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Exploring Factors that Influence Computational Thinking Skills in Elementary Students' Collaborative Robotics

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Abstract

Recently educational robotics has expanded into curriculum beyond traditional STEM fields, and which can also be used to foster computational thinking (CT) skills. Prior research has shown numerous interdisciplinary benefits related to CT, however, these influential factors have often been investigated with relatively few variables. This study investigated factors that may lead to 4th and 5th grade elementary school students' development of computational thinking skills in collaborative robotics activities by hypothesizing a model which proposed that a problem solving inventory, intrinsic motivation, and enjoyment were the main predictors of computational thinking skills. The model was then tested by surveying students with several psychometric inventories where a revised model was then constructed. The study found significant relationships between perceived competence and enjoyment, and learning motivation, and intrinsic motivation. Another important finding was that problem solving was a significant predictor of computational thinking skills. Results were interpreted with reference to implications for possible means of improving learning outcomes when using collaborative robotics in an educational setting.

Keywords: robotics, collaborative robotics, computational thinking skills, learning preferences, perceived competence, enjoyment, intrinsic motivation, problem solving inventory, elementary school

1. Introduction

The use of educational robotics has the potential to significantly impact the nature of science and technology education at all levels (Alimisis, 2013; Altin & Pedaste, 2013) and as such, schools are now expanding their use of educational robotics with various educational robotics platforms (e.g., Lego Mindstorms). Robotics, however, has largely been an element of Science, Technology, Engineering and Math (STEM) education (Chalmers, 2018; Goh & Ali, 2014; Sullivana & Heffernana, 2016; Tuluri, 2015). Robotics curricula, for example, can focus on basic coding activities (Jung & Won, 2018; Toháčeka et al., 2016) in order to control a robot's physical operation. Children and young students can find this fun and engaging because they are able to interact directly with both the electrical and mechanical processes and components of the machine.

Recently, educational robotics has been brought into other content areas beyond STEM subjects such as arts (Burhans & Dantu, 2017; Chung, 2014; Yanco et al., 2007) and music (Chung et al., 2014) and even into interdisciplinary classrooms (Birk, 2011; Heuer et al., 2017; Sabanovic et al., 2007). While students generally view the addition of robotics positively, the learning objectives for robotics integration into different content areas vary. For example, Chen and Chang (2018) reported significantly more positive perceptions of robotics when integrated with STEM since it strengthened students' knowledge, interest, and career orientation towards robotics-related fields. Eteokleous-Grigoriou and Psomas (2013) found that students felt their lessons were more interesting and enjoyable when robotics was integrated as an interdisciplinary learning tool. Other reasons for integrating robotics into curriculum include the

creation of an authentic learning environment (Khanlari, 2016) and acquisition of 21st century skills (Alimisis, 2013; Khanlari, 2016; Jung & Won, 2018) such as increasing students' creativity, collaboration and team-work, self-direction, communication skills, social and cross-cultural skills, and social responsibility.

Robotic activities also vary from simple assembly (Cook, et al., 2010; Poletz et al., 2010) to programming (Baek et al., 2019; Taylor & Baek, 2018, 2019). Programming robots can range from using drag-and-drop user interfaces to more sophisticated text-based coding languages. Coding can range from basic instructional input through a numeric keypad on the chassis of a robot to more complex graphical user interfaces with interconnecting blocks as a visual programming metaphor. More advanced students can learn to write technical code in sophisticated text-based languages. The primary purpose for coding in schools, however, tends to focus on problem solving skills to prepare students for future college and professional careers. By contrast, combining coding with robotics enables students to see their thinking in a more concrete form. As students code, they practice metacognition and can identify their mistakes in thinking. Such errors then manifest themselves as malfunctions (e.g., moving left instead of right) in the robot. This practice is more colloquially known as debugging. Existing studies (e.g., Eguchi, 2012; Grandgenett et al., 2012; Hwang & Wu, 2014) have identified numerous educational goals across various content areas (including social interaction) that can be achieved when students program robots. One developmental goal is Computational Thinking (CT).

1.1 Robotics and Computational Thinking

Computational thinking in relation to robotics is a new field of study. Since robotics is viewed as an interdisciplinary pathway to integrate and practice computational thinking (Shoop et al., 2016), there has been a growing research interest since 2006 when computational thinking skills became a hot topic (see Wing, 2006). Chen et al. (2017), for example, organized a robotics curriculum which asked participants to follow three steps: writing code on a piece of paper, test the code on a virtual robot, and then run the tested code on a physical robot. They found that the activities and curriculum improved students' computational thinking, especially in the context of robotics coding. In another study, Baratè et al. (2017) organized music notation activities with Lego blocks for elementary students where each block represented a musical note. Students then configured and reconfigured blocks in different shapes, colors, and positions in order to make unique musical scores. The resulting curriculum was not only a suitable learning framework for improving music skills, but one that also conveyed computational thinking concepts. In another study, Sullivan and Bers (2016) demonstrated that as early as pre-kindergarten, children were able to master foundational robotics coding concepts, and that children as young as seven years old were able to master complex coding concepts such as conditional statements. Lieto et al. (2017) also found a significant effect of educational robotics on robot coding skills and reported short-term beneficial effects of robotics with five to six-year-old children. As these studies show, educators can incorporate computational thinking skills along with robotics in curriculum as early as grade-school.

When it comes to computational thinking skills and robotics, Taylor and Baek (2018) concluded that group roles impacted student computational thinking skills. Baek et al. (2019) also found a significant increase in participants' computational thinking skills while coding robotics. Working on robotics in groups, however, can impact student benefits both positively and negatively. When using robotics in the classroom or for robotics projects after school, students often work in small groups or with partners. Group work in robotics has been recommended for numerous reasons such as limited availability of robotics kits (Eguchi, 2012; Mills et al., 2013; Yuen et al., 2014) in addition to the potential benefits that group work can provide students with such as learning, motivation, and social skills. Nevertheless, group dynamics can sometimes leave students with fewer opportunities to participate, resulting in less motivation to learn, or simply with a less enjoyable experience. When robotics activities are collaborative, however, there can be effects by grouping and pre-existing feelings towards group work (Huang & Huang, 2011; Taylor & Baek, 2019).

When robotics activities are viewed from the perspective of promoting computational thinking skills, factors leading to the students' success can be multiplied and combined with many psychological traits and attitudes- one such factor is a student's preferred interaction mode for learning, which is commonly referred to as a learning preference. Learning preferences are characterized as the way in which individuals approach different learning tasks (Cassidy, 2010). These preferences can provide structure but are also flexible enough to allow responsive or adaptive behavior. In simpler terms, a learning preference is the choice of one mode over another. Thus, these preferences can affect students' learning processes and/or perceived competences (Asfani et al., 2016). Lau and Yuen (2009) found that learning preferences were also related to coding performance where reflective learners outperformed active learners whereas verbal learners outperformed visual learners.

