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Modeling Elementary Students' Computer Science Outcomes With In-School and Out-of-School Factors

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MODELING ELEMENTARY STUDENTS' COMPUTER SCIENCE OUTCOMES WITH IN-SCHOOL AND OUT-OF-SCHOOL FACTORS

by

Umar Shehzad

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ABSTRACT

Modeling Elementary Students' Computer Science Outcomes with In-School and Out-of-School Factors

by

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Utah State University, 2023

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This multiple paper dissertation investigates factors that reside within and outside of school—specifically, students' perceptions of classroom instruction and perceived parental support—that influence Grade 5 students' attitudes towards learning computer science (CS) in educational settings.

The first paper examines how students' (n = 170) perception of parental support influences their interest and self-efficacy in computer programming. It also investigates how involving families in CS activities by sending a CS-themed board game home influences students' interest. Students were surveyed before and after the unit's implementations and the relationship in the data is explored using structural equation modeling (SEM). Results show that perceptions of parental support measured on the pre-survey are significant predictors of self-efficacy (Std $\beta = 0.37$, SE = 0.010, $p < .001$) and interest in computer programming (Std $= 0.328$, SE = 0.134, $p < .003$) as measured on the post-survey. Secondly, the effect of parental support (Std $\beta = 0.132$, 95 % CI [0.039, 0.399], 99% CI [0.017, 0.542]) on students' interest is mediated by whether they took the CS board game home.

The second paper focuses on developing reliable measurements of students' (N=1564) perceptions of mathematics and CS-integrated instructional activities using a kind of practical measure called exit tickets. Exit tickets are used by students to provide immediate feedback on their experiences after instructional activities. Building on prior research on validity arguments for practical measures, this paper uses structural equation modeling (SEM) to examine whether students' reported perceptions as measured by exit tickets predicted their affective outcomes in self-efficacy, interest, and CS identity as measured by summative pre/post-surveys. Results show that perceived enjoyment significantly predicts post-survey measurements of self-efficacy (Std = 0.34, SE = 0.14, p = .001), interest (Std β = 1.98, SE = 1.53, p = .05), and CS identity (Std β = 0.41, SE = 0.15, p $<$ .001). Perceived ease also significantly predicts post-survey measurement of self-efficacy (Std β = 0.26, SE = 0.16, p = .013) while controlling for the pre-survey measurement. The remaining correlations between exit ticket measures and post-survey measures are not significant. The findings suggest that student exit tickets are effective tools to gauge engagement and correlate with their affective responses. Specifically, students who report finding the lesson enjoyable and easy are more likely to express a positive attitude toward CS instructional activities. This suggests that brief exit ticket surveys could serve as effective indicators of student engagement, potentially replacing longer surveys.

The insights from this dissertation offer insights vital for creating effective instructional methods, curricula, and family engagement strategies. These strategies can cultivate a positive attitude toward CS, reshaping young learners' beliefs and countering computing stereotypes and thereby supporting broader participation in computing education.

(71 pages)

PUBLIC ABSTRACT

Modeling Elementary Students' Computer Science Outcomes with In-School and Out-of-School Factors

Umar Shehzad

This two-paper dissertation explores factors influencing the attitudes of Grade 5 students who are learning computer science (CS) in schools. It statistically examines the effects of out and in-school factors on students' attitudes toward computing. The first paper of this dissertation examines the influence of parental support as perceived by the students on their interest and their self-assessed ability to engage in computer programming, thus underscoring the crucial role of parental support on learners' attitudes. It also investigates how involving families in CS activities by sending a CS-themed board game influences students' interest. The study finds that perceptions of parental support positively influence students' interest and their self-assessed ability to engage in computer programming. It also finds that sending CS artifacts home can significantly mediate the influence of parental support on students' interest in programming. The second paper focuses on developing reliable measurements of students' perceptions of mathematics and CS-integrated instructional activities. These measures are called exit tickets and are used to collect immediate student responses relating to their experiences after instructional activities. Building on prior research, this paper statistically examines whether students' exit ticket responses predict self-assessed ability, interest, and identification with CS. Results show that perceived enjoyment reported on exit tickets significantly predicts self-assessed ability, interest, and identification with CS. Perceived ease also significantly predicts self-assessed ability. The remaining correlations between exit ticket measures and post-survey measures are not significant. The findings suggest that student exit tickets are effective tools to gauge engagement and correlate with student attitudes toward computing. Specifically, students who report

