those in the control group in each dimension of abstraction, namely filtering information [$t(46) = 5.36$, $p < 0.001$], mapping structures [$t(46) = 3.68$, $p < 0.005$], and locating similarities [$t(46) = 2.56$, $p < 0.05$]. In the dimension of mapping structures, the participants in the experimental group had a significantly lower grade on the pretest than those in the control groups, $t(46) = -4.24$, $p < 0.001$. Another interesting point in the comparison of mean scores for the two groups was that the control group earned a lower score in locating similarities during the posttests than that during the pretests. The following graphs (see Figure 9, Figure 10, and Figure 11) visualize the mean score change in each dimension of abstraction from the pretest and the posttest.

Overall, the results of the post-hoc analysis provided additional evidence about the effectiveness of the EGPA on fostering the participants' abstract thinking and its associated dimensions when added to the *Danger Zone* robotics curriculum. However, to better determine whether the EGPA was effective in fostering abstract thinking, an analysis of covariance (ANCOVA) was needed to offset the influence of the initial difference between two groups on the results.

**Table 20**

*Independent samples* t-*test analysis on the two groups' mean score changes in ACT assessment and its subtests assessing each dimension of abstraction.*

| Dimensions | Questions | Experimental vs. Control Pretest | | | Experimental vs. Control Posttest | | |
|---|---|---|---|---|---|---|---|
| | | t (46) | p | Cohen's d | t (46) | p | Cohen's d |
| Filtering Information | Q 1 | -1.207 | .233 | 0.35 | 5.561 | 0.000 | -1.61 |
| Mapping Structures | Q 2 | -4.242 | .000 | 1.23 | 3.680 | 0.001 | -1.06 |
| Locating Similarities | Q 3 | -0.753 | .455 | 0.22 | 2.560 | 0.014 | -0.74 |
| Abstraction | Total | -3.361 | .002 | 0.99 | 5.363 | 0.000 | -1.55 |

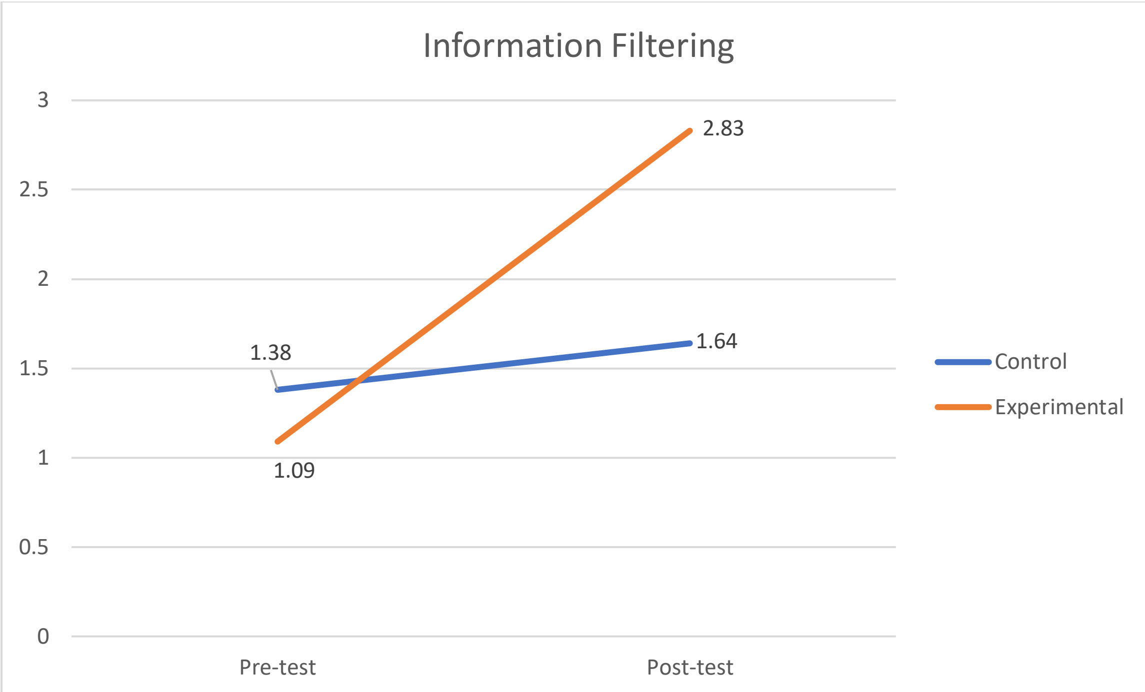



*Figure 9.* Pretest and posttest result of filtering information questions in the ACT assessments completed by the two groups.

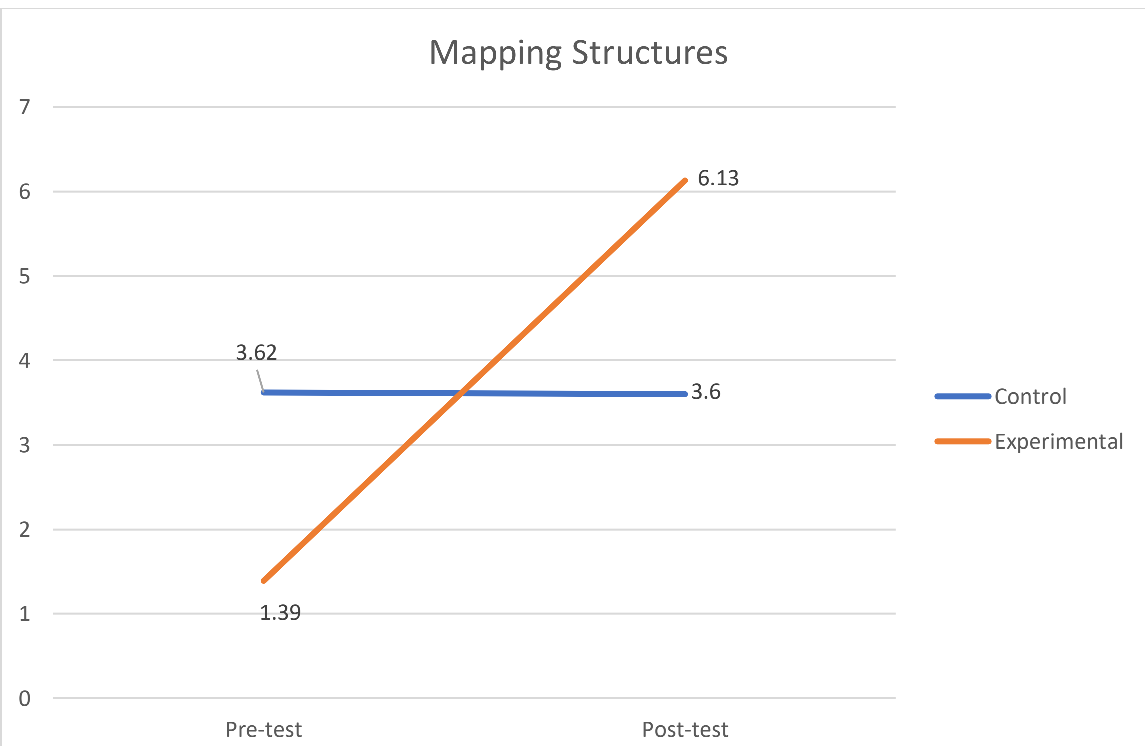



*Figure 10.* Pretest and posttest result of mapping structures in the ACT assessments completed by the two groups.

*Figure 11*. Pretest and posttest result of locating similarities in the ACT assessments completed by the two groups.

**Analysis of covariance (ANCOVA) results.**

An ANCOVA analysis was performed to compare whether there were any significant differences in abstract thinking and its associated dimensions between the experimental group and the control group after attending different STEM-integrative robotics curricula (i.e., comparing the posttest scores between these two groups). The ANCOVA analysis is often used to determine the influence of categorical independent variables (treatment) on the means of a dependent variable when the effects of other covariates are controlled (Rutherford, 2011). For this research, the pretest score was the covariate. The dependent variable was the total score earned in the posttest (continuous) and the independent variable was the group the students were assigned to (categorical). Using the ANCOVA analysis, this study mitigated the influence of any possible differences that might have already existed before attending the designated curriculums in the level of abstraction in computational thinking between these two groups (Green & Salkind, 2011).

Before conducting the ANCOVA analysis, the researcher tested the homogeneity of regression slopes assumption to make sure it satisfied the required conditions (Green & Salkind, 2011; Harwell & Serlin, 1988). Specifically, the covariates (e.g., pretest score) was not significantly related to the independent variable (e.g., group). This confirmed that the ANCOVA could be performed to investigate whether the integration of the EGPA into the *Danger Zone* robotics curriculum led to the difference in the level of abstract thinking between the control group and the experimental group, when the posttest result was represented by an adjusted mean score.

Table 21 provides the descriptive data and the ANCOVA of the experimental group's posttest results of the ACT assessments. The adjusted mean values of the posttest scores were 16.72 and 10.49 for the experimental group and the control group, respectively. The result of the ANCOVA identified a significant difference between the two groups ($F = 54.51$, $p < 0.005$, $\eta^2 = 0.548$), indicating that the integration of the EGPA into the *Danger Zone* robotics curriculum had significantly positive effects on the participants' abstract thinking skills in the experimental group. The researcher then administrated the ANCOVA analysis for each sub-question assessing each of the three different dimensions of abstraction. The results also indicated the experimental group outperformed the control group in filtering information ($F = 52.97$, $p < 0.005$, $\eta^2 = 0.541$), locating similarities ($F = 17.62$, $p < 0.005$, $\eta^2 = 0.281$), and mapping structures ($F = 29.43$, $p < 0.005$, $\eta^2 = 0.395$). The contrast between the two groups in the three different dimensions of abstraction is visualized in the Figure 12 (filtering information), Figure 13 (locating similarities), and Figure 14 (mapping structures).

**Table 21**

*ANCOVA Results of the ACT Assessment.*

| | | Control Group | | Experimental Group | | | | |
|---|---|---|---|---|---|---|---|---|
| | | Adjusted Mean | Std. Error | Adjusted Mean | Std. Error | F | p | $\eta^2$ |
| Filtering Information | Q1 | 1.57 | 0.13 | 2.90 | 0.13 | 52.97 | 0.000* | 0.541 |
| Mapping Structures | Q2 | 2.94 | 0.46 | 6.85 | 0.49 | 29.43 | 0.000* | 0.395 |
| | Q2.1 | 0.82 | 0.18 | 2.57 | 0.19 | 40.66 | 0.000* | 0.475 |
| | Q2.2 | 1.52 | 0.30 | 2.76 | 0.32 | 5.94 | 0.019* | 0.117 |
| | Q2.3 | 0.70 | 0.18 | 1.50 | 0.19 | 9.60 | 0.003* | 0.176 |
| Locating Similarities | Q3 | 5.91 | 0.19 | 7.06 | 0.20 | 17.62 | 0.000* | 0.281 |
| | Q3.1 | 2.16 | 0.11 | 2.57 | 0.12 | 6.24 | 0.016* | 0.122 |
| | Q3.2 | 1.97 | 0.09 | 2.43 | 0.09 | 12.94 | 0.001* | 0.223 |
| | Q3.3 | 1.80 | 0.10 | 2.09 | 0.10 | 4.37 | 0.042* | 0.088 |
| Overall | | 10.49 | 0.55 | 16.72 | 0.58 | 54.51 | 0.000* | 0.548 |

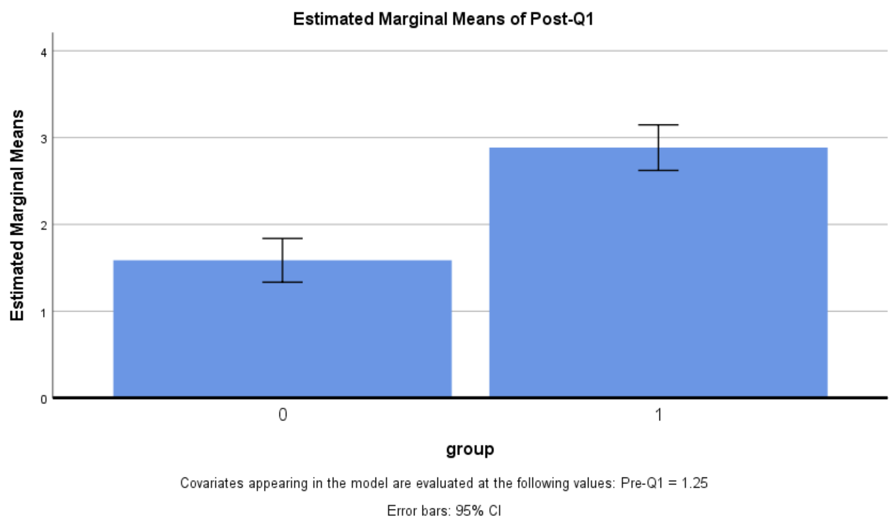



*Figure 12.* ANCOVA analysis result of the contrast between the experimental group (group 1) and the control group (group 0) in the posttest result of information filtering in the ACT assessments.