1.2 Robotics Curriculum Outcomes

Empirical research suggests that there is a link between enjoyment and basic needs in self-determination theory. For example, research by Tamborini et al. (2010) demonstrated that the satisfaction of autonomy, competence, and relatedness was not only related to enjoyment but also accounted for a considerable amount of variance. Based on their findings, Tamborini et al. broadly defined enjoyment as the satisfaction of intrinsic needs. Motivation and persistence are less likely to occur unless the activity is enjoyable (Lumby, 2011). Taken in sum, game enjoyment plays an essential role in achievement as it can lead players to learn and master the game (Sansone & Harackiewicz, 2000), while a lack of enjoyment or boredom can result in disengagement and/or failure in learning (Shernoff et al., 2003).

In robotics classrooms, students often achieve higher scores in problem solving (Barak & Zadok, 2009; Flowers & Gossett, 2002; Ortiz et al., 2015; Taylor & Baek, 2018; Turner & Hill, 2007). They also learn coding to promote their computational thinking skills. Chen et al. (2017) organized a robotics curriculum around specific topics that control basic movements, voice recognition, tactile sensors, and various other robotics-related skills and tasks. Children as young as four can learn computational thinking concepts and robotics with assembling and coding (Grover & Pea, 2013). Elkin et al. (2014) implemented a robotics curriculum which they integrated within a social science unit in a mixed-age Montessori classroom. This study is one example of using robotics uniquely as a tool to provide enriching learning experiences for children, while still achieving coding skills and developing computational thinking skills.

Perceived competence is an achievement belief that has also received considerable interest. Motivation studies have addressed competence from different perspectives, whether it is a desire to become competent, appear competent, feel competent, or avoid appearing incompetent to others (Urdu & Turner, 2005). In a study of working with robots, Tennent et al. (2017) found that worker's perceived competence increased when the robot interacted with a human. When coding for robotics, students are often provided with opportunities to develop their competence through iteration (repeated attempts), debugging (error resolution), as well as feedback. Thus, students can develop perceived competence when they attribute success and accomplishment to their own efforts and skills (Klimmt, 2003). Nevertheless, despite prior research showing numerous benefits related to CT, previous studies have not examined learning dynamics and/or traits comprehensively.

In order to investigate potentially multiple key factors thought to affect students' problem solving and computational thinking, this study draws on the cognitive evaluation theory (Deci & Ryan, 2000a, 2000b), Bandura's social cognitive theory (Cervone et al., 2001), and Harter's theory of competence motivation (Horn, 2014) to develop a conceptual model and research hypotheses. This study makes a contribution to computational thinking research through collaborative robotics by integrating key factors including learning style, feelings towards group work, perceived competence, learning motivation, intrinsic motivation, and problem solving, which have been studied in separation in previous studies. In collaborative robotics environments, interactions between these variables might manifest as a student's preferred mode of learning positively affecting their perceived competence in building and/or programming a robot, which in turn could make them more interested in taking on a leadership role in group work, etc. As a result, the interactions between these variables may also improve their computational thinking skills which are necessary for programming a robot to operate as desired. In simpler terms, determining if such relationships exist can provide a blueprint for student learning, curricular, and activity design in order to take advantage of any positive effects in the context of collaborative robotics. As such, the study was guided by the following research question:

RQ1: What factors influence computational thinking skills in elementary students' collaborative robotics?

2. Literature Review

One embedded theory in self-determination theory (SDT) (Ryan & Deci, 2000) is cognitive evaluation theory (CET) which suggests that there are events and conditions that promote a person's sense of competence and autonomy. This enhances their intrinsic motivation within a particular activity since lower feelings of autonomy or competence can reduce intrinsic motivation (Ryan et al., 2006). The basic tenets of CET is that autonomy supports changes in perceived competence which in turn changes in intrinsic motivation (Guay et al., 2001). In the context of play that includes robotics, intrinsic motivation is the core of education (Kaloti-Hallak et al., 2015). In fact, unlike many other activities, playing with robots is not only an intrinsically motivating activity, it also provides students with opportunities to satisfy certain psychological needs (Anwar et al., 2019). Further, it has also been proposed that individuals who are

intrinsically motivated enjoy doing an activity more when compared to those who are extrinsically motivated (Ryan & Deci, 2000). Using this line of reasoning, it is reasonable to suggest that students who engage in robotics activities also seek intrinsic satisfaction. And satisfaction can relate to one's perceived competence, which has often been used interchangeably with self-efficacy. According to Rodgers et al. (2014), both perceived competence and self-efficacy lead to goal pursuit, and promote learning, behavioral engagement, and skills. Perceived competence in SDT has been suggested to be closely related to task efficacy (Rodgers et al., 2014). That is to say, competence goes beyond an individual's ability to conduct a task to also include his or her personal assessment of task importance. Generally, self-efficacy has been suggested as a construct that deals mainly with the cognitive perceptions of competence (Hughes et al., 2011). In this study, we refer to the construct as perceived competence for consistency.

2.1 Individual Traits and Robotics

Students begin developing attitudes towards various subjects/content areas as early as elementary school (Kind, 2017). In order to promote computer science and coding as a possibility for all students, teaching these concepts at an early age allows students to gain an understanding of what robotics entails, as well as future possibilities (e.g., careers in robotics and ancillary fields in STEM) that might otherwise go unknown to them (Baek & Touati, 2017). Further, another complication of such a late-stage introduction of STEM fields is that later entering/switching career-fields can be prohibitively difficult due a lack of requisite background knowledge, motivation, or other ancillary skills (Lamb et al., 2015). The objective of educational robotics is to facilitate students' analytical skills and attitudes for operating robots, however, it also allows students to learn related STEM disciplines at an earlier age and in different ways. Educational robotics strengthens and supports students' cognitive skills, as well as develops their content knowledge through the creation, design, assembly, and operation of robots.

2.1.1 Learning Preferences, Feelings Towards Group Work and Enjoyment

Haddad and Kalaani (2015) claimed if the instruction of CT is tailored to fit student's learning preferences, then more students will perform better and grasp the concepts being taught more effectively. Generally, learning preferences could largely determine how efficient and/or effective the ways that learners choose to learn in ultimately are. For example, some learners may find learning in groups more helpful than learning individually, and learners who prefer group learning may have more positive feelings toward group work. Therefore, we hypothesized:

H1: Students' Learning Preferences will predict Feelings towards Group Work.

H2: Students' Learning Preferences will predict Perceived Competence.

2.1.2 Learning Preferences and Perceived Competence

Collaboration or group work has been widely defined as a particular form of interaction that engages participants to finish a task (Baek & Touati, 2017). Prior research has examined the relationship between collaboration and learning enjoyment in various contexts such as mathematics (Schukajlow et al., 2012) or robotics education (Somyürek, 2014). Other study findings have also suggested a positive relationship between these two variables. However, few studies have investigated the relationship between students' perceptions of collaboration and their learning enjoyment, or which have had positive results (Powell & Wimmer, 2016). Powell and Wimmer's (2016) study was conducted in a hands-on programming course with the aim of understanding the relationship between students' perceptions of the effectiveness of group work and learning enjoyment. Therefore, we hypothesized:

H3: Students' Feelings towards Group Work will predict Enjoyment.