finding the lesson enjoyable and easy are more likely to express a positive attitude toward programming. This suggests that brief exit ticket surveys could serve as effective indicators of student engagement, potentially replacing longer surveys. Identifying the factors that shape students' attitudes toward CS provides valuable insights into the design of instructional methods, curricula, and family engagement strategies. Such initiatives can foster a positive attitude among young learners towards CS, significantly contributing to shaping their beliefs and challenging stereotypes associated with computing.

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CHAPTER 1

INTRODUCTION TO MULTIPLE PAPER DISSERTATION

This multiple paper dissertation explores factors influencing the attitudes of Grade 5 students towards learning computer science (CS) within formal educational settings of schools. With the continuous growth of the digital age, the demand for CS skills is also increasing, highlighting the significance of this research. Given the scarcity of attention paid to elementary level CS education in existing research, this investigation seeks to fill a crucial void. By concentrating on this key stage of a child's education, this study's objective is to guide educational strategies that might enhance student learning in CS. The insights derived from identifying factors that shape students' attitudes towards CS will be instrumental in informing the design of instructional methods, curricula, and family engagement strategies. Such initiatives can foster a positive attitude among young learners towards CS, contributing significantly to shaping their beliefs and challenging stereotypes associated with computing, which often take root early in childhood.

The factors influencing students' attitudes towards computing can be divided into two broad categories: out-of-school and in-school factors. Out-of-school factors are those predictors residing outside the school environment that affect students' attitudes towards computing. In first paper of this multiple paper dissertation, I focus on the support that students receive from their parents in pursuing computer programming. Understanding the interrelationship of parental support and the different dimensions of students' attitudes, such as their self-efficacy and interest in computer programming, can provide insights into the challenges associated with elementary level computing education.

On the other hand, in-school factors are associated with instructional activities carried out within a school setting. Students' perceptions of these instructional activities can significantly shape their attitudes towards computing as a whole. However, accurately capturing students' "in-the-moment" perceptions of these activities presents a notable challenge, which the second paper of this multiple paper dissertation addresses.

Problem Statement

Despite the growing importance of CS skills, research focused on elementary level CS education is limited. This gap in research limits our understanding of factors influencing student outcomes at this crucial educational stage, especially the effects of factors like instructional practices and family support. Such factors have a significant impact on shaping student engagement and performance, especially during these formative years of formal education.

Unaddressed, this knowledge gap can adversely affect the elementary CS education which can cultivate foundational CS skills and interests. This can result in lower levels of CS literacy and engagement among students as they progress to higher education levels, and ultimately impact the readiness of future professionals for an increasingly digital world. Thus, there is an urgent need to analyze these factors that can provide valuable insights for improving CS education.

This multiple paper dissertation seeks to address two primary challenges associated with understanding the effects of in-school factors (students' perceptions related to instruction) and out-of-school factors (students' perceived parental support) on students' attitudes towards computing. Firstly, it aims to comprehend the mechanisms through which different dimensions of students' attitudes towards computing are related to each other. Secondly, it seeks to identify predictors of constructs associated with students' attitudes towards computing, allowing educators to adapt instructional strategies resulting in improved student attitudes towards programming.

Goals and Objectives

The focus of this research is to investigate factors determining students' attitudes towards computer programming. Key to this investigation are the constructs of self-efficacy, CS identity, and interest, used to represent attitudes towards computing. The first paper of this dissertation delves into the influence of perceived parental support on students' interest in and self-efficacy for computer programming, highlighting the vital role of external influences on learners' attitudes. It further examines if involving families in CS learning mediates the effect of parental support on students' interest in programming.