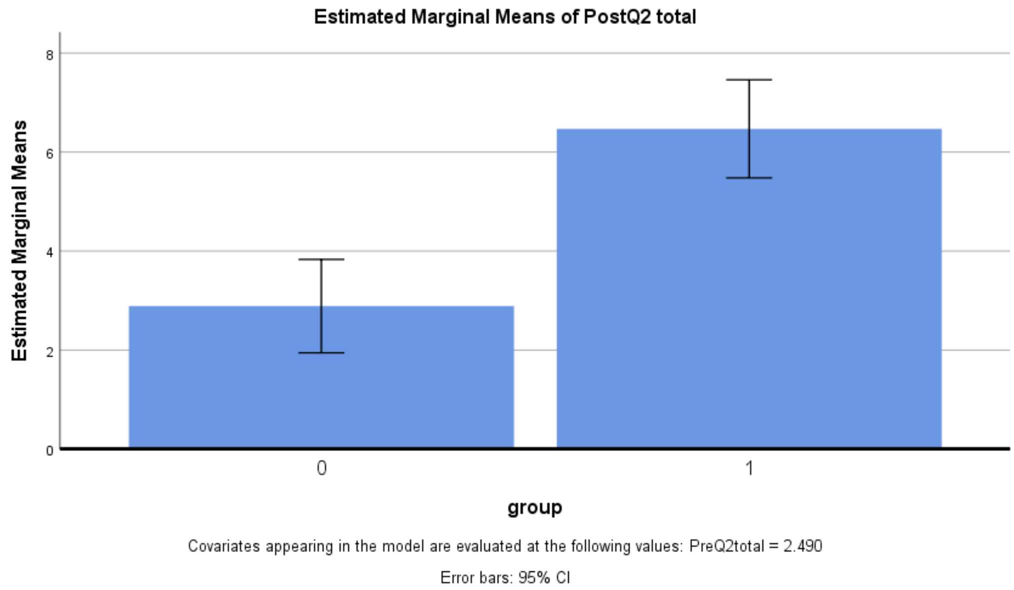



*Figure 13.* ANCOVA analysis result of the contrast between the experimental group (group 1) and the control group (group 0) in the posttest result of mapping structures in the ACT assessments.

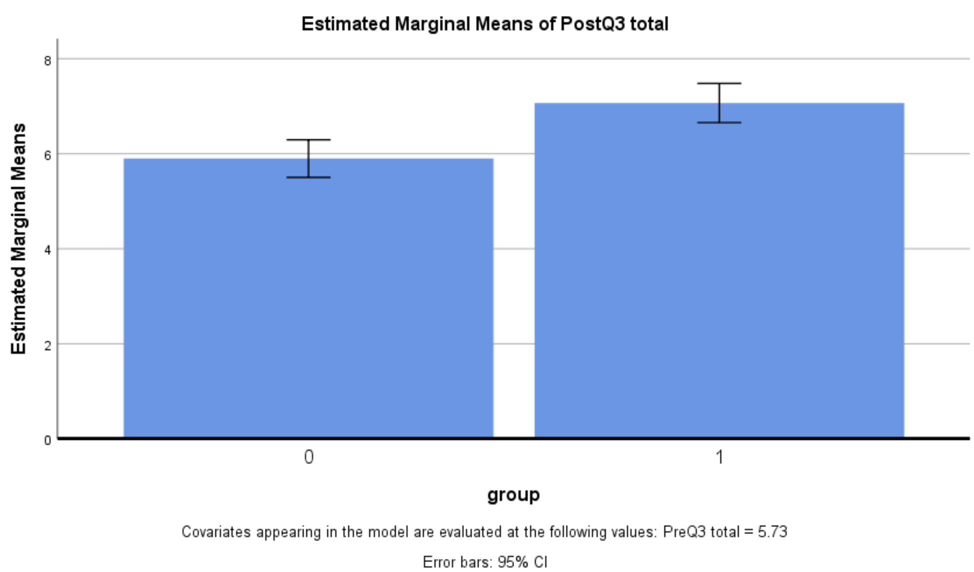



*Figure 14.* ANCOVA analysis result of the contrast between the experimental group (group 1) and the control group (group 0) in the posttest result of locating similarities in the ACT assessments.

**Research Question 2: What Are the Students' Experiences with the EGPA While Taking a STEM-integrative Robotics Curriculum?**

This section reports the students' experiences and perceptions with participating in the new Danger Zone curriculum on developing their abstraction. To answer this research question, three groups of students attending the new *Danger Zone* integrative-STEM robotics curriculum were interviewed in focus groups. From their interview transcripts, seven themes about students' experiences with the new *Danger Zone* curriculum were identified. Specifically, five themes were about students' meaningful experiences during a series of instructional activities and another two themes addressed students' challenges.

**Students' Meaningful Experiences**

**Engaged in an authentic problem-solving process.**

This theme described students' engagement in the activities to develop abstraction via solving an authentic problem. Eight of the participants described how the provided real-life examples helped them become engaged in the problem-solving process. Especially in the filtering information activity, solving authentic problems mitigated the risk of being exposed to an overload of information by providing relevant examples. For example, Student 3 mentioned that "I like earthquake one because it seemed more fun and the video when the persons was saved by a robot was pretty cool. And to see a robot do that is exciting" All the participants indicated that the filtering information activities in the robotics curriculum "help(s) us understand what was happening, why and where it was going on." They also thought efficiently filtering information was an important expertise for them as they felt "what we did was pretty good to help us prepare like an older student and know what we might do in the future." Overall, the participants' response focused on describing how providing real-life problems with a lot of information at the beginning engaged them to play an active role in the problem-solving process and empowered them to develop a better understanding of the situation.

**Developed better capabilities of problem identification.**

This theme presented students' experience of improving their ability to identify and represent problems by practicing relevant activities. The participants' responses focused on describing how these activities empowered them with a finer-tuned understanding of the problem structures and better capabilities in capturing the key information they needed. All groups described they could "learn about the volcano, what obstacles (of the tasks) are, or what robot can do (for the tasks)" from the rich information provided by the reading materials, but only when prompted to identify the main goal of the task assigned to them, were they able to determine what information was relevant to the task (see quotes below).

> I can read the information and pick out the important information. So, I know what the task is about and what the natural disasters are. So, there's different ways you need to code a robot because of the disaster… Now I found something that the need for the robot and I got to type in why I needed it. (Group 1)

**Formulated better understanding of the overarching problem structure.**

This theme mainly described the benefits of the decomposition activity in envisioning a better understanding of the overarching problem structure so the participants could monitor their problem-solving without repeated attempts of trial and error. One participant reported that "like before when we didn't have that (decomposition), we'd have to keep testing and keep testing and keep testing each till we got it. But now when you have that (time and delay) you can just put it on your computer programming". The other three groups also expressed their favor towards understanding the overarching structure of the problem, by stating they "like decomposition because it's easy and it keeps track of all your tasks. Because we did it on paper, then we did something wrong. That was supposed to go there. But it keeps track of your progress and it's very neat. So, you could tell what it goes with." Overall, the three groups mainly described how their experiences with the decomposition activities allowed them to monitor the progress of their work and prepare for the next tasks (e.g., manipulating and debugging the robot).

**Generated transferrable solutions.**

This theme addressed the students' perceived benefits of locating similarities in allowing them to identify analogical comparisons between two problems and thus develop solutions transferrable to similar but different cases. Overall, the three groups had a positive experience with the activity of locating similarities, especially comparing the volcano and earthquake rescue problems. The participants insisted that contrasting two similar but different examples helped them developed transferrable solutions to the analogical problems. Specifically, one participant stated that "We now know how to use this robot to do stuff like for volcano. We can just switch up a little bit of programming and make it work for solving different problems, like the earthquake (rescuing)."

**Collaborated with peers.**

This theme covered some of the positive experiences of collaborating with their peers. For example, two of the four groups were inspired by the representation of multiple perspectives in the process of filtering information. With enriched perspectives, they were able to understand the problem from different viewpoints, which could also further reinforce their engagement and enrich their understanding of the problem.

## Students’ Challenges

### Lacking sufficient expertise.

This theme described students’ struggles in the activities due to a lack of sufficient expertise, especially in the locating similarities activity and filtering information activity.

The participants commonly reported their struggles in identifying the deep level of similarities between two analogical examples as, “When you come to a deep and surface. The surface was easy, but the deep, it was hard and you really have to think about it and like my brain just like exploded.” Four students even reflected that they did not have a clear idea of how to differentiate the “deep” and “superficial” levels of similarities. One of the students reported, “I didn't really put like a deep thing here till teacher told us what the surface are and what the deep are. Then I realized I have to change mine, because I put a lot of basic things here.” Another student specifically talked about his concern about the commonalities between the volcano exploration example and the earthquake rescue and said, “Like volcanoes and earthquakes, they have a lot in common. But when I tried to find a deep one, I really can't just think about it that deep.”

All the groups insisted that some components of the filtering information activities were challenging for fifth graders, such as the capabilities of and the mindset for dealing with the large amount of information in the reading. For example, one participant complained that “it was hard trying to find information at volcano one. There is too much information!” Although authentic problems engaged them in reading, the potential risk of information overload was still a common concern for these fifth graders.

### Unfamiliarity with the activities.

This theme covered students' challenges in completing these novel activities. For example, students' challenges regarding decomposition were attributed to the lack of prior experience with similar activities. The participants generally needed longer than the assigned time to figure out the structure of the problem. One group of the participants shared, "Teacher said you better hurry up, and we started working faster and faster, but we hope to have more time working on it." However, most participants were positive about overcoming these challenges by stating that "it [the decomposition activity] was a bit frustrating, but it was like a 'good' frustration in the end."

## Research Question 3: What Are the Teacher's Experiences of Facilitating the EGPA Activities in a STEM-integrative Robotics Curriculum?

This section reports the teacher's experiences of facilitating the new *Danger Zone* curriculum to develop students' abstraction and her perceptions of student experiences. The following paragraphs will respond to this research question by addressing four aspects: the teacher's experiences, challenges, and perspectives of meaningful experience for students, and perspectives of students' challenges.

## Teacher Experiences

### Experience with integrated standards.

This theme illustrated the teacher's positive experience with the curriculum in addressing various subjects' course standards in an integrated manner. For example, the teacher insisted the integrated standards presented in this curriculum allowed her more flexibility for in-course facilitation by stating, "This curriculum definitely tied into social studies and math standards and language arts standard, especially science. It did fit and flow. I felt I can really relate the project to ELA and made it more project-based learning." Alignment with the course standards also presented the teacher with more flexibility in implementing the curriculum compared to the curriculum she used previously, as "in the past I would teach it after our testing at the end of the year, because it didn't fit the standards very well. Now I will do it in the middle of the year. I feel more comfortable doing it."

**Interests in meaningful activities**.

This theme discussed the teacher's experience of developing students' interest in these activities and her intention of continuing to use it in future classes. The teacher perceived these activities were meaningful for students. For example, the teacher reflected on her facilitating experience and picked the decomposition activity as the most meaningful because it combined all aspects of abstraction (see quote below).

> The decomposition I would say is probably the most meaningful. And I understand that the decomposition requires filtering important information so they kind of go together, but I think that we've filtered information in other subject areas but not to the degree that we filtered it in order to do the decomposition for robotics. So that's why I think where about the decomposition was probably the most meaningful. (The teacher)

The teacher's positive experience with the curriculum resulted in their intention to continue implementation. Specifically, the teacher expressed she would use this curriculum in her class next year, but in the meantime, she also planned to include more examples – especially examples from daily life, not relevant to robotics, in the next implementation (see quote below).

> I will surely use, but probably do a few more examples (which are) not even robot related. Even more specific if I had time. I mean because we did examples but even

maybe just a few more. Probably about life just completely different scenario. I would try to do more than before. (The teacher)

## Teacher Challenges

### Timing constrains.

This theme represented the teacher's challenge of not having enough time for students to complete the lessons. The teacher described her challenges in controlling the pace of the instruction and also the length of the time assigned to an activity. The teacher argued that "I pretty much just stayed surface with it because I was trying to get to the next example," and "I did not get to the last lesson (for students to work on it)". She also reported that in "the similarities and differences [activity] I felt like I might have moved too fast and just taken surface comparisons instead of going deeper with it. There was not enough time". The teacher remarked that the participants might need additional time to complete some activities, especially the locating similarities activity which "required relatively higher order of thinking for students" and also "were new to them, too".

### Pedagogical struggles.

This theme represented the challenging situations the teacher encountered when she had to deal with uncertainty about "how", "what", and "when" as relevant to her facilitation practice. The teacher said, "I hadn't seen the whole big picture yet of how we were doing. So, it is hard to know how to organize it because I was not grasping it. You gave us a ton of information, but it was so much information, I can't grasp it all." Moreover, for the activity of locating similarities, the teacher described her incompetence in addressing the performance gap of some students. She stated, "some of them just do not transfer that [the identified similarity] very well but, see, and I don't know how to teach that other than just continuing to compare things." Overall, the teacher noted that facilitating the new curriculum was a novel experience for her, which led to pedagogical struggles in efficiently delivering the content.

**Difficulties in engaging students.** This theme addressed the teacher's challenges of engaging the participants in each activity. The teacher reported that engaging the elementary students till the completion of the activities was challenging. For example, in the filtering information task, she struggled prompting her students to read through the long passage with so much information provided. She said, "my students don't want to read for details. They want to skim over something. So, I'd like to make them stop and think about things that they actually need to pull out and explain why it was important."

### Teacher Perceptions of Students' Meaningful Experiences

**Become active problem-solvers**.

This theme interpreted a perceived meaningful change in students' roles as problem solvers after engaging with this curriculum. The teacher reported that students no longer focused on waiting for the answers but sought to actively solve a problem. Taking the example of filtering information activities, she mentioned students attempted to actively filter information to grasp an understanding of the main idea and to solve problems, rather than just briefly browsing the information about answers (see quote below).

> I think the kids did not like to read that much information before. They wanted to look for information just to answer a specific question. Now they are instead looking at it as a whole package and trying to filter out the parts that they need to do something with. They can understand the value, like, why they have to look at all the information and being able to assimilate that information. (The teacher)

**Build collaborative mindsets.**

This theme indicated perceived improvement in students' experience with group collaboration. The teacher noted group collaboration was an important component of the curriculum. The small-group interaction allowed the participants to negotiate different perspectives and then learned how to reach an agreement to identify key information relevant to the mission. For instance, the teacher said, "I loved the way that they compare their individual readings in a small group and then come to consensus in that small group to figure out what worked, what was the important information that the whole group felt was pertinent to the mission."

**Perform purposefully planning.**

This theme outlined perceived improvement in students' experiences in purposefully planning to solve a problem. The teacher felt attending to the decomposition activities helped her students become more proactive in planning for the problem-solving process. For example, she said, "The decomposition really helped them [students] plan ahead. Before solving the problem, I felt that they [students] had a better understanding of how everything should work." The teacher also felt it was meaningful for students to engage with the decomposition activity to become prepared for the programming. Specifically, she insisted the decomposition activity "definitely solved the programming even faster and it helped that they had already worked out the, I guess, the specifics of how their specific robot moved, how many units it went with what speed and at what angle it. So, it really helped that they had already worked that out."