2.2 Individual Traits and Computational Thinking Skills

2.2.1 Perceived Competence and Enjoyment

Competence, described as a need for challenge or feelings of effectance (Deci & Moller, 2005), is also a centerpiece in theory of competence motivation (Gaskin, 2013). This theory contends that successful attempts to master particular skills enhance one's perceived competence, which in turn, leads to increased intrinsic motivation. Individuals who are intrinsically motivated experience a natural desire to stay involved in the activity. While it has been highlighted that positive affect increases people's interest and enjoyment in moderately interesting activities (Isen & Reeve, 2005),

previous studies have shown that perceived competence and enjoyment are positively correlated. For instance, in a research study involving primary school children, positive and significant relationships were found between children's perceived competence and enjoyment in physical education (Carroll & Loumidis, 2001). A similar study by Fairclough (2003) also found that secondary students' perceived competence and enjoyment of physical activity were positively correlated. More closely related to the present study, Ryan et al. (2006) investigated undergraduate students' perceived in-game competence and autonomy in a commercially available platform game and found that these two psychological needs were significantly associated with game enjoyment. Therefore, we hypothesized:

H4: Students' Perceived Competence will predict Enjoyment.

2.2.2 Perceived Competence, Learning Motivation, and Intrinsic Motivation

The importance of intrinsic motivation for learning has been stressed and documented in existing literature (e.g., Grant, 2008; Patall et al., 2008). For instance, Patall et al. (2008) concluded that intrinsic motivation was strongly associated with high levels of effort and task performance. Students with greater levels of intrinsic motivation usually demonstrate stronger persistence to learn, perform more strongly, achieve higher scores in school, and are simply more productive (Grant, 2008).

Augustyniak et al. (2016) investigated medical students' levels of intrinsic motivation by administering the "Intrinsic Motivation Inventory" in which perceived competence was theorized to be one of the predictors and measures of intrinsic motivation. Brian et al. (2019) similarly examined the predictors of autonomous motivation in children and adolescents with visual impairments and found that perceived motor competence could significantly predict autonomous motivation. In another study, Li et al. (2005) investigated the relationship between dispositional ability conceptions, intrinsic motivation, perceived competence, experience, persistence, and performance involving 98 kinesiology college students, and found that perceived competence was one of the positive predictors of intrinsic motivation.

Several previous seminal studies have laid a solid foundation for the existence of the positive relationship between perceived competence and the development of motivation (e.g., Ryan & Deci, 2000a, 2000b). Based on these studies, we hypothesized that:

H5: Students' Perceived Competence will predict Learning Motivation.

H6: Students' Perceived Competence will predict Intrinsic Motivation.

Other studies have shown the importance of enjoyment as one of the key factors in determining learning outcomes (e.g., Blunsdon et al., 2003; Gomez et al., 2010). Similar to enjoyment, learning motivation is another critical factor in the learning process that has been extensively documented in extant literature. Its importance for learning outcomes has been found in several studies (e.g., Gomez et al., 2010; Tella, 2007). However, only a handful of studies have investigated the relationship between learning enjoyment and motivation, all of which suggested a positive relationship between these two important learning-related factors. For instance, Sisman and Kucuk (2019) investigated some pre-service teachers' perceptions and experiences in an educational robotics course and found that enjoyment and motivation were strongly correlated with each other. In another study closely related to the present study, Haapasalo and Samuels (2011) argued that the enjoyment by means of robotics in mathematics education could increase students' learning motivation. Thus, we hypothesized that:

H7: Students' Enjoyment will predict Learning Motivation.

H8: Students' Intrinsic Motivation will predict Learning Motivation.

As will be discussed in the following section in relation to H8, we also hypothesized:

H10: Students' Learning Motivation will predict Problem Solving.

H11: Students' Intrinsic Motivation will predict Problem Solving.

2.3. Enjoyment, Learning Motivation, Intrinsic Motivation, and Problem Solving

A large amount of research attention in education has focused on problem solving (Karatas & Erden, 2017; Song & Grabowski, 2006) since it is one of the most important learning skills students have to master. Baars et al. (2017) assumed autonomous motivation could facilitate the use of self-regulated learning skills, and Pekrun et al. (2002) found that intrinsic motivation is related to positive affection such as enjoyment, hope, and pride. Studies have shown that the development of students' problem-solving skills requires task persistence (Jögi & Kikas, 2016). Other studies have also suggested that students with higher levels of motivation are usually more persistent (e.g., Hardre & Reeve, 2003), indicating that motivated students are more likely to show better skills in solving problems. Therefore, we hypothesized:

H9: Students' Enjoyment will predict Problem Solving.

H10: Students' Learning Motivation will predict Problem Solving.

Quite a few studies have demonstrated the importance of intrinsic motivation for learning (e.g., Grant, 2008; Patall et al., 2008). For instance, Patall et al. (2008) found that intrinsic motivation was strongly associated with high levels of effort and task performance. Problem solving skills have been regarded as one of the most important learning skills for students given that they will likely be expected to solve ill-structured problems in everyday practice (Song & Grabowski, 2006). This is especially true in robotics education where students should find solutions to address certain design challenges via problem-solving. However, few studies have examined the relationship between intrinsic motivation and problem solving in the context of robotics education. Cho and Lin's (2010) study involving some scientifically talented students found that students' intrinsic motivation could predict their creative problem-solving skills. It is worth noting, however, that even though the Cho and Lin's (2010) study was conducted in mathematics and science rather than in robotics, the two contexts are in close proximity. Therefore, we hypothesized:

H11: Students' Intrinsic Motivation will predict Problem Solving.

2.4. Computational Thinking Skills and Problem Solving Skills

Barr et al. (2011) proposed that CT is a unique combination of cognitive skills which enable a novel form of problem-solving. This process is also closely tied to various tools (e.g., computers, robots), and can make aspects of problem-solving (i.e., testing, iteration) far more accessible to learners. While there is no consensus on the sub skills that definitively make up CT (or required at a minimum to comprise CT), definitions of CT include skills ranging from abstraction, systematic information processing, symbol systems and representation to algorithmic concepts such as flow and control (Grover & Pea, 2013). Since Wing's 2006 seminal paper, definitions and conceptualizations of CT have continued to evolve.

Problem solving in 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 of analysis, 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. To solve problems, students need to harness several important components (e.g., abstraction) in computational thinking skills. Therefore, we hypothesized:

H12: Students' Problem Solving will predict Computational Thinking.

3. Material and Methods

The purpose of this study was twofold: a) to investigate how certain factors- e.g., learning preferences, perceived competence, learning motivation, enjoyment, and intrinsic motivation- could predict problem solving, and b) to explore the relationship between problem solving and computational thinking skills. The hypothesized model was constructed based on 12 hypotheses. First, this study sought to explore learning preferences as a predictor of feeling towards group work and perceived competence. Since learning preferences represent differences in how students prefer to learn, the study assumed that participants with certain learning preferences would experience different feelings towards group work and perceived competence. Enjoyment was predicted to be linked to feelings towards group work and perceived competence. Perceived competence was assumed to affect enjoyment, learning motivation,

and intrinsic motivation. Additionally, enjoyment, learning motivation, and intrinsic motivation were considered as independent variables that predicted problem solving. Lastly, researchers introduced problem solving as a predictor of computational thinking skills in an attempt to explore whether there was a direct association between these two variables.