The second paper of this dissertation addresses the challenge of reliably measuring students' perceptions related to instructional activities. Building on previous work done on the validity of practical measures (Bryk et al., 2015; Kosovich et al., 2015; Penuel et al., 2018), it also examines the effect of students' perceptions of the instructional activities on their attitudes towards computing.

Significance of Study

The significance of this research lies in its potential to reshape our understanding of computer science (CS) education at the elementary level, a domain that has historically been under-researched (Shehzad, Recker, et al., 2023). As we move further into the digital age, the demand for CS skills continues to escalate. This increasing demand places a spotlight on the importance of cultivating a robust foundation of CS skills and interests from an early age.

In particular, there is a notable lack of understanding surrounding the role of many factors that shape students' attitudes towards computing. This study is significant in that it seeks to address these knowledge gaps, exploring the impact of both instructional practices and family support on students' attitudes towards CS. This will allow educators to adapt their instructional strategies accordingly, ultimately leading to improved student attitudes towards programming.

Moreover, the findings from this research could inform the development of early interventions aimed at diminishing common stereotypes and misconceptions about CS. Given that beliefs and stereotypes around learning form early during childhood, these interventions could be pivotal in fostering a positive attitude towards CS among young learners, laying the groundwork for a more comprehensive and effective CS learning trajectory in later years.

Definition of Terms

- *Mother's support:* A student's perception of the support that they get from their mother in learning computer science.
- *Father's support:* A student's perception of the support that they get from their father in learning computer science.
- *Parental support:* A combined effect of mother's support and father's support. A student's perception of the support that they get from their parents in learning computer science.
- *Self-efficacy:* Self-efficacy is an individual's belief in their ability to perform a task, playing a critical role in human agency (Bandura, 1977).
- *Programming interest:* According to model of interest development of Hidi and Renninger (2006), interest evolves through four sequential and distinct stages. However, the differentiation of these stages in practice has proven challenging due to the lack of precise measurements (Clarke-Midura et al., 2020; Renninger & Hidi, 2011). Therefore, Clarke-Midura et al. (2019) adapted measures widely used in the motivation literature to measure students' interest in and enjoyment of computer programming, which is what we used in this study.
- *CS Identity:* Survey items pose questions to ascertain the extent to which students identify with computer science.
- *Practical measures:* Focus on actionable aspects of learning and teaching practices. They constitute indicators derived from everyday classroom activities and are closely tied to instruction and learning processes. Such measures can range from informal teacher observations to brief student surveys and quizzes (Penuel et al., 2018).

- *Exit tickets:* Are brief surveys administered at the end of each instructional unit (Morozov et al., 2014). They serve to inform educators' instructional practices (Penuel et al., 2018) and can be repeated to guide recurring practices. They may also be used to predict significant outcomes (Yeager et al., 2013).

- *Outcome measures:* Examine end results, offering a summative perspective. These measures track changes over time, offering a longitudinal understanding of cognitive, affective, or behavioral constructs related to computing education.

- *Enjoyment:* Is a feeling that underlies the value that students find in a task. The present research assessed enjoyment by asking students to rate their agreement with the statement: "I enjoyed programming in today's class."

- *Perceived ease:* Is an individual's perception of easiness or difficulty of a task. Thus, perceived difficulty represents the same construct but its effect is the opposite of perceived ease.

- *Creating connections between computer science and math:* Students' perceptions of the connections between these two subject areas.

- *Working theory:* Is a visual representation of the hypothesized relationships between cognitive, behavioral, or affective constructs. In this research, a working theory represented the relationships between predictors and their outcomes.