## Teacher Perceptions of Students' Challenges

### Unfamiliarity with activities.

This theme represented the perceived challenge resulting from students' unawareness of what they were expected to accomplish in some of the activities. The teacher reported that her students were frustrated by the unfamiliar task of comparing and contrasting, filtering information, and also problem decomposition, but performed much better after completing a similar activity. She noted, "I think they [students] did a much better job [on compare and contrast] because it was familiar at that point. They [students] kind of knew what they were expected to do. Before that, I felt like at the beginning it was overwhelming to them and they were frustrated."

### Inflexible knowledge transfer.

This theme illustrated the perceived challenge in flexibly transferring knowledge or solutions to similar but different situations. The teacher reported students encountered challenges in figuring out the deep similarities between the two analogical cases in the task of locating similarities. The teacher specified the reason why students failed to find the deep similarities was because "they [were] stuck in the box" (see quote below).

> but then other kids were stuck in this box of well that's what that is. And they tend to think of another thing. So, I, I just, I think it is just part of this observation and being able to transfer that knowledge of what you observed in one thing and, being able to say I see this in another thing that it looks a little different in this thing. (The teacher)

### Negative emotion about collaboration.

This theme presented the teacher's perceptions of the challenges that students encountered while resolving problems with their partners. The teacher reported "inefficient partnership" as an issue that might contribute to students' failures during this robotics curriculum. Students experienced challenges and gained negative emotions from partners who were controlling during the collaborative problem-solving process. The teacher described the condition in which "students assigned in the same pairs did not want to work together" so efficient intervention from the teacher to help clarify the meaning of partnership was necessary for the students to remain engaged in the collaborative problem-solving process. The teacher emphasized that it was necessary to help students understand their role as a partner and also get to look beyond their emotions.

## Synthesis of the Findings

Overall, the research investigated the effectiveness of the EGPA integrated in the *Danger Zone* robotics curriculum on fostering elementary students' abstraction. The quantitative analysis result confirmed that attending the EGPA and relevant activities had a significant effect on the improvement of elementary students' abstract thinking as well as its three dimensions. In addition, after attending the EGPA, the experimental group had a significantly higher level of abstract thinking than the control group without taking these activities. The qualitative analysis results also revealed that the participants had a positive experience with the EGPA and relevant activities. Furthermore, both from the teacher's and the participants' perspectives, the activities relevant to the three specific dimensions of abstraction were perceived as useful and integral components for problem-solving. It is also worth noting that abstraction is a high-order thinking ability, so it might take time to see improvement in participants' level of abstract thinking. This speaks to the future design of similar curriculum – there needs to be more time assigned for students to complete required activities. Moreover, facilitating activities dedicated to high-order thinking may need some real-life examples or pre-instructions. In this way, elementary students may understand what guidelines they need to follow and what they are expected to accomplish in the activity. Lastly, it is important to ensure teachers receive some effective pre-training to establish a profound understanding of each course activity and thereby support their facilitation of the activities more efficiently.

CHAPTER 5

# CONCLUSION

This chapter concludes the empirical research by presenting the findings aligned with each research question and also an overall discussion in relation to the implications for future efforts in K-12 robotics education to foster students' abstraction and computational thinking. Specifically, this chapter begins with an overview of the research findings from each research question. In addition, this chapter discusses the theoretical implications for researchers and also practical implications for educators and practitioners investing in STEM education, computational thinking, and robotics education. In the end, the limitations of this research and also suggestions for future research regarding abstraction are discussed.

## Overview of the Findings

The empirical research confirmed that the explicit guidance and practices on abstraction (EGPA) built upon the proposed guidelines in Chapter 2 was effective in fostering K-12 students' abstraction and its three dimensions. In addition, the instructor and the students discussed the benefits and challenges of the EGPA activities in the development of students' abstract thinking. The findings addressing each of the three research questions, from both quantitative and qualitative data analysis, are summarized below.

### Research Question 1: What is the Effect of the EGPA on the Development of Fifth Graders Abstraction in Computational Thinking While Taking a STEM-integrative Robotics Curriculum?

The result confirmed that by practicing the EGPA in the *Danger Zone* STEM-integrative robotics curriculum elementary students enhanced their abstraction and also its three dimensions. Specifically, the mixed ANOVA analysis indicated the interaction between time and treatment was significant for the improvement of students' abstract thinking. The paired samples t-test and independent samples t-test were conducted as the post-hoc analysis to further investigate the interaction. The overall result confirmed that the EGPA was effective to improve elementary students' abstraction and its three dimensions. Furthermore, the independent samples t-test analysis compared the students' abstraction after taking two versions of the *Danger Zone* curriculum. The results indicated that students practicing the EGPA had a higher level of abstract thinking in the end than those who did not, although they started with a lower level of abstraction. This result provides supplemental evidence to conclude the effectiveness of the EGPA in improving the level of abstraction for fifth graders.

**Research Question 2: What Are the Students' Experiences with the EGPA While Taking a STEM-integrative Robotics Curriculum?**

Overall, the interviewed participants described a positive experience with the EGPA in fostering their abstraction in computational thinking. Completing the three activities better prepared them for the following task of programming the robot, as they were equipped with a clear goal of the task, an explicit structure of the problem, and also a transferable solution from another analogical case. With the positive experience, the participants commonly perceived the EGPA activities as integral components for them to solve complex problems. However, it is worth noting that relevant activities are missing in the existing curriculum in elementary education.

Participants also experienced a series of challenges in completing the activities. Specifically, most of the participants did not have prior experience with these types of activities so they were unaware of what was expected. In addition, the relatively inadequate time for each activity brought challenges for the participants. Furthermore, the participants described the unique challenges associated with each activity. For example, participants expressed concerns regarding the potential risk of information overloading when reading the rich information provided in the filtering information tasks. Accordingly, the participants recommended to include some clear cues in the reading to make the filtering information more straightforward. Moreover, participants generally reported their incompetence to identify any deep level similarities between analogical cases. As a response, the participants recommended including more contextual clues to help them recognize the analogy and justify why the two examples are analogical.

### Research Question 3: What Are the Teacher's Experiences of Facilitating the EGPA Activities in a STEM-integrative Robotics Curriculum?

The teacher of the experimental group reported her experiences with the curriculum and teaching challenges as well as her perspective of the meaningful experiences and challenges for students. Facilitating the EGPA activities was a positive experience, especially given these activities well-aligned with the state standards. She also expressed her interest in continuing to implement this curriculum in the future. In addition, the teacher described her challenges in implementing this curriculum. Since the teacher did not have any experience in teaching abstraction, she pointed out she may have needed time to plan ahead. For example, pacing the instruction was challenging while leaving an appropriate length of time for students to complete each activity. Furthermore, the teacher discussed her the meaningful experiences she perceived for her students such as knowledge transfer, problem decomposition, information filtering, and collaboration. In particular, decomposition was ranked as the most meaningful experience for her students, considering this activity also involved the other two dimensions of abstraction. Moreover, the teacher discussed students' challenges from her own viewpoint, such as students' unfamiliarity with the activities and their incompetence to perform as expected. In sum, the teacher's overall experience with the EGPA was positive. She asserted most of the activities assisted in the development of elementary students' abstract thinking, but she also made recommendations to further optimize some of the EGPA activities to address students' needs.

## Discussion

### Enhancing Fifth Graders' Abstraction Cannot Rely on Only Directly Teaching Coding

This research concurred that fostering students' abstraction cannot solely rely on teaching them coding as computational thinking goes beyond programming (Hazzan & Kramer, 2007; Grover & Pea, 2013; Sengupta et al., 2013; Weintrop et al, 2016). The results, especially the performance difference in abstraction tests between the two groups, imply that only teaching coding with robots did not sufficiently improve students' abstraction. Students may need a series of unplugged instructional activities in a STEM integrative curriculum to develop their abstraction. For this study, computational thinking and its components were conceptualized as a problem-solving process instead of a synonym of programming (Grover & Pea, 2013; Wing, 2006). Accordingly, abstraction in computational thinking plays the role of formulating generalized representations of a complex task that allow computers or other computing technologies to develop optimized solutions transferrable to multiple contexts. With that being said, abstraction as an important component of computational thinking also precedes programming a computer (Hazzan & Kramer, 2007). In this research, the EGPA enabled a problem-oriented learning environment for students to undergo major cognitive processes of abstraction and foster their abstract thinking skills. The significant improvement in experimental group students' abstract thinking skills supports the argument that fostering the fifth-grade students' abstraction requires opportunities to solve authentic problems by applying their abstract thinking skills, and not only teaching them how to program a computer or a robot (Sengupta et al., 2013; Weintrop et al, 2016).

### Fostering Fifth Graders' Abstraction Requires Them to Practice Abstraction

The results of this study indicated that students who attended the curriculum with EGPA improved more than the students who attended the curriculum without EGPA. It confirmed that the development of abstraction for elementary school students requires specific activities for them to practice abstraction. This finding echoed Kramer (2003) that fostering students' abstraction requires students to intentionally practice it rather than adopting direct instruction. For each dimension of abstraction, specific instructions are needed to foster fifth graders' relevant competences of abstraction. The following paragraphs will discuss the implications of each guideline in regard to each dimension of abstraction.

#### Guideline 1: Prompt filtering information with authentic problems requiring multiple-level abstraction.

Results implied integrating the first guideline in the EGPA was necessary, especially for fostering fifth graders' capacities of information filtering.  In this study, filtering information was acknowledged by the students and the teacher as an important skill for fifth graders to capture the essence of a complex problem and thereby to solve it. However, as the teacher and students in this research discussed, the importance of filtering information for problem solving was overlooked in traditional K-12 curriculum, resulting in a lack of relevant competences for some of the students. For example, teachers usually provide “simplified” curriculum for students to easily comprehend, but in reality, students need to challenge themselves by simplifying problems. Guideline 1 proposed to provide students with an opportunity to practice filtering information in an authentic context with provided prompts and scaffolds, in response to this gap in K-12 education. The improvement in the capacity of filtering information for the experimental group echoed Yadav et al. (2017) that providing an authentic problem-oriented environment is a precondition to enhance students’ expertise in filtering information.

However, it is also noted that exposure to too much information in this authentic problem-oriented environment led to information overloading for some of the participants. Actually, the potential risk of overloading might be a common concern for implementing any authentic curricula in fifth-grade classrooms. One possible reason that students were overwhelmed with information may be a lack of clear structure in the narratives of the authentic scenarios. The EGPA adopted authentic cases with information being presented in several disparate chunks instead of being organized more cohesively with provided headers. Structuring the filtering information activities may help reduce the information overload. Another possible reason might result from fifth graders’ limited capabilities of retaining key information in mind while preparing to make justifications at the end. Many students identified necessary information while reading, but then failed to retain this information until the end. Future revisions and implementations might consider enabling “highlight” functions for students to highlight or take notes while reading in response to excessive information exposure.

In addition, integrating Guideline 1 in the EGPA might allow fifth graders to undergo the practices of mapping problem structures. The teacher and students in this study indicated activities relevant to mapping structures were engaging and useful. They also believed mapping structures was integral for fifth graders to solve complex problems, but relevant practices were missing in the traditional curriculum. This lack of relevant practices in K-12 curriculum resulted in students' insufficient expertise in decomposing problems. Most students in this research tended to decompose a problem into a single layer rather than figure out the complex, multiple-level representations of authentic problems (Jonassen, 1997). To allow fifth graders to efficiently decompose problems, developing authentic cases involving multiple-level problem structure with each level being bonded by structural relationships is important (Guideline 1). The finding regarding fifth graders' improvement in decomposing problems supports the effectiveness of integrating Guideline 1 in the curriculum.

**Guideline 2: Support mapping structures using visual representation tools.**

Results implied integrating visual representation tools helped fifth graders map out the multiple problems underlying complex authentic problems. Participants shared that using visual represent tools facilitated the translation from problem descriptions to visual structures, resulting in a more consolidated understanding of structural relations among different levels of problem representation. This also concurred with Fiorella and Mayer (2016) who argued translating textual signals into structural information allowed students to enhance their ability to efficiently outline the underlying structures.

Using visual representation tools might help fifth graders identify multiple layers of abstraction but students also reported their challenges in using these tools. The teacher and the students in this study attributed their challenges to the lack of relevant experience and explicit instructions on how to map out the problem structure. This finding also conforms to the recommendations offered by Fiorella and Mayer (2016); students without prerequired knowledge or experience should be provided efficient pre-instructions on how to use visual representation tools to decompose problems to help them strengthen their abstract thinking via such instructional activities.

**Guideline 3: Assist in clarifying the understanding of complex problems.**

Results implied integrating Guideline 3 in the design of the EGPA was important. The use of question prompts was especially necessary for fifth graders to efficiently filter information, map out the problem structure, and locate similarities. Specifically, students described only after they were prompted to identify the main goal of the task, could they better understand the background of the tasks and problem structure. In this research, question prompts such as "what is the goal of the task?" and "what is the information you must know to accomplish the task?" "what is the sub-tasks?" were included. By responding to the question prompts, the students in the experimental group were spurred to identify relevant information essential to solve the task and also grasp the structural relationship underlying the hierarchy of problems. Furthermore, understanding the fundamental information helped students in the experimental group outperform their peers in the control group regarding locating similarities between two analogical problems and contextualizing the solutions efficiently in a new setting. The results echoed previous research findings that providing effective instructional scaffolds (e.g., question prompts) could assist students in clarifying their understanding so as to grasp the main goal of this task (Choi et al., 2005; Ge & Land, 2003) and to mitigate the lack of expertise in recognizing the fundamental information of a problem (Chi et al., 1981; Son et al., 2008).