3.1 The Proposed Model

Based on the hypothesized relationships, the following model was constructed to illustrate the assumed interrelationships of the variables under investigation. First, learning preference was predicted to be positively related to perceived competence, which in turn, was assumed to predict enjoyment, learning motivation, and intrinsic motivation. Lastly, the proposed model predicts that computational thinking skills, as a final outcome, would directly be influenced by problem solving.

Figure 1

The Proposed Model

[Insert Figure 1]

H1: Students' Learning Preferences will predict Feelings towards Group Work.

H2: Students' Learning Preferences will predict Perceived Competence.

H3: Students' Feelings towards Group Work will predict Enjoyment.

H4: Students' Perceived Competence will predict Enjoyment.

H5: Students' Perceived Competence will predict Learning Motivation.

H6: Students' Perceived Competence will predict Intrinsic Motivation.

H7: Students' Enjoyment will predict Learning Motivation.

H8: Students' Intrinsic Motivation will predict Learning Motivation.

H9: Students' Enjoyment will predict Problem Solving.

H10: Students' Learning Motivation will predict Problem Solving.

H11: Students' Intrinsic Motivation will predict Problem Solving.

H12: Students' Problem Solving will predict Computational Thinking.

3.2 Participants

The participants in this study consisted of four 4th-grade classes and three 5th-grade classes at a suburban school in Idaho, USA. The students ranged in age from 9 to 11 years old. The distribution of students by grade-level and gender are presented in Table 1.

Table 1

[Insert Table 1]

The fourth and fifth grade students in the study attended an engineering class for one hour each week. Most of the students in the study have been participating in engineering classes since kindergarten. The engineering teacher has been teaching robotics since 2017, has been teaching in the engineering classroom since 2018, and also participated as a researcher in this study.

Prior to the start of the study, permission was secured through the school principal and district administrator. Approval consisted of an informed consent letter to parents for students in the robotics classes. The purpose of the study was shared with all students, emphasizing the process as a learning experience for the teacher and researchers rather than an assessment of the students' abilities. Identities of the students were protected with a code system that provided anonymity in the data set.

3.3 Procedures

The study consisted of three students per group for a total of 38 groups. Groups were randomly paired for a mix of males and females, and all student groups were assigned to work collaboratively for this study over a three-month period. Students worked with the same partner for the duration of each class where they shared a single robot. Each group's task was to work together to code a Botball robot using the C++ coding language and complete various coding challenges that became increasingly more difficult as students progressed through the curriculum. Student groups learned to code various motor, servo, and sensor functions.

In groups, participants first learned how to log off of the school's Wi-Fi network and to connect instead to the Botball robot via Wi-Fi. They then went on to learn how to write code for servo (arm and claw control) and sensor (e.g., light, sound) functions. Each student group then began programming the Botball robot with basic motor function (directional movement) codes. The pairs were challenged to code their robot to move forward using the following code: motor (0,100); motor (3,100); msleep (2000). The robots used ports 0 and 3 for the motors.

When the students completed this basic challenge, they were tasked with progressively more complex challenges. For instance, the next task was to code the robot to move forward and touch an aluminum can. Then students coded the robot to move forward, touch a can, and return to its starting position. Student groups then used motor functions to move the Botball robot around the can which increased in difficulty from moving in straight lines to moving in the shape of a figure 8 around two cans. After completing these basic motor function challenges, they progressed to using servos. After the student groups completed servo challenges, they were introduced to sensors. Although the Botball robot has five sensors, students were only taught functions for the Infrared (IR) sensor. The purpose of the IR sensor was to complete a challenge where the robot needed to follow a moving black line. Not all students were able to reach this challenge.

A common component of each coding challenge was compiling code. If the coding was incorrect, an error message would appear. Students then went back through their code to find errors and correct them. As the students improved their coding skills, student groups took turns helping each other code as the challenges became more difficult. This included using servo functions for the robot's arm and claw, as well as being taught additional C++ functions over the course of the three-month unit.

3.4 Measures of Psychometric Properties and Data Collection

To measure the hypothesized psychometric properties, the following questionnaires for this study were used: 1) Learning Motivation Assessment for Computer Science; 2) Learning Style Inventory; 3) Intrinsic Motivation Inventory; and the 4) Enjoyment, Perceived Competence, Problem Solving Inventory, and Computational Thinking Test. The engineering teacher (who is one of the researchers) administered the surveys before the intervention with the exception of the Problem Solving Inventory and Computational Thinking Test, which were administered afterwards.

3.4.1 Learning Preference Inventory

This study adopted the learning style inventory developed by Duff (2004). This scale consists of two constructs: Concreteness versus abstractness and Reflection versus action. The first construct has seven items. Each item is a Likert scale with six points to create a range from concreteness to abstractness. The higher the score becomes, the more abstract it is. The second construct, Reflection versus action, has seven Likert items on a six-point scale. If the score gets higher, it moves from reflection to action. The scale with two constructs is positively and strongly correlated with academic achievement showing that the most effective learners are likely to emphasize abstract conceptualization and active experimentation. Duff (2004) concluded that the scale of fourteen items is both a valid and useful measure of learning preference. In terms of terminology, the authors recognize the lack of empirical evidence for "learning

styles” in the literature (see Kirschner, 2017); we point out however that the terminology (i.e., styles) here is reproduced as originally written by Duff. Throughout this paper, we have deliberately used the term learning preference instead to describe a mode of interaction that can be chosen.

3.4.2 Feeling Towards Group Work

Attitude towards group work was measured by the "feelings towards group work scale" developed by Cantwell and Andrews (2002). The questionnaire consists of 22 Likert items on a five-point scale with 1 indicating “not at all true of me” to 5 being “very true of me”. Five areas of group work make up the instrument: 1) a general liking of groups (I enjoy working within a group); 2) group composition (I prefer working within a group of the same sex); 3) self-efficacy in groups (I feel more accepted by others after working within a group); 4) group dynamics (I usually make a strong personal contribution to group work); and 5) group organization (Groups should organize themselves so that the work is divided evenly). The three domains of feelings relevant to group work are ‘Preference for individual work’, ‘Preference for group work’ and ‘Discomfort in group work’.

Seven items were included in the scale derived from ‘Preference for individual learning’. These items solicit perceptions of strong dissatisfaction with group work, including feelings of being let down by group members, seeing group work as confusing and less effective than individual learning, preferring to work alone, and expressing a lack of involvement and enjoyment in group situations. The reliability estimate for the seven-item scale (Cronbach’s alpha) was .78.