- *Structural Equation Modeling (SEM):* Offers an approach of statistical analysis that allows for simultaneous estimation of multiple, interrelated relationships (Kline, 2016). Furthermore, SEM allows for the analysis of latent variables and measurement error, permitting a more precise and nuanced understanding of underlying constructs and relationships within the data. In addition, SEM supports the testing of complex, interrelated relationships between multiple variables simultaneously, hence providing a comprehensive view of the data landscape.

- *Factor loadings:* In the SEM framework, factor loadings are essentially the strengths of the relationships between observed variables (like survey items or test scores) and the underlying latent variables (also known as factors) they are thought to measure. Latent variables are things you can't directly measure, like self-efficacy, whereas the observed variables are items related to self-efficacy that are directly measured.
- *Model fit:* Refers to how well a statistical model represents the collected data. Essentially, it evaluates how close the predicted or theoretical model is to the observed data.

Summary

In essence, this multiple paper dissertation investigates the key factors influencing CS learning outcomes for Grade 5 students. Recognizing the escalating demand for CS skills and the dearth of research at the elementary level, it focuses in on constructs like self-efficacy, CS identity, and interest. By examining their interrelationships and potential predictors, this dissertation places equal importance on both in-school and out-of-school factors, understanding that the confluence of these elements shapes student engagement and performance.

Dissertation Outline

This dissertation follows a three-chapter format. The first chapter serves as the introduction. The second chapter is the first paper and examines the effects of the out-of-school factor of parental support on students' attitudes towards computing. The third chapter is the second paper and examines validity of practical measures. Together, these papers aim to enhance the understanding of the factors that predict students' attitudes towards computer programming, providing actionable insights for educators.

CHAPTER 2

Examining the Role of Parental Support on Youth's Interest in and Self-Efficacy of Computer Programming

Abstract

Objectives. The increasing demand for computing skills has led to a rapid rise in the development of new computer science (CS) curricula, many with the goal of equitably broadening participation of underrepresented students in CS. While such initiatives are vital, factors outside of the school environment also play a role in influencing students' interests. In this paper, we examined the effects of students' perceived parental support on their interest in computer programming and explored the mechanisms through which this effect may have been established as students participated in an introductory CS instructional unit.

Participants. This instructional unit was implemented with upper primary (grade 5) school students and was designed to broaden trajectories for participation in CS. The participants in the current study (N=170) came from six classrooms in two rural schools in the western United States.

Study Method. The seven-week instructional unit began with students playing a commercial CS tabletop board game that highlighted fundamental programming concepts, and transitioned to having students create their own board game levels in the block-based programming language, Scratch. Further, because the board game could be taken home, the instructional unit offered opportunities to involve the family in school-based CS activities. To investigate the effect of students' perception of parental (specifically father and mother) support on their interest in and self-efficacy to pursue CS, we surveyed students before and after the unit's implementations and explored the structural relationship of the data using structural equation modeling (SEM).

Results. We present three findings. First, the combined effect of students' perceived mother's and father's support measured prior to the implementation (pre-survey) predicted

students' self-efficacy (Std B = 0.37, SE = 0.010, $p < .001$) and interest in computer programming (Std B = 0.328, SE = 0.134, $p < .003$) measured after the implementation (post-survey). Secondly, the combined effect of perceived mother and father support (Std B = 0.132, 95% CI [0.039, 0.399], 99% CI [0.017, 0.542]) on students' interest was mediated by whether or not they took the CS board game home.

Conclusions. Our findings indicate that perceived parental support has the potential to play an important role in students' self-efficacy and interest in computer programming and that providing opportunities for students to bring CS artifacts home has the potential to further affect students' interest in computer programming.

Introduction

Research has shown that when parents value something their children tend to value it too (Wang & Eccles, 2012). Accordingly, research has explored the role that parental support plays (Ma et al., 2016) in influencing students' interest, belief in their own abilities to perform a task (i.e., self-efficacy), and subsequent career choices (Jodl et al., 2001; Palmer & Cochran, 1988; Paloş & Drobot, 2010; Turner & Lapan, 2002). While the existing research in this area helps establish a correlation between students' perceived parental support, self-efficacy, and interest, there is a need for research that explores how perceived parental support is related to youths' self-efficacy and interest in computer programming. A more comprehensive understanding of the interdependencies between these concepts has the potential to inform the design of CS interventions intended to broaden the participation of underrepresented and underserved group in CS.