**Guideline 4: Strengthen generalized representations by providing similar but different problems.**

Results implied Guideline 4 might also contribute to fifth graders' improvements in abstract thinking, especially when provided with analogical problems. Students' capacities of locating similarities were enhanced in regard to generating and applying transferrable solutions to solve similar but different problems. In this research, students in the experimental group were prompted to compare and contrast two analogical cases (e.g., volcano exploration and earthquake rescue) which presented different situations with similar solutions. By addressing analogical cases, these fifth graders were able to detect the shared principles or solutions underlying two cases and then formulate a generalizable problem solution upon this fundamental commonality (Duit, 1991; Gentner et al., 2009; Gick & Holyoak, 1983).

However, allocating enough time for students to interact with the intervention might also be taken into account to improve the design of instructional activities geared towards locating similarities. It might take extensive time to arouse significant improvement in the fifth-grade students' expertise in locating fundamental similarities by attending to EGPA activities. In this research, although the mean score of the experimental group significantly increased in the relevant activities, the range of the increase is relatively limited. As the teacher reflected, it might be due to the three-week length of the curriculum that cannot spark any larger improvements in this dimension.

**Guideline 5: Encourage self-explaining during the abstract thinking process.**

Results implied Guideline 5 was effective in improving fifth graders' capabilities of filtering information and locating similarities, especially when opportunities were afforded for these students in the experimental group to self-explain how they selected information and found the commonalities. In this research, the teacher prompted students to think aloud by asking them to justify the information they selected and similarities they identified. While thinking aloud, these students constantly compared the newly formulated representation with their mental models so as to persistently prompt themselves by selecting the relevant information and locating the most essential commonalities between two similar instances (Chi et al., 1989; Roy & Chi, 2005). This intra-personal interaction encouraged students to grasp a deep understanding of the task rather than focus on superficial information presented in the text (Fiorella & Mayer, 2016). In sum, self-explaining activities might enhance students' capabilities of efficiently filtering irrelevant information and locating similarities, concurring with Chi et al. (1989) as well as Fiorella and Mayer (2016).

Though the students and the teacher found it useful, they also reported in the interview transcripts that it was challenging to self-explain why the selected information was relevant or the process of locating similarities. For example, one group of the participants mentioned justifying why to select the information was even harder than merely selecting the information. One possible reason is because justifications require students to logically compare and contrast multiple chunks of information with a profound understanding of the problem and its structural relations. To ensure students formulate a fundamental understanding, some prompts (e.g., questions prompts) might be needed to guide students to undergo self-explanation. In addition, students' comments highlighted a need for pre-instruction on how to restate justifications using their own words (Fiorella & Mayer, 2016).

## Recommendations and Implications

This research explores the effective design of a STEM curriculum for the development of elementary students' abstract thinking. The practical implementations for future research and practices are as follows.

First, it is important to acknowledge that direct instruction might not be effective in fostering students' abstract thinking. Instead, students may need to be provided with a problem-oriented learning environment to obtain abstract thinking skills by practicing each cognitive process of abstraction (Kramer, 2003).

Second, it is also important to acknowledge that 1) abstraction is a higher-order thinking skill; 2) most younger students might not have the minimum required expertise to follow the procedures designed in the instructional activities. With that being said, we need to provide efficient pre-instruction or question prompts for elementary students to gradually follow the procedure and develop a sound understanding of the problem (Fiorella & Mayer, 2016). On the other hand, this also supports the development of fifth graders' abstract thinking. In addition, the instructional activities designed to foster abstraction might take extensive time to spark significant changes in the level of this high-order thinking. In future curriculum design, the length of the intervention needs to be considered in that phase.

Third, the EGPA integrated in the STEM-integrative robotics curriculum significantly promoted the development of elementary students' abstract thinking, but more elaborations are needed regarding the design of robotics curriculum for the development of computational thinking and its associated components such as abstraction. The integrative nature of STEM-integrative robotics curriculum might hold the future of STEM education (Kopcha et al., 2017), especially in regard to the development of computational thinking and relevant significant thinking skills.

## Limitations and Future Research

There are several limitations of this research. First, the duration of the intervention cannot ensure its effectiveness in supporting elementary students to reinforce their skill in locating similarities. Second, the EGPA did not involve any instructional activities specifically dedicated to revolving around multiple layers of abstraction. Revolving around multiple layers of abstraction is also an important dimension of abstraction that differentiates abstraction in computational thinking from that in other settings (Wing, 2006; 2008). The reasons why EGPA did not specifically address students' challenge in revolving around multiple layers are twofold: 1) Many college students even have difficulty attaining a higher layer of abstraction and only attend to lower layers (Perrenet & Kaasenbrood, 2006; Perrenet, 2010). With that being said, it might be harder for elementary students to reach a higher level. 2) Students' overall performance in abstract thinking skills is not satisfactory in either pre- or post- tests. Therefore, the main focus of this research was to explore strategies for fostering the three horizontal dimensions of abstraction.

Third, the research was conducted in the same grade within a single school district, which might limit the generalization of its findings. Fourth, the instrument for assessing abstraction was developed by the primary investigator of this research. Though undertaking several rounds of revisions with the integration of experts' (both domain and research) suggested changes, it needs further validation with a larger sample of similar population. Fifth, mixed method investigations were adopted in this research, but answering the questions in the qualitative interview might be challenging for these elementary students which limited the scope of the findings of this research.

To further optimize the research and reinforce the validity of the research findings, future research might consider validating the instrument and also this experiment in a larger population in different grades from different school districts. In addition, future research might consider the design of instructional activities specifically addressing the flexible movement between different levels of abstraction. Deliberate practices can also help college students proceed towards the higher level of abstraction so it may be a focus of future research to design specific guidance and practice to teach elementary students how to revolve around multiple layers of abstraction to efficiently solve complex problems. Furthermore, future research might also follow the quasi experimental method, especially in investigating the effect of the designed interventions or curriculum on the development of abstraction, which is still a topic that invites more empirical research.

## References


Aharoni, D. (2000). Cogito, Ergo sum! cognitive processes of students dealing with data structures. *ACM SIGCSE Bulletin*, *32*(1), 26-30.

Aho, A. V., & Ullman, J. D. (1995). *Foundations of computer science*. Computer Science Press.

Armoni, M. (2013). On teaching abstraction in CS to novices. *Journal of Computers in Mathematics and Science Teaching*, *32*(3), 2.

Armoni, M., & Gal-Ezer, J. (2006). Reduction--an abstract thinking pattern: the case of the computational models course. *ACM SIGCSE Bulletin*, *38*(1), 389-393.

Anderson, R. C. (1984). Role of the reader’s schema in comprehension, learning, and memory: Learning to read in American schools. *Basal Readers and Content Texts*, *29*, 243-257.

Atkinson, R. C., & Shiffrin, R. M. (1968). Human memory: A proposed system and its control processes. *Psychology of Learning and Motivation*, *2*, 89-195.

Balka, D. (2011). Standards of mathematical practice and STEM. *Math-science Connector Newsletter*, 6-8.

Barr, V., & Stephenson, C. (2011). Bringing computational thinking to K-12: What is involved and what is the role of the computer science education community?. *ACM Inroads*, *2*(1), 48-54.

Barsalou, L. W. (2003). Abstraction in perceptual symbol systems. *Philosophical Transactions of the Royal Society of London B: Biological Sciences*, *358*(1435), 1177-1187.

Bates, P. C., & Wileden, J. C. (1983). High-level debugging of distributed systems: The behavioral abstraction approach. *Journal of Systems and Software*, *3*(4), 255-264.

Bennett, J., & Müller, U. (2010). The development of flexibility and abstraction in preschool children. *Merrill-Palmer Quarterly*, *56*(4), 455-473.

Berland, M., & Wilensky, U. (2015). Comparing virtual and physical robotics environments for supporting complex systems and computational thinking. *Journal of Science Education and Technology*, *24*(5), 628-647.

Beth, E. W. & Piaget, J. (1966). *Mathematical epistemology and psychology* (W. Mays, Trans). Dordrecht: Reidel.

Bilalić, M., McLeod, P., & Gobet, F. (2009). Specialization effect and its influence on memory and problem solving in expert chess players. *Cognitive Science*, *33*(6), 1117-1143.

Bisra, K., Liu, Q., Nesbit, J. C., Salimi, F., & Winne, P. H. (2018). Inducing self-explanation: A meta-analysis. *Educational Psychology Review*, *30*(3), 703-725.

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, *3*(2), 77-101.

Breuning, M. (2003). The role of analogies and abstract reasoning in decision making: Evidence from the debate over Truman's proposal for development assistance. *International Studies Quarterly*, *47*(2), 229-245.

Bucci, P., Long, T. J., & Weide, B. W. (2001). Do we really teach abstraction?. *Sigcse Bulletin*, 3326-30.

Buitrago Flórez, F., Casallas, R., Hernández, M., Reyes, A., Restrepo, S., & Danies, G. (2017). Changing a generation’s way of thinking: Teaching computational thinking through programming. *Review of Educational Research*, *87*(4), 834-860.

Bybee, R. W. (2010). Advancing STEM education: A 2020 vision. *Technology And Engineering Teacher*, *70*(1), 30

Campbell, D. T., & Stanley, J. C. (2015). *Experimental and quasi-experimental designs for research.* Ravenio Books.

Carson, R. N., & Rowlands, S. (2007). Teaching the conceptual revolutions in geometry. *Science & Education*, *16*(9-10), 921-954.

Chase, W. G., & Simon, H. A. (1973). Perception in chess. *Cognitive psychology*, *4*(1), 55-81.

Chi, M., Bassok, M., Lewis, M., Reimann, P., & Glaser, R. (1989). Self-explanations: how students study and use examples in learning to solve problems. *Cognitive Science*, *18*, 439-477. doi:10.1207/s15516709cog1302_1.

Chi, M., Feltovich, P., & Glaser, R. (1981). Categorization and representation of physics problems by experts and novices. *Cognitive Science*, *5*(2), 121-152.

Choi, I., Land, S. M., & Turgeon, A. J. (2005). Scaffolding peer-questioning strategies to facilitate metacognition during online small group discussion. *Instructional Science*, *33*(5-6), 483-511.

Cho, Y. H., & Jonassen, D. H. (2012). Learning by self-explaining causal diagrams in high-school biology. *Asia Pacific Education Review*, *13*(1), 171-184

Christoff, K., & Keramatian, K. (2007). *Abstraction of mental representations: Theoretical considerations and neuroscientific evidence*. New York: Oxford University Press.

Clarke, V., & Braun, V. (2013). Teaching thematic analysis: Overcoming challenges and developing strategies for effective learning. *The Psychologist*, *26*(2), 120-123

Colburn, T., & Shute, G. (2007). Abstraction in computer science. *Minds and Machines*, *17*(2), 169-184.

Cook, T. D., & Campbell, D. T. (1979). The design and conduct of true experiments and quasi-experiments in field settings. In *Research in organizations: Issues and controversies*. Goodyear Publishing Company.

Creswell, J. W. (2007). *Qualitative inquiry and research method: Choosing among five* *approaches*. Thousand Oaks, CA: Sage.

Creswell, J. W. (2014). *Research design: Qualitative, quantitative, and mixed methods approaches* (4th ed.). Thousand Oaks, CA: Sage.

Creswell, J. W., & Clark, V. L. P. (2017). *Designing and conducting mixed methods research*. Thousand Oaks, CA: Sage publications.

Czerkawski, B. C., & Lyman III, E. W. (2015). Exploring issues about computational thinking in higher education. *TechTrends, 59*(2), 57-65.

Derry, J. (2008). Abstract rationality in education: From Vygotsky to Brandom. *Studies in Philosophy and Education*, *27*(1), 49-62.

DeSchryver, M. D., & Yadav, A. (2015). Creative and computational thinking in the context of new literacies: Working with teachers to scaffold complex technology-mediated approaches to teaching and learning. *Journal of Technology and Teacher Education*, *23*(3), 411-431.

Drijvers, P. (2000). Students encountering obstacles using a CAS. *International Journal of Computers for Mathematical Learning*, *5*(3), 189-209.

Driscoll, D.L. (2014). Psychological Foundations of Instructional Design. In R.A. Reiser & J.V. Dempsey (Eds.), *Trends and issues in instructional design and technology* (pp.35-45), Upper Saddle River, N.J: Merrill/Prentice Hall.

Dubinsky, E. (2002). Reflective abstraction in advanced mathematical thinking. In Tall, D. (Ed.), *Advanced mathematical thinking* (pp. 95-126). The Netherlands: Springer.

Duit, R. (1991). On the role of analogies and metaphors in learning science. *Science Education*, *75*(6), 649-672.

Edwards, A. L. (1951). *Experimental design in psychological research*. New York, NY: Holt, Rinehart & Winston.

Faber, M., Unfried, A., Wiebe, E. N., Corn, J., Townsend, L. W., & Collins, T. L. (2013). Student attitudes toward STEM: The development of upper elementary school and middle/high school student surveys. In the Proceedings of the *120th American Society of Engineering Education Conference*. Washington, DC: ASEE.

Fiorella, L., & Mayer, R. E. (2016). Eight ways to promote generative learning. *Educational Psychology Review*, *28*(4), 717-741.

Gall, M. D., Gall, J. P., & Borg, W. R. (2007). Collecting research data with questionnaires and interviews. *Educational Research: An Introduction*, 227-261.

Gelman, S. A., & Kalish, C. W. (2006). Conceptual development. In D. Kuhn, R. S. Siegler, W. Damon, R. M. Lerner (Eds.), *Handbook of child psychology: Cognition, perception, and language, Vol. 2* (6th ed., pp. 687-733). Hoboken, NJ: John Wiley & Sons Inc.

Gentner, D. (1983). Structure-mapping: A theoretical framework for analogy. *Cognitive Science*, *7*, 155–170.

Gentner, D., & Hoyos, C. (2017). Analogy and abstraction. *Cognitive Science*, *9*(3), 672-693

Gentner, D., & Loewenstein, J. (2002). Relational language and relational thought. In E. Amsel, J. P. Byrnes (Eds.), *Language, literacy, and cognitive development: The development and consequences of symbolic communication* (pp. 87-120). Mahwah, NJ: Lawrence Erlbaum Associates Publishers.