Eight items were included in the scale derived from ‘Preference for group learning’. These items are related to a strong sense of commitment to and fulfilment in group learning situations - a sense of enhanced understanding, enjoyment in sharing the responsibility for the workload and credit for group achievements, a greater sense of personal contribution to learning combined with a preference for choice in group membership. The reliability estimate for the eight-item scale was .71.

Four items were included in the scale derived from ‘Discomfort in group learning’. These items measure a sense of discomfort when learning in a group context - feelings of nervousness and an inability to relax, a fear of asking for help, and difficulty in understanding the nature of group tasks. The reliability estimate for the four-item scale was .60.

3.4.3 Perceived Competence

Perceived competence was measured using the perceived competence subscale of the Intrinsic Motivation Inventory (IMI) which has been used in previous studies related to intrinsic motivation (see Ryan & Deci, 2000b). This measure includes six items, such as “I think I am pretty good at this activity” and one negative item, “This was an activity that I couldn’t do very well.” Each item was assessed using a seven-point Likert scale from 1 (strongly disagree) to 7 (strongly agree). The scale has been shown to be reliable and valid because the Cronbach alpha was reported as high as .80 -.94 (Choi et al., 2009).

3.4.4 Enjoyment

Enjoyment was measured using an instrument developed by Fang et al. (2010). The 11-item scale measures three dimensions of computer game enjoyment: affective ($\alpha = .73$), cognitive ($\alpha = .77$), and behavioral reactions ($\alpha = .83$). The instrument’s affective dimension contains five items, four of which are reversed items focused on negative affect during gameplay (e.g., I feel unhappy/I feel exhausted/ I feel worried/I feel miserable then playing this game). Three items on behavior aim to assess the player’s viewing intent and behaviors, while another three items on cognition focus on judgments of characters’ actions during the gameplay (Fang et al., 2010).

3.4.5 Learning Motivation Assessment for Computer Science

This questionnaire developed by Law et al. (2010) examined the key motivating factors affecting students’ learning in computer coding courses. This test consisted of intrinsic and extrinsic factors spread over 19 items; intrinsic factors focus on the individual rather than the environmental setting. The factors generally include individual attitude and expectation, and challenging goals (including emotions). Extrinsic factors stem from the environment external to the learning. The six factors affecting student motivation towards computer coding are: ‘individual attitude and expectation (four items)’, ‘challenging goals (three items)’, ‘clear direction (two items)’, ‘reward and recognition

(three items)', 'punishment (two items)', and 'social pressure and competition (four items)'. The value of factor loadings verified the validity of all constructs except one- items of 'Punishment'. The discriminant validity of each construct was checked using a multi-trait matrix and ranges .66 to .89, showing high validity coefficients of the individual constructs. The Cronbach's alpha value of this test was .95 (a high level of internal reliability).

3.4.6 Intrinsic Motivation

The intrinsic motivation scale used in this study was adopted from Hanus and Fox (2015). It comprises seven items within four subscales: interest/enjoyment, perceived choice, perceived competence, and pressure/tension. Items on the IMI are measured on a five-point Likert scale from 1 (strongly disagree) to 5 (strongly agree). Additionally, a total of 10 negative or reversed items are present in all four subcategories: interest/enjoyment (two reversed items), perceived choice (five reversed items), perceived competence (one reversed item), and pressure/tension (two reversed items). The IMI instrument originally contains 45 items and assesses users' experiences on seven dimensions: interest/enjoyment, perceived/competence, effort/importance, pressure/tension, perceived choice, value/usefulness, and relatedness. The Cronbach alpha of the 22 item scale was reported as .86 by Hanus and Fox (2015).

3.4.7 Problem Solving Inventory

The Problem-Solving Inventory (PSI) in the study of Kourmoussi et al. (2016) was adopted to measure perceptions of one's problem-solving ability, as well as behaviors and attitudes associated with problem-solving styles. It yields three underlying dimensions, Problem-Solving Confidence, Approach-Avoidance Style, and Personal Control. Not only are these factors intercorrelated, but they have been proven to be distinct dimensions. The first factor, Problem-Solving Confidence, consisted of 11 items. The second factor, Approach Avoidance Style, consisted of 16 items and the third factor, Personal Control, consisted of five items. The test-retest reliabilities were as follows: Problem-Solving Confidence, $r = .85$; Approach Avoidance Style, $r = .88$; Personal Control, $r = .83$; and the total inventory, $r = .8$. Micoogullari and Ekmekci (2018) reported that Cronbach's alpha (α) reliability indices for the respective subscales were as follows: Problem Solving Confidence (PSC) (.69), Approach and Avoidance (AA) (.73), and Personal Control (PC) (.68) with a Turkish population. Huang and Flores (2011) reported that the Cronbach's alpha coefficients were .86 for PSI total, .77 for PSC, .76 for AAS, .66 for PC with Mexican-Americans. Kourmoussi et al. (2016) reported a Cronbach's alpha of 0.90 for Problem Solving Confidence, 0.89 for Approach-Avoidance Style, 0.79 for Personal Control and 0.91 for the total PSI score. Thus, this inventory is considered to be a valid and reliable measurement.

3.4.8 Computational Thinking Skill

The Computational Thinking Test (CT-test) was first developed by Marcos Román González as a 40-item test but was later refined to 28-items (CT-test 2.0). The CT-test can be used as a pre-test to measure students' initial CT levels and to detect special skills or special needs in coding (Román-González, 2015). Another aim of the CT-test according to Román-González et al. (2017) is to assess students' (grades K-5 and K-10) development level in CT.

The CT-test assesses the user's computational thinking levels on five dimensions: computational concept addressed, environment-interface of the item, answer alternatives style, existence or non-existence of nesting, and required tasks (Román-González et al., 2017). Regarding the first dimension, the test comprises items that address computational concepts such as 1) basic directions and sequences (four items); 2) loops-repeat times (four items); 3) loops-repeat until (four items); 4) if-simple conditional (four items); 5) if/else-complex conditionals (four items); 6) while conditional (four items); and 7) simple functions (four items). All these items are arranged in order of increasing difficulty. For the second dimension, there are 23 items presented in 'The Maze' environment-interface while five items are in 'The Canvas' interface. Both interfaces are commonly used for learning how to code (Román-González et al., 2017). Another commonly used feature for learning how to code is the use of visual arrows and visual blocks which are included as answer alternatives style in the third dimension (eight items use visual arrows and 20 items use visual blocks). Regarding the fourth and the fifth dimensions, Román-González et al. (2017) pointed out 29 items where nesting of computational concepts exists and 11 items where these concepts are non-existent. The required task dimension, however, is more focused on cognitive tasks which include sequencing, a set of commands, completion, and debugging. These tasks are fundamental in solving problems that relate to CT. As for the reliability of the CT-test, Román-González et al., (2017) reported a good internal consistency of the 28 items ($\alpha=0.793$).

4. Results

The hypothesized model predicted enjoyment, learning motivation, and intrinsic motivation as predictors of problem solving. The model also hypothesized a possible correlation between learning preferences and feeling towards group work, and perceived competence while perceived competence was assumed to predict enjoyment, learning motivation, and intrinsic motivation as illustrated in Figure 2.