In this paper, we use the lens provided by the Socio Cognitive Career Theory (SCCT) to explore students' affect prior to and after participating in an instructional unit for introductory CS. Specifically, this paper explores relationships between the constructs of self-efficacy, interest, and social influences in the form of parental support. The unit was designed to provide introductory CS instruction in an unplugged fashion to remove barriers associated with traditional computational media (Lee et al., 2020). We hoped that this would enable new participants to gain entry and thus broaden participation of upper primary school students (ages 10-11) at two rural primary schools in the western United States. Underlying the design of the unit was the conjecture that playing board games has the potential to support learning and reasoning (Berland & Lee, 2011), including developing foundational knowledge for programming. The instructional sequence started with students playing an unplugged computer science-themed tabletop board game called //CODE: On the Brink, which included fundamental programming concepts in its game mechanics (Poole et al., 2021). The board game featured levels, or challenges, where players navigated an agent (a robot token) along a grid-based path from the 'Start' to the 'Finish' by programming its movements. After playing the game, students designed their own board game levels using the block-based programming language, Scratch. The instructional unit consisted of seven weekly lessons that spanned the classroom and school library and consisted of both unplugged (board game play) and plugged activities (programming in Scratch (Poole et al., 2021). An important component in the design of the unit was that students were able to sign out a copy of the board game to take home as they would a book in the school library.

In the following sections, we first review key socio-cognitive constructs that are thought to play important roles in attracting and retaining upper primary students in CS instruction (self-efficacy, interest, and parental support). We present our research design, results, followed by our discussion and implications for future research.

Self-efficacy in CS Education

Self-efficacy is an individual's belief in their ability to perform a task and plays a critical role in human agency (Bandura, 1977). In particular, self-efficacy is a major determinant of whether an individual chooses to engage in or avoid an activity, how much effort that person invests in the activity, and how long they persist in the face of difficulties (Bandura, 1986). Self-efficacy has been shown to predict student achievement (Usher & Pajares, 2008) as well as career interest (Lent et al., 1994).

In studies involving primary and secondary students, researchers have examined the relationship between self-efficacy in computer programming and career orientation. Studies have found that higher self-efficacy correlated with intentions to pursue programming in the future. Conversely, low self-efficacy played a role in students' decisions not to pursue programming. For example, in one study, students' initial self-efficacy in computing affected their career identification after participating in a summer camp on programming (Aritajati et al., 2015). In another study of a summer programming camp, girls who saw themselves as computer scientists and were more confident in their computing abilities were also more open to a computing career (Friend, 2015). In a study in Spain (Sáinz & Eccles, 2012), the self-concept of ability, which is a construct that closely relates to self-efficacy, was found to be positively associated with the intention to pursue a career in CS. Similarly, in another study with secondary-aged girls participating in a summer camp, confidence in CS and AI was found to be correlated with their interest in pursuing a career in AI (Vachovsky et al., 2016). In a formal learning context, Aivaloglou & Hermans (Aivaloglou & Hermans, 2019) found self-efficacy to be correlated to career orientation only for female students. In another study conducted in a school that focused on English language learners (Elizabeth Casey et al., 2018), students increased in their self-efficacy to program as well as their perception about the value of STEM careers.