Gentner, D., Loewenstein, J., Thompson, L., & Forbus, K. D. (2009). Reviving inert knowledge: Analogical abstraction supports relational retrieval of past events. *Cognitive Science*, *33*(8), 1343-1382.

Gentner, D., & Toupin, C. (1986). Systematicity and surface similarity in the development of analogy. *Cognitive Science*, *10*(3), 277-300.

Ge, X., & Land, S. M. (2003). Scaffolding students' problem-solving processes in an ill-structured task using question prompts and peer interactions. *Educational Technology Research and Development*, *51*(1), 21-38.

Gick, M. L., & Holyoak, K. J. (1983). Schema induction and analogical transfer. *Cognitive Psychology, 15*(1), 1-38.

Gikas, J., & Grant, M. M. (2013). Mobile computing devices in higher education: Student perspectives on learning with cellphones, smartphones & social media. *The Internet and Higher Education*, *19*, 18-26.

Girden, E. R. (1992). *ANOVA: Repeated measures*. Thousand Oaks, CA: Sage publications.

Gobet, F. (1997). A pattern-recognition theory of search in expert problem solving. *Thinking & Reasoning*, *3*(4), 291-313.

Gobet, F., & Simon, H. A. (1996). Templates in chess memory: A mechanism for recalling several boards. *Cognitive psychology*, *31*(1), 1-40.

Golafshani, N. (2003). Understanding reliability and validity in qualitative research. *The Qualitative Report*, *8*(4), 597-606.

Gonulal, T. (2019). The development and validation of an attitude towards MALL instrument. *Educational Technology Research and Development*, *67*(3), 733-748.

Greene, J. C. (2007). *Mixed methods in social inquiry*. San Francisco: Jossey-Bass.

Green, S. B., & Salkind, N. J. (2011). *Using SPSS for Windows and Macintosh: Analyzing and understanding data* (6th ed.). Upper Saddle River, NJ: Prentice Hall.

Grover, S., & Pea, R. (2013). Computational thinking in K–12 a review of the state of the field. *Educational Researcher, 42*(1), 38-43.

Guzdial, M. (2008). Education: Paving the way for computational thinking. *Communications of the ACM*, *51*(8), 25-27.

Gwet, K. L. (2014). *Handbook of inter-rater reliability: The definitive guide to measuring the extent of agreement among raters*. Advanced Analytics, LLC.

Harwell, M. R., & Serlin, R. C. (1988). An empirical study of a proposed test of nonparametric analysis of covariance. *Psychological Bulletin*, 104(2), 268

Hazzan, O. (2003). How students attempt to reduce abstraction in the learning of mathematics and in the learning of computer science. *Computer Science Education*, *13*(2), 95-122.

Hazzan, O., & Kramer, J. (2007). Abstraction in computer science & software engineering: A pedagogical perspective. *Frontier Journal*, *4*(1), 6-14.

Hibbing, A. N., & Rankin-Erickson, J. L. (2003). A picture is worth a thousand words: Using visual images to improve comprehension for middle school struggling readers. *The Reading Teacher*, *56*(8), 758-770.

Ho, C. H. (2001). Some phenomena of problem decomposition strategy for design thinking: Differences between novices and experts. *Design Studies*, *22*(1), 27-45.

Huberty, C. J., & Morris, J. D. (1989). Multivariate analysis versus multiple univariate analyses. *Psychological bulletin*, *105*(2), 302.

Israel, M., Pearson, J. N., Tapia, T., Wherfel, Q. M., & Reese, G. (2015). Supporting all learners in school-wide computational thinking: A cross-case qualitative analysis. *Computers & Education*, *82*, 263-279.

ISTE, C. (2011). *Computational thinking in Ke12 education leadership toolkits*. Retrieved from https://www.iste.org/resources/attachmentdownload?ID=3413.

ISTE, & CSTA. (2011). *Operational definition of computational thinking for K-12 education*. Retrieved from http://www.iste.org/docs/ct-documents/ computational-thinking-operational-definition-flyer.pdf.

Jain, A. K., & Duin, R. P. W. (2004). Introduction to pattern recognition, In R. L. Gregory (Eds.), *The Oxford Companion to the Mind* (2nd ed., pp 698-703). Oxford: Oxford University Press.

Jang, H. (2016). Identifying 21st century STEM competencies using workplace data. *Journal of Science Education and Technology*, *25*(2), 284-301.

Johnson, C. I., & Mayer, R. E. (2010). Applying the self-explanation principle to multimedia learning in a computer-based game-like environment. C*omputers in Human Behavior, 26*, 1246-1252. doi:10.1016/j.chb.2010.03.025.

Jonassen, D. H. (1997). Instructional design models for well-structured and ill-structured problem-solving learning outcomes. *Educational Technology Research and Development*, *45*(1), 65-94.

Joyce, L. K. (1977). A study of formal reasoning in elementary education majors. *Science Education*, *61*(2), 153-158.

Joyner, D. A., Majerich, D. M., & Goel, A. K. (2013). Facilitating authentic reasoning about complex systems in middle school science education. *Procedia Computer Science*, *16*, 1043-1052.

Kazimoglu, C., Kiernan, M., Bacon, L., & MacKinnon, L. (2012). Learning programming at the computational thinking level via digital game-play. *Procedia Computer Science*, *9*(2), 522.

Kim, B., Kim, T., & Kim, J. (2013). Paper-and-pencil programming strategy toward computational thinking for non-majors: Design your solution. *Journal of Educational Computing Research*, *49*(4), 437-459.

Kopcha, T. J., McGregor, J., Shin, S., Qian, Y., Choi, J., Hill, R., ... & Choi, I. (2017). Developing an integrative STEM curriculum for robotics education through educational design research. *Journal of Formative Design in Learning*, *1*(1), 31-44.

Kramer, J. (2007). Is abstraction the key to computing?. *Communications of the ACM*, *50*(4), 36-42.

Kwon, J. & Ahn, S. (2014). A study on creative problem solving founded on computational thinking. *International Journal of Applied Engineering Research*, *9*(21), 9185-9198.

Landis, J. R., & Koch, G. G. (1977). The measurement of observer agreement for categorical data. *Biometrics*, *33*, 159-174.

Leopold, C., & Leutner, D. (2012). Science text comprehension: drawing, main idea selection, and summarizing as learning strategies. *Learning and Instruction*, *22*(1), 40-49.

Leutner, D., & Schmeck, A. (2014). The generative drawing principle in multimedia learning. In Mayer, R. E. (Ed), *The Cambridge Handbook of Multimedia Learning* (pp. 433-448). New York, NY: Cambridge University Press.

Liikkanen, L. A., & Perttula, M. (2009). Exploring problem decomposition in conceptual design among novice designers. *Design Studies*, *30*(1), 38-59.

Limshuebchuey, A., Duangsoithong, R., & Windeatt, T. (2015). Redundant feature identification and redundancy analysis for causal feature selection. In *2015 8th Biomedical Engineering International Conference* (pp. 1-5). Piscataway, NJ: IEEE.

Lin, C. C., Zhang, M., Beck, B., & Olsen, G. (2009). Embedding computer science concepts in K-12 science curricula. *In ACM SIGCSE Bulletin*, *41*(1), 539-543.

Liskov, B., & Guttag, J. (2000). *Program development in JAVA: Abstraction, specification, and object-oriented design.* London: Pearson Education.

Loewen, S., & Gonulal, T. (2015). Exploratory factor analysis and principal components analysis. In Plonsky, L. (Ed.), *Advancing quantitative methods in second language research* (pp. 182-212). New York, NY: Routledge.

Lowell, W. E. (1977). An empirical study of a model of abstract learning, *Science Education*, *61*(2), 229-242.

Lye, S. Y., & Koh, J. H. L. (2014). Review on teaching and learning of computational thinking through programming: What is next for K-12?. *Computers in Human Behavior*, *41*, 51-61.

Marr, D. (1982). *Vision: A computational investigation into the human representation and processing of visual information.* New York, NY: Henry Holt and Co.

Merriam, S. B. (2009). *Qualitative research: A guide to design and implementation* (3rd ed.). San Francisco, CA: Jossey-Bass.

Miles, M. B., & Huberman, A. M. (1994). *Qualitative data analysis: A sourcebook of new methods* (2nd ed.). Thousand Oaks, CA: Sage Publications.

Mitchelmore, M. C., & White, P. (2012). *Abstraction in mathematics learning*. In Encyclopedia of the Sciences of Learning (pp. 31-33). New York, NY: Springer US.

Muller, O., Ginat, D., & Haberman, B. (2007). Pattern-oriented instruction and its influence on problem decomposition and solution construction. *In ACM SIGCSE Bulletin*, *39*(3), 151-155.

Muller, O., & Haberman, B. (2008). Supporting abstraction processes in problem solving through pattern-oriented instruction. *Computer Science Education*, *18*(3), 187-212.

National Research Council. (1999). *How people learn: Bridging research and practice.* National Academies Press.

National Research Council. (2010). *Report of a workshop on the scope and nature of computational thinking.* National Academies Press.

National Research Council. (2011). *Successful K-12 STEM education: Identifying effective approaches in science, technology, engineering, and mathematics.* National Academies Press.

National Research Council. (2013). *Monitoring progress toward successful K-12 STEM education: A nation advancing?*. National Academies Press.

Nicholson, K., Good, J., & Howland, K. (2009). Concrete thoughts on abstraction. Proceedings from PPIG' 09: *21st Annual Psychology of Programming Interest Group Workshop,* Ireland: University of Limerick.

Ojose, B. (2008). Applying Piaget's theory of cognitive development to mathematics instruction. *The Mathematics Educator*, *18*(1), 26-30.

Ozmantar, M. F. (2005). Mathematical abstraction: A dialectical view. *Proceedings of the British Society for Research into Learning Mathematic*s, *25*(2), 79-84.

Pal. S. K., & Pal, A. (2001). *Pattern recognition: From classical to modern approaches*. Singapore: World Scientific Publishing Co. Pte. Ltd.

Patel, V. L., Groen, G. J., & Arocha, J. F. (1990). Medical expertise as a function of task difficulty. *Memory & Cognition*, *18*(4), 394-406.

Perrenet, J. C. (2010). Levels of thinking in computer science: Development in bachelor students' conceptualization of algorithm. *Education and Information Technologies*, *15*(2), 87-107.

Perrenet, J., & Kaasenbrood, E. (2006). Levels of abstraction in students' understanding of the concept of algorithm: The qualitative perspective. *In ACM SIGCSE Bulletin*, *38*(3), 270-274.

Piaget, J. (1970). *Science of education and the psychology of the child.* New York, NY: Viking.

Plonsky, L., & Gonulal, T. (2015). Methodological synthesis in quantitative L2 research: A review of reviews and a case study of exploratory factor analysis. *Language Learning*, *65*(S1), 9-36.

Reeves, L., & Weisberg, R. W. (1994). The role of content and abstract information in analogical transfer. *Psychological Bulletin*, *115*(3), 381.

Renkl, A. (1997). Learning from worked-out examples: A study on individual differences. *Cognitive Science*, *21*(1), 1-29.

Research for the Advancement of Innovative Learning (2015). *Danger Zone: A STEM-integrated robotics unit – my design journal*. Seoul, Korea: Roborobo Co., Ltd.

Rittle-Johnson, B., & Star, J. R. (2007). Does comparing solution methods facilitate conceptual and procedural knowledge: An experimental study on learning to solve equations. *Journal of Educational Psychology*, *99*(3), 561–574. doi:10.1037/0022-0663.99.3.561

Rowlands, S. (2010). A pilot study of a cultural-historical approach to teaching geometry. *Science and Education*, *19*(1), 55-73.

Roy, M., & Chi, M. T. (2005). The self-explanation principle in multimedia learning. In Mayer, R. E. (Ed), *The Cambridge handbook of multimedia learning* (pp. 271-286). New York, NY: Cambridge University Press.

Rowe, P. G. (1987). *Design thinking.* Cambridge, MA: MIT press.

Rutherford, A. (2011). *ANOVA and ANCOVA: A GLM approach*. Hoboken, NJ: John Wiley & Sons.

Sahin, E., & Akman, V. (2009). Analogy-making in situation theory. *Artificial Intelligence: New Research*, 299-321.

Schank, R. C. (1999). *Dynamic memory revisited* (2nd ed.). Cambridge, UK: Cambridge University Press.

Schmidt, D. C. (2006). Model-driven engineering. *Computer-IEEE computer society*, *39*(2), 25.

Schwartz, D. L., Chase, C. C., Oppezzo, M. A., & Chin, D. B. (2011). Practicing versus inventing with contrasting cases: The effects of telling first on learning and transfer. *Journal of Educational Psychology*, *103*(4), 759.

Schwenk, C. R. (1984). Cognitive simplification processes in strategic decision-making. *Strategic management journal*, *5*(2), 111-128.

Schwenk, C. (1985) The use of participant recollection in the modeling of organizational decision processes. *Academy of Management Review*, *10*(3), 496-503.

Sengupta, P., Kinnebrew, J. S., Basu, S., Biswas, G., & Clark, D. (2013). Integrating computational thinking with K-12 science education using agent-based computation: A theoretical framework. *Education and Information Technologies*, *18*(2), 351-380.

Shadish, W. R., Cook, T. D., & Campbell, D. T. (2002). *Experimental and quasi-experimental designs for generalized causal inference*. Boston: Houghton Mifflin.

Shagrir, O. (2010). Marr on computational-level theories. *Philosophy of Science*, *77*(4), 477-500.

Skemp, R. (1986). *The psychology of learning mathematics* (2nd ed.). Harmondsworth: Penguin.

Snalune, P. (2015). The benefits of computational thinking. *ITNOW*, *57*(4), 58-59.

Son, J. Y., Smith, L. B., & Goldstone, R. L. (2008). Simplicity and generalization: Short-cutting abstraction in children's object categorizations. *Cognition*, *108*, 626–638.

Susac, A., Bubic, A., Vrbanc, A., & Planinic, M. (2014). Development of abstract mathematical reasoning: The case of algebra. *Frontiers in Human Neuroscience, 8*(679), 1-9.

Tall, D. (Ed.). (1991). *Advanced mathematical thinking* (Vol. 11). New York, NY: Springer Science & Business Media.