4.1. The Predicted Model

Figure 2

The Predicted Model

[Insert Figure 2]

4.2 Correlation Matrix

A Pearson Correlation analysis was conducted to investigate the relationships between the variables in the predicted model in Table 2. Results revealed that learning preference was not significantly correlated with feeling towards group work (correlation coefficient = -0.058, $p = 0.406$); thus H1 was not supported. However, learning preference was found to have a significant relationship with perceived competence (correlation coefficient = 0.251, $p < 0.01$). Furthermore, correlation analysis results revealed that intrinsic motivation was not significantly correlated with learning motivation (correlation coefficient = 0.003, $p = 0.965$), nor with problem solving (correlation coefficient = -0.005, $p = 0.941$). Thus, H8 and H11 were not supported. As predicted, correlation results showed a significant relationship between perceived competence and enjoyment (correlation coefficient = 0.379, $p < 0.01$), and learning motivation (correlation coefficient = 0.358, $p < 0.01$), and intrinsic motivation (correlation coefficient = 0.150, $p < 0.05$). In addition, correlation results showed a significant relationship between enjoyment and learning motivation (correlation coefficient = 0.283, $p < 0.01$). Lastly, the results of our analysis showed a significant relationship between enjoyment and problem solving (correlation coefficient = 0.335, $p < 0.01$), and between learning motivation and problem solving (correlation coefficient = 0.335, $p < 0.01$). A significant link was also found between problem solving and computational thinking skills (correlation coefficient = 0.441, $p < 0.01$).

Table 2

[Insert Table 2]

4.3 Multiple Regression

A linear regression analysis was conducted to test whether all of the hypothesized predictions were supported or not in Table 3. The results of the regression indicated the learning preference was a significant predictor of perceived competence ($R^2 = .063$, $F(1, 206) = 13.881$, $p < .01$). Therefore H2, which predicted that more abstract and action-based students would be higher in their perceived competence, was supported. Feelings towards group work ($\beta = .260$, $p < .01$) and perceived competence ($\beta = .358$, $p < .01$) were significant predictors of enjoyment ($R^2 = .211$, $F(2, 205) = 14.243$, $p < .01$). These results supported H3 and H4. That is, students who felt more positive towards group work and perceived more competence were higher in their enjoyment. Perceived competence ($\beta = .292$, $p < .01$) and enjoyment ($\beta = .173$, $p < .05$) were significant predictors of learning motivation ($R^2 = .154$, $F(2, 205) = 18.594$, $p < .01$). Thus, H5 and H7 were supported. This means that students would be more motivated to learn when they perceive competence and enjoyment. Perceived competence also predicted intrinsic motivation ($R^2 = .023$, $F(1, 206) = 4.752$, $p < .05$), supporting H6. This means that the more students perceive competence, the more intrinsically motivated they are. Enjoyment ($\beta = .280$, $p < .01$) and learning motivation ($\beta = .199$, $p < .01$) were significant predictors of problem solving ($R^2 = .067$, $F(2, 205) = 7.308$, $p < .01$) which supported H9 and H10. That is, students who were higher in enjoyment and learning motivation would also be higher in problem solving. Lastly, problem solving was a significant predictor of computational thinking skills ($R^2 = .361$, $F(1, 206) = 116.406$, $p < .01$, $\beta = .181$, $p < .01$) and supported H12, meaning the higher students scored in problem solving, the higher their computational thinking skills.

Table 3

[Insert Table 3]

Another regression analysis was conducted to investigate the relationships between the variables that were significantly correlated in Table 4. First, a regression analysis was conducted on feelings towards group work as a predictor of learning motivation. Table 4 shows that feelings towards group work was a significant predictor of learning motivation ($R^2 = 0.101$, $F [1, 206] = 23.220$, $p < 0.01$) with the model explaining 9.7% of the variance. Second, a multiple regression test was conducted to explore how problem solving can be predicted by the variables which had positive correlations with problem solving in the model. As such, enjoyment, learning motivation, perceived competence, and learning preference were entered as predictors of problem solving. The overall model was significant ($R^2 = 0.116$, $F [4, 203] = 6.661$, $p < 0.01$) and results showed that problem solving was significantly predicted by two variables: learning preference ($\beta = 0.178$, $p < 0.01$) and learning motivation towards computer science ($\beta = .181$, $p < 0.05$). Third, a multiple regression test was conducted to explore how computational thinking skills can be predicted by the three variables having positive correlations with computational thinking skills. This overall model was also significant ($R^2 = 0.076$, $F [3, 204] = 5.627$, $p < 0.01$) and results showed that perceived competence and learning motivation towards computer science were not significant predictors, while problem solving ($\beta = .176$, $p < 0.01$) was.

Table 4

[Insert Table 4]

4.3 The Revised Model

Based on the data analysis of the predicted relationships, we constructed a revised model which also includes the un-hypothesized relationships supported by both correlation and regression analysis results. This is illustrated in Figure 3. The revised model excludes learning preference and intrinsic motivation since the analysis showed no significant relationships between problem solving and the other variables in the model.

Figure 3

The Revised Model

[Insert Figure 3]

5. Discussion

The hypothesized model considered the effects of learning preferences on feelings towards group work, perceived competence, enjoyment, learning motivation, intrinsic motivation, and problem solving and we found that relationships were both supported and not supported. The final revised model (Figure 3) shows the nuance between these effects and we interpret the relationships from the perspective of them being one-directional. For instance, although the findings do not provide evidence for learning preferences as a direct predictor of computational thinking skills which is in line with prior research (e.g., Falvo & Pastore, 2005), learning preference was found to have a significant relationship with, and be a predictor of, perceived competence. In turn, perceived competence and feelings towards the group surfaced as determinants of computational thinking skills with links to enjoyment and learning motivation, as well as problem solving. Problem solving was found to be significantly predicted by two variables: learning preference and learning motivation towards computer science. Thus while learning preference may not be a direct determinant of computational thinking skills in our revised model, there is still value in its consideration of a learning environment as a whole.

The implication of these results suggests that multiple psychometric properties need to be considered in collaborative robotics learning environments in order to foster the best possible outcomes as certain traits can be sequentially influential even if not directly so. In practical terms, understanding the interconnectedness of traits such as learning preference on perceived competence, and subsequently perceived competence and intrinsic motivation, etc., can assist in the design of curriculum and learning activities. Based on the revised model, we suggest that effort should be made to develop perceived competence and self-confidence in elementary school students so that they are primed psychologically for collaborative learning environments where computational thinking skills are the desired outcomes.

Similarly, since the collaborative nature of such a learning environment requires group work and interaction, elementary students should have routine exposure to, and positive reinforcement of group work in educational settings. We found that feelings towards group work was a significant predictor of learning motivation, underscoring the importance of social learning and the potential it has to motivate students to learn. Chen and Chang (2018) similarly found positive relationships with STEM-integrated robotics and students' subsequent interest in STEM in general and with robotics specifically. In short, clear factors and determinants are present in collaborative robotics that can be targeted with educational interventions from a holistic point of view.