Thai, K. P., Son, J. Y., & Goldstone, R. L. (2016). The simple advantage in perceptual and categorical generalization. *Memory & cognition*, *44*(2), 292-306.

Tokmak, H. S., Incikabi, L., & Ozgelen, S. (2013). An investigation of change in mathematics, science, and literacy education pre-service teachers' TPACK. *The Asia-Pacific Education Researcher*, *22*(4), 407-415

Tracy, S. J. (2010). Qualitative quality: Eight "big-tent" criteria for excellent qualitative research. *Qualitative Inquiry*, *16*(10), 837-851.

Treffers, A. (1987). *Three dimensions. A model of goal and theory description in mathematics education.* Dordrecht, The Netherlands: Kluwer.

Van Oers, B. (2012). Meaningful cultural learning by imitative participation: The case of abstract thinking in primary school. *Human Development, 55*(3), 136-158.

Verschaffel, L. & Greer, B., (2014). Mathematics education. In J.M. Spector, M.D. Merrill, J. Elen, & M.J. Bishop, (Eds.), *Handbook of research on educational communications and technology* (pp. 553-563). New York, NY: Springer.

Von Ende, C. N. (2001). Repeated-measures analysis. In S. M. Scheiner & J. Gurevitch (Eds.), *Design and Analysis of Ecological Experiments* (2nd ed., pp. 134-157), New York, NY: Oxford University Press.

Weintrop, D., Beheshti, E., Horn, M., Orton, K., Jona, K., Trouille, L., & Wilensky, U. (2016).

Defining computational thinking for mathematics and science classrooms. *Journal of Science Education and Technology*, *25*(1), 127-147.

Wertsch, J. V., & Sohmer, R. (1995). Vygotsky on learning and development. *Human Development*, *38*(6), 332-337.

Wilensky, U., Brady, C., & Horn, M. (2014). Fostering computational literacy in science classrooms. *Communication ACM, 57*(8), 17-21.

Wilensky, U., & Reisman, K. (2006) Thinking like a wolf, a sheep, or a firefly: Learning biology through constructing and testing computational theories—an embodied modeling approach. *Cognition and Instruction*, *24*(2), 171-209.

Wing, J.M. (2006). Computational thinking, *Communication of ACM.* 49(3). 33-35.

Wing, J. M. (2008). Computational thinking and thinking about computing. Philosophical Transactions of the Royal Society of London. *Mathematical*, *Physical and Engineering Sciences*, *366*(1881), 3717-3725.

Wing, J. (2011). Research notebook: Computational thinking—what and why? *Retrieved from http://link.cs.cmu.edu/article.php?a=600*

Yadav, A., Gretter, S., Good, J., & McLean, T. (2017). Computational thinking in teacher education. In: Rich P., Hodges C. (Eds), *Emerging research, practice, and policy on computational thinking* (pp. 205-220). Cham, Switzerland: Springer.

Yang, K. L. (2013). A framework for analyzing textbooks based on the notion of abstraction. *For the Learning of Mathematics*, *33*(1), 33-39.

Zeki, S. (2000). Abstraction and idealism. *Nature*, *404*(6778), 547-547.

Zollman, A. (2012). Learning for STEM literacy: STEM literacy for learning. *School Science and Mathematics*, *112*(1), 12-19.

# APPENDIX A

## TEACHER RECRUITMENT LETTER

Dear Teacher:

What if you and your students had an opportunity to explore math and science by building and navigating robots? I am a professor in the Department of Career and Information Studies at The University of Georgia, and I am excited to invite you and your class to participate in such an exciting learning opportunity, called *Robots for Everyone.*

The project is an innovative teaching and learning initiative to help students learn about building and programming robots, while learning math and science in the process. Classroom activities include your students working together to build and navigate robots, complete reflection activities about their thinking, and complete a series of assessments of their learning and experiences.

By participating in this project, it is anticipated that you will benefit immediately and long term. You will have access to innovative teaching and learning materials to use as you see fit. You will also benefit from the STEM-related process of thinking about the design and function of robots; the practices and thinking associated with these tasks are likely to transfer into other aspects of your teaching.

There are a few research activities related to this project that I would like your permission for you to participate in. You and your class can still take part in the project, even if you don’t want to participate in the research activities. These activities include an interview with research team members (40-60 minutes total). In addition, you may volunteer to be observed and/or your class be video recorded. We anticipate doing this 8-10 times throughout your instruction, for a total of 8-10 hours.

Your involvement in the research activities is voluntary, and you may choose not to participate in the research activities or to stop at any time. Your identity will be protected to maintain your confidentiality

To volunteer to take part in the research activities of this study, you must sign the attached consent form, which contains further details. Please sign two copies; keep one for your records and return one to me, the researcher.

Thank you for your consideration!

IKSEON CHOI, Ph.D.

Associate Professor

Career and Information Studies

University of Georgia

212 River's Crossing

Athens, GA 30602

Phone: 706.583.0794

Email: ichoi@uga.edu

APPENDIX B

TEACHER CONSENT FORM

**UNIVERSITY OF GEORGIA**

**TEACHER CONSENT FORM**

**Researcher's Statement**

I am asking you to take part in a few research activities related to *Robots for Everyone Robots: Work and Play* project. Before you decide to participate in these research activities, it is important that you understand why the research is being done and what it will involve. This form is designed to give you the information about the research activities so you can decide whether you will participate in these activities or not. Please take the time to read the following information carefully. Please ask the researcher if there is anything that is not clear or if you need more information. When all your questions have been answered, you can decide if you want to participate in the research activities or not. This process is called "informed consent." A copy of this form will be given to you.

**Principal Investigator:** Dr. Ikseon Choi
Career and Information Studies
ichoi@uga.edu

**Purpose of the Research**

The purpose of the research activities is to inform me of the success of the instructional program for the project, as well as examine student thinking and learning as a result of the instructional program.

**Research Activities**

For the *Robots for Everyone* project, you will be provided with innovative teaching and learning materials and resources, including a teacher's guide, a student's guide, and any additional support material created as we work together. If you agree to participate in this research, I will be asking you to do some additional research activities to evaluate the usefulness of the project. The interview will include at least five questions, of which the most personal question to be asked is, "Describe the most challenging or weakest part of the instructional program."

Research activities include classroom observation (8-10 visits) by the researcher during the course of the classroom activities as well as a 40-60 minutes recorded audio interview between you and me or a member of my research team. If you are willing, we seek to video-record you and your classroom during those observations.

Overall, you could be expected to spend 7-9 hours participating in the research activity (60 min max. for the interview, 8-10 hours for classroom observations).

**Risks and discomforts**

I do not anticipate any risks to you from participating in the research activities.

**Benefits**

There are no direct benefits to you by participating in this research. The data collected from you in the research activities has the potential to benefit society or humankind because they will be used to improve the instructional program for future participants, who will benefit from an established avenue by which students can learn to build, program, and design robots in the future.

**Privacy/Confidentiality**

In order for me to answer a series of research questions, classroom observation data and interview responses will be collected and analyzed. The data will be processed and stored in Microsoft Word and Excel. Dropbox.com with password-protected access will be used to store and access this data. Since Internet communications are insecure, there is a limit to the confidentiality that can be guaranteed due to the technology. To protect your identity and to maintain confidentiality, personal identifiers in the data will be replaced with randomly assigned research numbers before being uploaded to DropBox. Approved researchers will access this data according to the IRB guideline. All information that could be used to identify you will be deleted after completion of data collection.

The project's research records may be reviewed by departments at the University of Georgia responsible for regulatory and research oversight. Researchers will not release identifiable results of the study to anyone other than individuals working on the project without your written consent unless required by law.

**Taking Part is Voluntary**

Your involvement in the research activities is voluntary and you may choose not to participate in the research activities or to stop at any time without penalty or loss of benefits to which you are otherwise entitled. You can still participate in the *Robots for Everyone* project, even if you do not want to participate in the research. If you decide to stop or withdraw from the study, the information/data collected from or about you up to the point of your withdrawal will be kept as part of the study and may continue to be analyzed.

**If You Have Questions**

The main researcher conducting this study is Dr. Ikseon Choi, a professor at the University of Georgia. Please ask any questions you have now. If you have questions later, you may contact Dr. Choi at ichoi@uga.edu or at 706.583.0794. If you have any questions or concerns regarding your rights as a research participant in this study, you may contact the Institutional Review Board (IRB) Chairperson at 706.542.3199 or irb@uga.edu.

**Research Subject's Consent to Participate in Research:**

To voluntarily agree to take part in the research activities of this project, the classroom observation and the interview, you must sign on the line below. Your signature below indicates that you have read or had read to you this entire consent form and have had all of your questions answered.

**Audio Recording**

If you agree to be interviewed, please provide initials below if you agree to have your interview audio recorded or not. You may still participate in the research interview even if you are not willing to have the interview recorded. The audio recordings will be destroyed as soon as they have been transcribed.

_____I do not want to have the interview recorded.

_____I am willing to have the interview recorded.

**Classroom Observations / Video Recording**

If you agree to be observed, please provide initials below. If you are willing to have your classroom activities video recorded, please also provide initials below. *You may still participate in the classroom observations even if you are not willing to have the interview recorded.* The video recordings will be destroyed as soon as they have been transcribed; video clips that are retained for publication and presentation will have all identifiable features blurred out before being shown to anyone else.

| Classroom Observations | Video Recording |
| --- | --- |
| _____I do not want to be observed. | _____I do not want to have the observations recorded. |
| _____I am willing to be observed. | _____I am willing to have the observations recorded. |

______________________________________________________________

Name of Researcher Signature Date

______________________________________________________________

Name of Participant Signature Date

**Please sign both copies, keep one and return one to the researcher.**

APPENDIX C

PARENT RECRUITMENT LETTER

Dear Parent:

What if you and your students had an opportunity to explore math and science by building and navigating robots? I am a professor in the Department of Career and Information Studies at The University of Georgia, and I am excited to invite you and your class to participate in such an exciting learning opportunity, called *Robots for Everyone.*

The project is an innovative teaching and learning initiative to help students learn about building and programming robots, while learning math and science in the process. Classroom activities include your students working together to build and navigate robots, complete reflection activities about their thinking, and complete a series of assessments of their learning and experiences.

By participating in this project, it is anticipated that your child will benefit immediately and long term. In the immediate, your child will be learning about robots in a way that provides an authentic context for also learning math and science. Long term, your child will be learning an important set of STEM skills and thinking.

There are a few research activities related to this project that I would like your permission for your child to participate in. Your child will still participate in the project, even if you don't want your child to participate in the research activities. These activities include classroom observations, a few surveys and tests, and access to their ongoing written reflections throughout the project. Overall, your child could be expected to spend a total of 3-4 hours (three 45-60 min class periods) participating in research activities.

To voluntarily allow your child to take part in the research activities of this project, you must sign the attached permission form, which contains further details. Please sign two copies; keep one for your records and return one to the researcher.

Thank you for your consideration!

Sincerely,

IKSEON CHOI, Ph.D

Associate Professor

Career and Information Studies

University of Georgia

212 River's Crossing

Athens, GA 30602

Phone: 706.583.0794

Email: ichoi@uga.edu

APPENDIX D

PARENT CONSENT FORM

**UNIVERSITY OF GEORGIA**

**PARENTAL PERMISSION FORM**

**Researcher's Statement**

I am asking your permission for your child to take part in a few research activities related to a project they will be doing in class: *Robots for Everyone*. Before you decide to allow your child to participate in these research activities, it is important that you understand why the research is being done and what it will involve. This form is designed to give you the information about the research activities so you can decide whether your child will participate in these activities or not. Please take the time to read the following information carefully. Please ask the researcher if there is anything that is not clear or if you need more information. When all your questions have been answered, you can decide if you want your child to participate in the research activities or not. This process is called "informed consent." A copy of this form will be given to you.

**Principal Investigator:** Dr. Ikseon Choi
Career and Information Studies
ichoi@uga.edu

**Purpose of the Research**

The purpose of the research activities is to inform me of the success of the *Robots for Everyone* project in helping students learn about science and mathematics by building and exploring robotics.

**Research Activities**

For the *Robots for Everyone* project, your child's teacher will be provided with innovative teaching and learning materials and resources, including robotics kits, teacher and student materials, and other materials developed for the project, for the class to study math, science, and robotics. If your child participates in the research, there are some voluntary research activities that we will ask your child to do. Research activities include:

- Up to ten (10) classroom observations by the researcher during the course of the classroom activities. Observations will each last one class period (45-60 min).
- A 20-minute survey which we will ask your child to complete after the project.
- A 30-minute Learning Assessment which we will ask your child to complete before, during, and after the project
- Collection and study of your child's artifacts generated during the project (e.g., ongoing written reflections, still images of the robots your child builds) to find evidence of thinking and learning processes related to engineering and robotics.

Overall, your child could be expected to spend 3 hours completing surveys and assessments; classroom observations will take up to 10 hours.

**Risks and discomforts**

I do not anticipate any risks to your child from participating in the research activities.

**Benefits**

There are no direct benefits to your child by participating in this research. The data collected from your child in the research activities has the potential to benefit society or humankind because they will be used to improve the experience of learning about robotics for future participants, who will benefit from an established avenue by which students can learn from a young age how to build and learn from building robots.

**Privacy/Confidentiality**

In order for me to answer a series of research questions, classroom observation data, survey responses, work samples, and interview responses will be collected and analyzed. The data will be processed and stored in Microsoft Word and Excel. Dropbox.com with password-protected access will be used to store and access this data. Since Internet communications are unsecure, there is a limit to the confidentiality that can be guaranteed due to the technology. To protect your child's identity and to maintain his/her confidentiality, personal identifiers in the data will be replaced with randomly assigned research numbers before being uploaded to DropBox. Approved researchers will access this data according to the IRB guideline. All information that could be used to identify your child will be deleted after completion of data collection. Even though the investigator will emphasize to all participants that comments made during the focus group interview sessions should be kept confidential, it is possible that participants may repeat comments outside of the group, which is out of the researchers' control.