6. Conclusion

This study sheds insight into the multiple factors that influence computational thinking skills in collaborative robotics environments. This study is one of the first to investigate the role of learning preferences and their effects on computational thinking skills. While learning preferences as a determinant for computational thinking skills was not supported, this study presents a revised factor model where five of the hypothesized relationships (perceived competence, feelings towards group work, enjoyment, learning motivation, problem solving) were supported in having significant relationships on computational thinking skills. Nevertheless like any study, the findings should be considered judiciously since there are limitations that require consideration when considering how these results may apply to other populations or contexts. First, the total number of participants in this population is relatively small which limits statistical power to some degree. Second, the socio cultural context of participants (Idaho, USA) may limit the broader applicability of findings when generalizing the results to students of different backgrounds in other locations. These factors, nonetheless, have important implications for curriculum, activity, and learning environment design where collaboration, social learning, and perceived competence are likely key to student success. Future research can investigate ways of developing these factors in students for the most effective curriculum and activity design. Further in this study, the correlations were interpreted as one variable being the predictor of the others, though these interactions and potential two directional correlations could be future studies. This will be added to the section on future research in the conclusion. In turn, CT development may be strengthened in learners, promoting robotics, CT, and STEM ultimately as potential areas of study and career paths.

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Figures and Tables

Figure 1

The Proposed Model

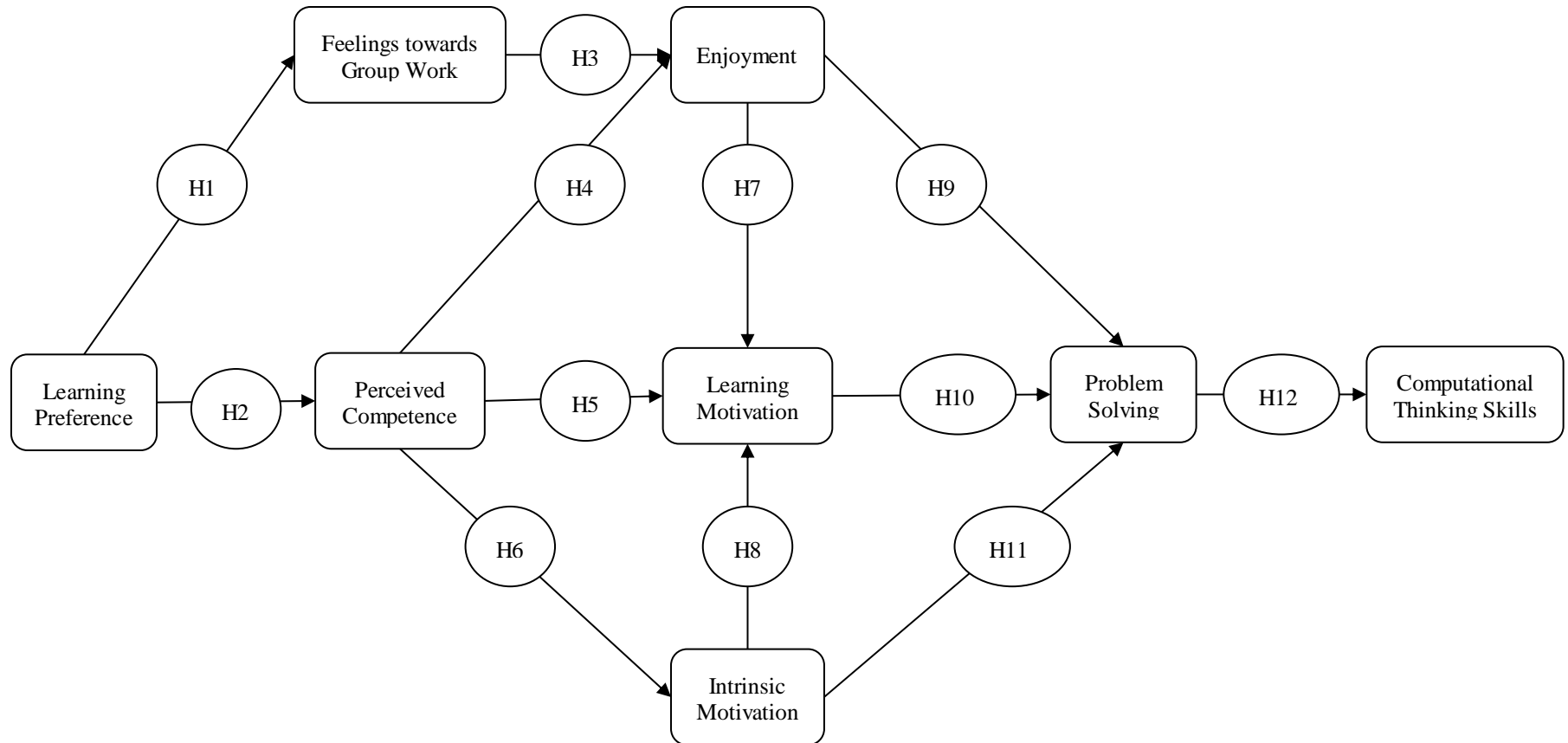


Figure 2

The Predicted Model

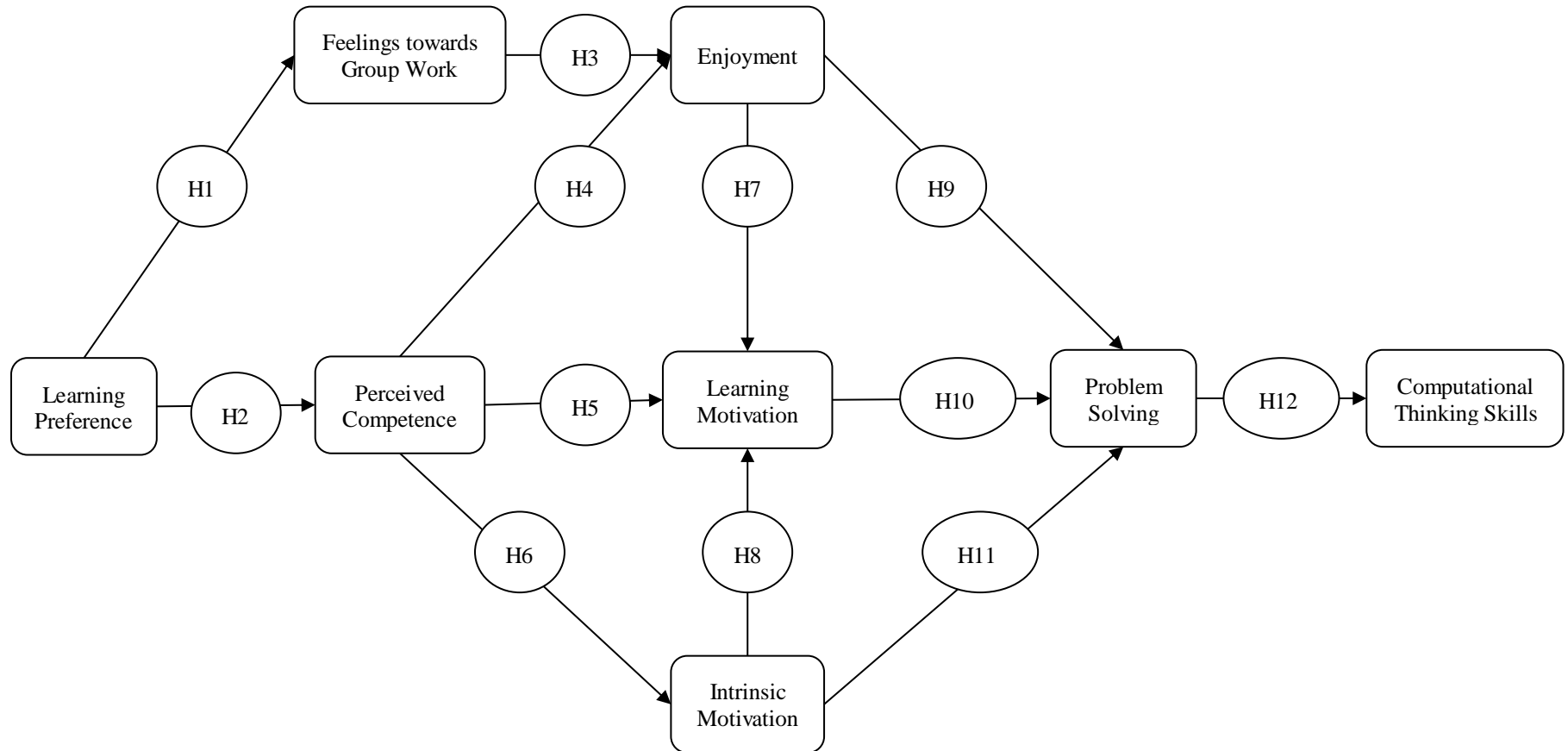
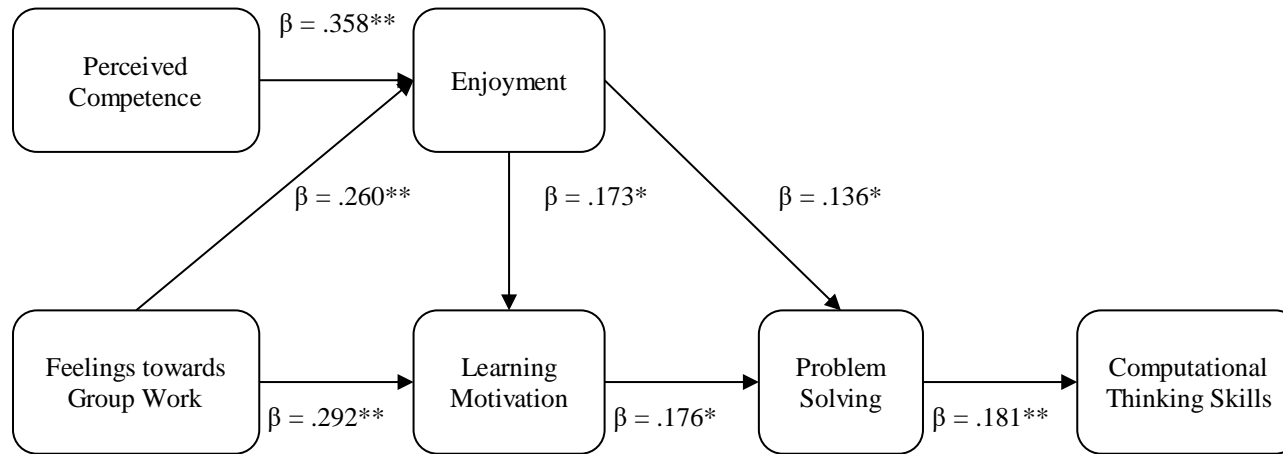


Figure 3

The Revised Model



* $p < .05$, ** $p < .01$

Table 1

Cross-tab of Participant Gender and Grade Level