The project's research records may be reviewed by departments at the University of Georgia responsible for regulatory and research oversight. Researchers will not release identifiable results of the study to anyone other than individuals working on the project without your written permission unless required by law.

**Taking Part Is Voluntary**

Your child's involvement in the research activities is voluntary, and you may choose not to allow your child to participate in the research activities or to stop at any time without penalty or loss of benefits to which your child is otherwise entitled. Your decision whether or not to allow your child to participate in the research will not influence his/her grades or class standing. If your child decides to stop or you withdraw your child from the study, the information/data collected from or about your child up to the point of your withdrawal will be kept as part of the study and may continue to be analyzed.

**If You Have Questions**

The main researcher conducting this study is Dr. Ikseon Choi, a professor at the University of Georgia. Please ask any questions you have now. If you have questions later, you may contact Dr. Choi at ichoi@uga.edu or at 706.583.0794. If you have any questions or concerns regarding your child's rights as a research participant in this study, you may contact the Institutional Review Board (IRB) Chairperson at 706.542.3199 or irb@uga.edu.

**Research Subject's Consent to Participate in Research:**

To voluntarily allow your child to take part in the research activities of this study, you must sign on the line below. Your signature below indicates that you have read or had read to you this entire Parental Permission Form, and have had all of your questions answered.

**Video Recording**

Your child's teacher may be willing to allow the researchers to video record the classroom observations. With your permission, your child will be video recorded during those observations, including the use of a mobile recording device that your child can wear. You may choose not to allow your child to be video recorded, but still participate in the other research activities (e.g., classroom observations, surveys, etc.).

Please provide initials below if you agree to having your child video recorded. The video recordings will be destroyed as soon as they have been analyzed. We may choose to retain short clips of your child for publication purposes - in such cases, we will use a special effect (i.e., blurring out) to hide your child's identity.

______I do not want my child video recorded.

______I am willing to have my child video recorded.

**What if I do not want my child to participate in this research project?**

Students not participating in research activities will still be allowed to complete the instruction associated with the *Robots for Everyone* project. They will not be video recorded or included in any classroom observations. However, they will still complete the assessments and surveys, and construct artifacts within the class. These will be used by the teacher for evaluation purposes and to inform the design and delivery of the instruction, but will not be used for research purposes.

If you consent to allowing your child to participate in the research project, please complete this information below:

Your Child's Name:_______________________________________________________

Your Signature:_______________________________ Date:___________________

Your Printed Name:______________________________________________________

Signature of Researcher:______________________ Date:__________________

Printed Name of Researcher:____________________________________________

Please sign both copies, keep one and return one to the researcher.

APPENDIX E

STUDENT CONSENT FORM

## Consent Form for Participation in Research

Very soon, your teacher is going to be teaching you a lesson about robots. You will work to build a robot and make it move.

- I am doing a project where I want to see how you like the lesson and to see if it helps you learn, both before and after the lesson.
- I would like you to let me have a copy of any journal writings you write about the robot lesson.
- I would also like you to let me watch you while you learn.

You do not have to say "yes" if you don't want to. No one, including your parents or teachers, will be mad at you if you say "no" now or if you change your mind later. I have also asked your parents if it is ok if you do this. Even if your parents or teachers say "yes," you can still say "no." Remember if you say yes now, you can ask me to stop at any time. If you take part in my robot project or not, it will not affect your class grade. Even if you do not want to be in my project, you will still be able to take part in the class with the robot lesson.

**Video Recording**

I might video record the robot lesson. I want to know if you will let me record you. Please write your initials on one of the lines below. Even if you do not want to be video recorded, you will still be able to take part in the class with the robot lesson.

_____I do not want to be video recorded.

_____I am willing to be video recorded.

**Name of Child:** ______________________________ **Parental Permission on File:** Yes No

**Writing your name on the line below means that you have read this letter or had it read to you and that you want to take part in the robot project (research). If you don't want take part in the research part of the lesson, do not sign below. Please ask me if you have any questions about what it means to write your name on this letter.**

**Signature of Child:** ________________________________ **Date:** ___________________

**Signature of Researcher:** ____________________________ **Date:** ___________________

# APPENDIX F

# THE ACT ASSESSMENT

## Section I: Filtering Information

In this year, 70,090 firefighters in the U.S. were injured with 61 deaths in the line of duty due to they being exposed to dangerous conditions to save lives. To decrease the number of injuries and deaths of the on-duty firefighters, your local government would like to fund a team to design a firefighting robot. As an engineer, you are hired by the local government to lead this team. Now the manager of the local government allocates you two months to develop a model of the robot showing your plan. “The firefighter robot should include a sensor to detect its environment, computer programs to control the robot, and a remote-controller to assist with robot operation,” said Alex Thomas, associate administrator for the local government.  “In addition, the firefighter robot should be made from magnesium alloys and composite materials that can resist high temperatures. It also has to travel at a speed of 35 MPH and carry a full tank of foam when leaving for a fire rescuing task. Each tank should hold a total of 5 gallons of foam.” In particular, based on your conversation with the manager, he expects that the robot will be tested at the Fire Station 7 which is located on the southwest corner of the city. The robot should be able to accurately calculate and map out the shortest route to the location quickly.

Part 1: Please read the story above and summarize the goal of the task in the box.

| |
|---|
| As an engineer, what is your task based on the give scenario? |

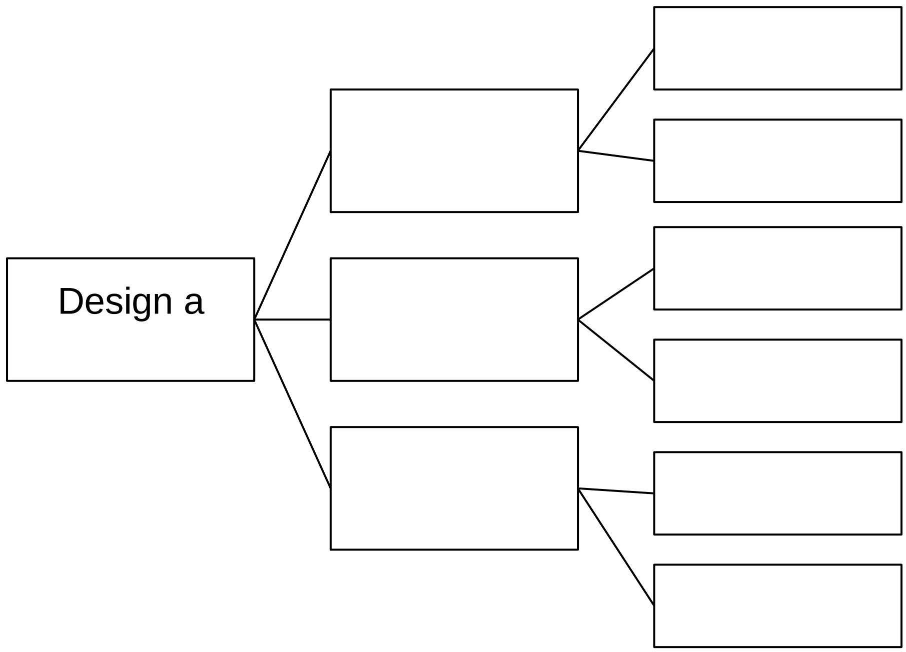
Part 2: What is the information you must know to accomplish the task? Copy and paste the important information in the left column and then explain why you need this information to complete the task.

| The information that you must know | Why do you need this information? |
|---|---|
| 1. | |
| 2. | |
| 3. | |
| 4. | |
| 5. | |
| 6. | |
| 7. | |

**Section II: Problem Decomposition**

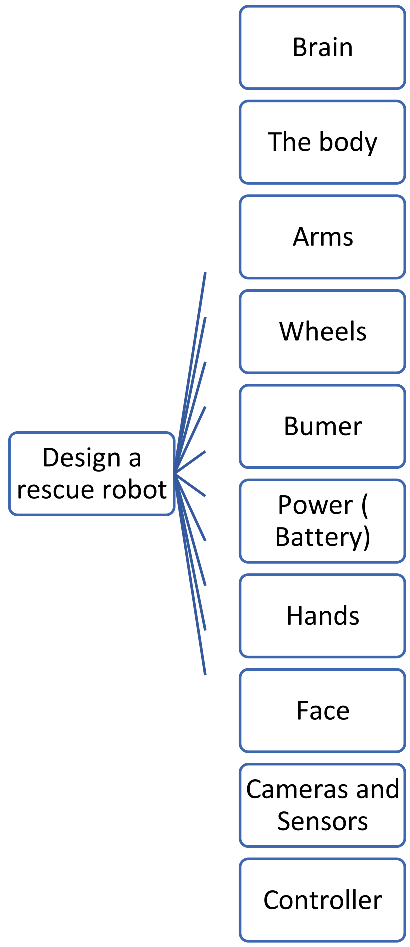
**Problem Decomposition:** Break a “big” problem or task down into smaller ones (See the example below)

For example, Often, big problems/tasks are just lots of little problems/tasks stuck together. If you want to design a bicycle. It is more straightforward if the whole bike is separated into smaller parts, and you design each part to see how it works in more detail.

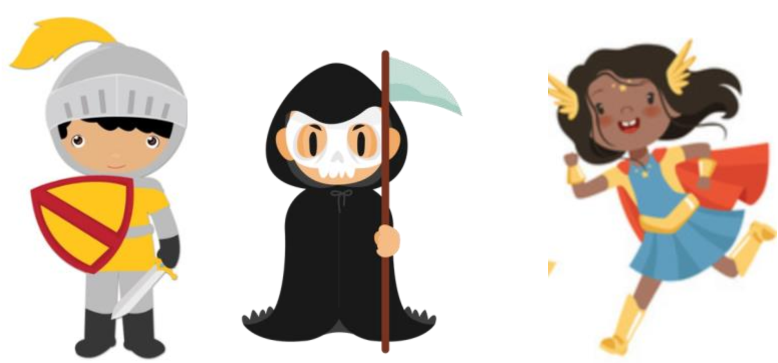


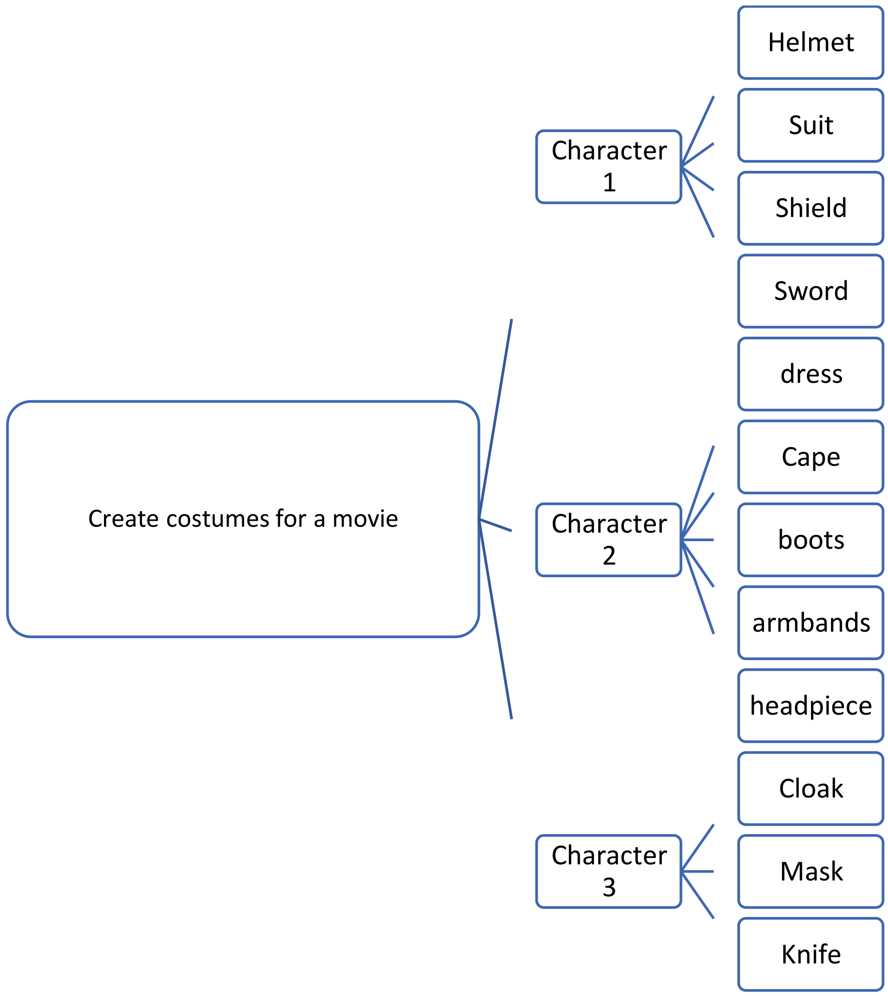

1. How would you design a rescue robot? We would like you to list all smaller problems you have to work on to complete the design task.

   "Based on the research, we find that major components of the physical design of rescue robots included the tracks or wheels, motors, body frame, CPU board, joints, and controller. Attached to its heads are lights and cameras, which researchers can access through video screens. Some rescue robot also includes arms, hands, bumper, battery case, and sensors. Most robots' body are metal. The metal covers have to be added to protect the components from potential damage. USGS scientists also suggest that all electronic components should remain inside the vehicle and make sure this robot dust resistant due to heavy dust environment."




2. How would you create three costumes as the images show below for a movie. We would like you to list all smaller problems you have to work on to complete the task.






3. List a complex task or a problem with your present living situation (home, neighborhood, school, whatever) in the given box.

Now we would like you to list possible smaller problems to resolve the problem/task you listed above

**Section III: Locating Similarities**

Part 1: For the following item, list as many similarities as you can. The more similarities you think of, the better. Do not worry about spelling.

1. How is riding a bike to school like walking to school?

2. How is using a computer like using a phone?

3. How is using a robot to rescue three persons after earthquake like using a robot to rescue a person in a fire.

APPENDIX G

STUDENT LEARNING EXPERIENCES QUESTIONNAIRE FOR EXPERIMENTAL GROUP

**Your Name: ___________________________**

**After you have carefully read a statement, decide whether or not you agree with it. If you agree, decide whether you agree mildly or strongly. If you disagree, decide whether you disagree mildly or strongly. You may decide that you are uncertain or cannot decide. Then, respond to each statement by drawing a check in the circle for only ONE answer for each statement. If you have any questions, please ask your teacher.**

Strongly Disagree

Disagree

Undecided

Agree

Strongly Agree

**Information About Me**

**Please draw a check in the circle with your choice.**

1. I am a…

   ○ Boy ○ Girl

2. How would you describe your racial or ethnic background? Please fill in the circles for as many as apply.

   ○ African American ○ Asian American Pacific Islander

   ○ Alaskan/Native American ○ White or European American

   ○ Hispanic/Latino ○ Other_________________

| This is the course satisfaction survey about the class that you participated in. | Strongly Disagree | Disagree | Neutral | Agree | Strongly Agree |
|---|---|---|---|---|---|
| 1. I enjoyed the robotic class. | ○ | ○ | ○ | ○ | ○ |
| 2. I understood the class contents well. | ○ | ○ | ○ | ○ | ○ |
| 3. I had enough time to complete all activities. | ○ | ○ | ○ | ○ | ○ |
| 4. I think I made good relationship between my team members for collaboration. | ○ | ○ | ○ | ○ | ○ |
| 5. While I use robotic equipment in the class, I was able to participate in the class well without any technical problems. | ○ | ○ | ○ | ○ | ○ |
| 6. My teacher encouraged students to share their ideas about things we are studying in class. | ○ | ○ | ○ | ○ | ○ |

| | | | | | |
|---|---|---|---|---|---|
| 7. My teacher expected me to do my best all the time. | ○ | ○ | ○ | ○ | ○ |
| 8. My teacher wanted us to become better thinkers, not just memorize things. | ○ | ○ | ○ | ○ | ○ |

| In the robotics class: | Strongly Disagree | Disagree | Undecided | Agree | Strongly Agree |
|---|---|---|---|---|---|
| 1. The activities helped me learn | ○ | ○ | ○ | ○ | ○ |
| 2. The activities were interesting to me | ○ | ○ | ○ | ○ | ○ |
| 3. I learned a lot by working with other students | ○ | ○ | ○ | ○ | ○ |
| 4. Building the robot was easy | ○ | ○ | ○ | ○ | ○ |
| 5. Programming the robot was easy | ○ | ○ | ○ | ○ | ○ |

| | | | | | |
|---|---|---|---|---|---|
| 6. The filtering information activity was easy | ○ | ○ | ○ | ○ | ○ |
| 7. The reading about volcano was easy | ○ | ○ | ○ | ○ | ○ |
| 7. The reading about earthquake was easy | ○ | ○ | ○ | ○ | ○ |
| 8.The problem decomposition task was easy | ○ | ○ | ○ | ○ | ○ |
| 9. The compare and contrast activities were easy | ○ | ○ | ○ | ○ | ○ |
| 10. I think other students should do this class | ○ | ○ | ○ | ○ | ○ |
| 11. I usually look forward to this class. | ○ | ○ | ○ | ○ | ○ |
| 12. I work hard to do my best in this class. | ○ | ○ | ○ | ○ | ○ |

| | | | | | |
|---|---|---|---|---|---|
| 13. Sometimes I get so interested in my work I don't what to stop. | ○ | ○ | ○ | ○ | ○ |
| 14.The topics (volcano and earthquake) we studied are interesting and challenging. | ○ | ○ | ○ | ○ | ○ |

**Open-Ended Questions**

*Please write your response below.*

1. What did you like most about this project? (i.e. filtering information task, problem decomposition task, and compare/contrast task).

| |
|---|
| |

2. What was the most useful thing you learned from this project? (i.e.  filtering information task, problem decomposition task, and compare/contrast task).

3. What did you like least about this project? (i.e.  filtering information task, problem decomposition task, and compare/contrast task).

4. What challenges did you have with this project?

5. What would make this project better?

APPENDIX H

STUDENT LEARNING EXPERIENCES QUESTIONNAIRE FOR CONTROL GROUP

**Your Name: ___________________________**

**After you have carefully read a statement, decide whether or not you agree with it. If you agree, decide whether you agree mildly or strongly. If you disagree, decide whether you disagree mildly or strongly. You may decide that you are uncertain or cannot decide. Then, respond to each statement by drawing a check in the circle for only ONE answer for each statement. If you have any questions, please ask your teacher.**

Strongly Disagree

Disagree

Undecided

Agree

 Strongly Agree

**Information About Me**

**Please draw a check in the circle with your choice.**

1. I am a…

   ○ Boy ○ Girl

2. How would you describe your racial or ethnic background? Please fill in the circles for as many as apply.

   ○ African American ○ Asian American Pacific Islander

   ○ Alaskan/Native American ○ White or European American

   ○ Hispanic/Latino ○ Other_________________

| This is the course satisfaction survey about the class that you participated in. | Strongly Disagree | Disagree | Neutral | Agree | Strongly Agree |
|---|---|---|---|---|---|
| 1. I enjoyed the robotic class. | | | | | |
| 2. I understood the class contents well. | | | | | |
| 3. I had enough time to complete all activities. | | | | | |
| 4. I think I made good relationship between my team members for collaboration. | | | | | |
| 5. While I use robotic equipment in the class, I was able to participate in the class well without any technical problems. | | | | | |
| 6. My teacher encouraged students to share their ideas about things we are studying in class. | | | | | |

| | | | | | |
|---|---|---|---|---|---|
| 7. My teacher expected me to do my best all the time. | ○ | ○ | ○ | ○ | ○ |
| 8. My teacher wanted us to become better thinkers, not just memorize things. | ○ | ○ | ○ | ○ | ○ |

| In the robotics class: | Strongly Disagree | Disagree | Undecided | Agree | Strongly Agree |
|---|---|---|---|---|---|
| 1. The activities helped me learn | ○ | ○ | ○ | ○ | ○ |
| 2. The activities were interesting to me | ○ | ○ | ○ | ○ | ○ |
| 3. I learned a lot by working with other students | ○ | ○ | ○ | ○ | ○ |
| 4. Building the robot was easy | ○ | ○ | ○ | ○ | ○ |
| 5. Programming the robot was easy | ○ | ○ | ○ | ○ | ○ |

| | | | | | |
|---|---|---|---|---|---|
| 6. I think other students should do this class | ○ | ○ | ○ | ○ | ○ |
| 7. I usually look forward to this class. | ○ | ○ | ○ | ○ | ○ |
| 8. I work hard to do my best in this class. | ○ | ○ | ○ | ○ | ○ |
| 9. Sometimes I get so interested in my work I don't what to stop. | ○ | ○ | ○ | ○ | ○ |

**Open-Ended Questions**

*Please write your response below.*

1. What did you like most about this project?

| |
|---|
| |

2. What was the most useful thing you learned from this project?

3. What did you like least about this project?

4. What challenges did you have with this project?

5. What would make this project better?

APPENDIX I

FOCUS GROUP INTERVIEW PROTOCOL

**Protocol for the Semi-structured Focus Group Interview with the Students in the Experimental Group**

*TO BE READ BY MEMBER OF THE RESEARCH TEAM: Thank you for participating in this interview about your experience teaching robotics over the past few weeks. As a reminder, we will audio record this interview - if you do not want your interview audio recorded, please let me know. You may ask me to stop audio recording at any time; you may also choose to end the interview at any time.*

Focus group interviews with the students in the experimental group - After the intervention, three groups of students (each group had four students) were selected. Each group had a face-to-face semi-structured focus group interview with the researcher (approximately 45 to 60 mins).

1. What were the most useful learning activities of this curriculum (i.e., filtering information, problem decomposition, and finding similarities)? Please explain why you think they are useful and what you learn from these activities.

2. What were the most interesting learning activities of this curriculum (i.e., filtering information, problem decomposition, and finding similarities)? Please explain why you think they are interesting.

3. What were the challenges you experienced during the activities (i.e., filtering

information, problem decomposition, and finding similarities)? Please explain why and also how you overcome the challenges.

4. What improvements on the activities and the curriculum do you expect? Please explain why they need to be improved.

5. Is there anything else you want to share with me?

APPENDIX J

INTERVIEW PROTOCOL

## Protocol for Semi-structured Interview with the Teacher

*TO BE READ BY MEMBER OF THE RESEARCH TEAM: Thank you for participating in this interview about your experience teaching robotics over the past few weeks. As a reminder, we will audio record this interview - if you do not want your interview audio recorded, please let me know. You may ask me to stop audio recording at any time; you may also choose to end the interview at any time.*

Interviews with the teacher in the experimental group - After intervention, the teacher will have a face-to-face semi-structured individual interview (45 to 60 mins).

1. Based on your observation, what were the most meaningful learning activities your students experienced during the project (i.e., filtering information, problem decomposition, and finding similarities)? Please explain why you think they are meaningful.

2. Based on your observation, what were the challenges your students experienced during the activities (i.e., filtering information, problem decomposition, and finding similarities)? Please explain why.

3. What were the most meaningful teaching experiences during the project (i.e. filtering information, problem decomposition, and finding similarities)? Please explain why.

4. What were the challenges you experienced while implementing the curriculum (i.e. filtering information, problem decomposition, and finding similarities)? Please explain why.

5. What would you change in your next implementation to avoid these challenges? Please explain why.

6. Is there anything else you want to share with us?

APPENDIX K

LESSON PLAN FOR THE REVISED DANGER ZONE CURRICULUM WITH THE EGPA

*Comparisons between the revised Danger Zone* curriculum *with the EGPA and the Danger Zone curriculum. Major differences in the lesson objectives are marked with grey highlights. The specific contents with the integration of the EGPA are marked in italic and bold fonts.*

| **Lesson(s)** | **Time** | **Lesson Objectives** | |
|---|---|---|---|
| | | **The *Danger Zone* for the Control Group** | **The Revised *Danger Zone* with the EGPA for the Experimental Group** |
| **1**<br>**Danger Zone** | 2 hours | Analyze the problem scenario provided with a short description of the context; identify problem goal and problem constraints; and develop solutions | Analyze the problem scenario ***provided with unnecessary information***; Differentiate necessary and unnecessary information (Activity: Filtering Information); identify problem goal. |
| | | Explore the scientific content underlying the task (i.e. volcanoes) | Explore the science content of the task (i.e. volcanoes) |
| | | Explain the steps in the engineering design process | Explain the steps in the engineering design process |
| **2**<br>**Build-a-Bot** | 2 hours | Construct a robot | Construct a robot |
| | | Identify the mechanical components of the robot under construction | Identify the mechanical components of the robot under construction |
| | | Define the role of the central processing unit (CPU) | Define the role of the central processing unit (CPU) |
| | | Explain the difference between input and output devices | Explain the difference between input and output devices |
| **3:**<br>**Primary Programming** | 1 hour | Act out the basic programming commands | Act out the basic programming commands |
| | | Practice programming the robot in Rogic | Practice programming the robot in Rogic |
| | | Apply the mathematical concepts of decimals to program their robot to follow basic commands | Apply the mathematical concepts of decimals to program their robot to follow basic commands |
| | | | Acquire mathematic knowledge and information required for decomposition tasks by ***measuring the distance that a robot can travel at two different speed settings***. |
| **4**<br>**Purposeful Programming** | 2 hours | Further examine science content that will impact programming (i.e. specific types of volcanic terrains) | Further examine science content that will impact programming (i.e. specific types of volcanic terrains) |

| | | | |
|---|---|---|---|
| | | Apply the mathematical concepts of decimals, measurement, and coordinate grids to their programming | Apply the mathematical concepts of coordinate grids to their movement plan. |
| | | Engage in the engineering design process to program and navigate their robot (e.g., plan, test, evaluate, and revise their programs) in order to complete the task. | ***Engage in the instructional activities to decompose the complex task (Activity: Task Decomposition).*** This activity will help students understand the significance of problem decomposition and learn about how to decompose a program. |
| **5 Prime Optimization** | 2 hours | | ***Use visual representation tools to decompose the complex task into smaller pieces (Activity: Task Decomposition).*** This is the continuance of problem decomposition activity in Lesson 3 wherein students will be fostered to decompose problem. |
| | | Apply the mathematical concepts of decimals, measurement, coordinate grids, and variables to their programming. | Apply the mathematical concepts of decimals, measurement, coordinate grids, and variables to their programming. |
| | | Engage in the engineering design process to program and navigate their robot (e.g., plan, test, evaluate, and revise their programs) in order to complete the task. | Engage in the engineering design process to program and navigate their robot (e.g., plan, test, evaluate, and revise their programs) in order to complete the task. |
| | | Determine their best problem solution. | Determine their best problem solution. |
| **6 Additional Challenge** | 3 hours | Analyze a new problem in the same scenario (e.g., exploring the volcano areas) with a higher level of difficulty (e.g., the robot needs to move to five locations to collect five samples). | ***Analyze the earthquake rescuing scenario provided with unnecessary information***; Differentiate necessary and unnecessary information (Activity: Filtering Information); identify problem goal. |
| | | Apply the mathematical concepts of decimals, measurement, coordinate grids, and variables to program for this more difficult problem. | ***Engage in the instructional activities to decompose the complex task*** (Activity: Task Decomposition). This problem decomposition activity is analogical to that in the volcano scenario. Students will decompose the problem into several pieces. |
| | | Engage in the engineering design process to program and navigate their robot (e.g., plan, test, evaluate, and revise their programs) in order to complete this complicate task; and Determine the best problem solution. | ***Identify underlying commonalities of two scenarios*** (i.e., volcano exploring and earthquake rescuing); and ***attain generalized representations*** (i.e. generalized algorithms, underlying equations) (Activity: Locating Similarities). |
| **7 Reflect and Share** | 1 hour | Share their results with peers | Share their results with peers |
| | | Explain and justify their approach to solving the problem | Explain and justify their approach to solving the problem |
| | | Engage in academic discussions around programming challenges | Engage in academic discussions around programming challenges |