Grade-level x Gender	Male	Female
4th Grade (4 classes)	45 (48%)	49 (52%)
5th Grade (3 classes)	49 (43%)	65 (57%)
7 Classes Total (n=208)	94 (45%)	114 (55%)

Table 2

Correlation Matrix

	1	2	3	4	5	6	7	8
1. Learning Preference	-	-.058	.251**	.087	.027	.030	.234**	.092
2. Feelings towards Group Work	-.058	-	.083	.289**	.318**	.100	.026	-.039
3. Perceived Competence	.251**	.083	-	.379**	.358**	.150*	.206**	.182**
4. Enjoyment	.087	.289**	.379**	-	.283**	-.124	.195**	.128
5. Learning Motivation Towards CS	.027	.318**	.358**	.283**	-	.003	.217**	.181**
6. Intrinsic Motivation	.030	.100	.150*	-.124	.003	-	-.005	.059
7. Problem Solving	.234**	.026	.206**	.195**	.217**	-.005	-	.601**
8. Computational Thinking	.092	-.039	.182**	.128	.181**	.059	.601**	-

Note: * $p < .05$, two-tailed. ** $p < 0.01$, two-tailed. N=208, CS=Computer Science

Table 3

<i>Regression Analysis</i>				
<i>Predictor of Perceived Competence</i>	B	SE B	β	<i>t</i>
Learning Preference	.091	.024	.251**	3.726
R ²		.063		
F		13.881**		
<i>Predictors of Enjoyment</i>				
Feelings towards Group Work	.176	.042	.260**	4.171
Perceived Competence	.443	.077	.358**	5.743
R ²		.211		
F		27.355**		
<i>Predictors of Learning Motivation</i>				
Perceived Competence	.619	.147	.292**	4.212
Enjoyment	.294	.119	.173*	2.484
R ²		.154		
F		18.594**		
<i>Predictor of Intrinsic Motivation</i>				
Perceived Competence	.155	.071	.150*	2.180
R ²		.023		
F		4.752*		
<i>Predictors of Problem Solving</i>				
Enjoyment	.280	.136	.145*	2.062
Learning Motivation (CS)	.199	.080	.176*	2.503
R ²		.067		
F		7.308**		
<i>Predictor of Computational Thinking Skills</i>				
Problem Solving	.181	.017	.601**	10.789
R ²		.361		
F		116.406**		

Note: * $p < .05$, ** $p < .01$, N=208, CS=Computer Science

**

Table 4

Regression Analysis

<i>Predictor of Learning Motivation</i>	B	SE B	β	<i>t</i>
Feelings towards Group Work	.367	.076	.318**	4.819
R ²		.101		
F		23.220**		
<i>Predictors of Problem Solving</i>				
Learning Preference	.189	.080	.178**	2.032
Learning Motivation (CS)	.192	.083	.181*	2.403
R ²		.116		
F		6.661**		
<i>Predictor of Computational Thinking Skills</i>				
Problem Solving	.191	.015	.176**	2.080
R ²		.023		
F		5.627**		

Note: * $p < .05$, ** $p < .01$, N=208, CS=Computer Science

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