Numerous studies have focused on the relationship between students' self-efficacy and career pathways, and their influences on broadening participation in CS in higher education (Alshahrani et al., 2018; Beyer, 2014; Blaney & Stout, 2017; Dempsey et al., 2015; Denner et al., 2014; Gorson & O'Rourke, 2020; Lehman, 2016; Lishinski & Rosenberg, 2021; Rosson et al., 2011; Singh et al., 2007; Steinhorst et al., 2020). In a study where students were interviewed about their reasons for choosing to study CS (Alshahrani et al., 2018), students identified self-efficacy (i.e., the ability to do well) as one of the reasons for choosing a CS major. Another study found that students' self-efficacy at the start of a CS1 course predicted their interest at the end of the course (Lishinski & Rosenberg, 2020). Self-efficacy has also been found to be highly correlated with intention to pursue the study of CS (Dempsey et al., 2015) and having an orientation towards a CS career (Rosson et al., 2011) in undergraduate students.

Self-efficacy has also been linked to issues of inequitable participation in CS according to a subset of this literature. One study reported that women in college who did not take a computer-related course reported low computer self-efficacy as a reason (Beyer, 2014). For first-generation women in university, self-efficacy in computing after an introductory computing course strongly predicted their sense of belonging in the field (Blaney & Stout, 2017). Another study identified the differences in self-efficacy as the main reason for the disparity in participation among different groups (Lishinski & Rosenberg, 2021). Hence, the disparity in the initial levels of self-efficacy is an important factor contributing to inequitable participation in CS (Singh et al., 2007).

As discussed, a large portion of the research on the relationship between CS education and self-efficacy focuses on higher education (Clarke-Midura et al., 2020), in particular in entry-level CS courses. Much of the research on self-efficacy in primary and secondary aged-students has occurred in informal learning contexts which are flexible, in that they allow learners to engage at their own pace and time frame. In contrast, formal education follows a more predetermined structure (Sawyer, 2006) allowing students fewer opportunities to pursue their interests and shape their learning experiences. As such, there remains a need to explore the determinants of self-efficacy in formal CS education contexts at the primary level. Despite the gap, the existing literature guided our understanding of the association between self-efficacy in CS and intention to pursue a career in CS. Thus, in this study, we use the construct of self-efficacy which relates to students' perceived ability to do well in their CS learning and future career trajectory.

Interest in CS Education

Self-efficacy also plays a critical role in interest development and is a pre-cursor to interest in that people will develop interest in an activity in which they feel efficacious (Lent et al., 1994). In their model of interest development, Hidi and Renninger (Hidi & Renninger, 2006) propose that interest progresses in four sequential and distinct stages: triggered situational interest, maintained situational interest, emerging individual interest, and well-developed individual interest. Situational interest refers to the psychological state and affective reaction to an external (e.g., an object or an environmental condition) stimulus in the moment, while individual interest is an enduring predisposition to seek repetitive engagement in an activity over time. In addition, situational interest is the precursor to individual interest, and it takes time for the former to turn into a well-developed individual interest.

The research on interest and CS education has reported mixed results in that many intervention studies have not found significant changes in interest (Clarke-Midura et al., 2020; Sabin et al., 2017; Starrett et al., 2015; Webb & Rosson, 2011). The studies that did show a change in interest did not explain what factors affected interest in programming other than the ones that are specific to those studies. For example, AlSulaiman &

Horn (AlSulaiman & Horn, 2015) reported differences in what activities were considered interesting by boys and girls based on the gendered cultural forms used in the activity. In contrast, Chen et al. (Chen et al., 2019) reported no improvement in students' interest in programming and attributed this to a ceiling effect. These inconsistent results are also likely due to how interest is measured. Renninger and Hidi (Renninger & Hidi, 2011) state that when measuring interest, researchers should be clear about how they conceptualize interest; otherwise, the empirical findings may not be helpful in instructional interventions designed to generate interest in learners.

Parental Support and CS

Research on self-efficacy suggests it is influenced by support from teachers, peers, and parents (Lent & Brown, 2008; Wang & Eccles, 2012). In previous research, we found that parents' support of their children's pursuit of CS affected children's beliefs about the usefulness of CS, and these beliefs affected to what extent they were interested in CS (Clarke-Midura et al., 2018). According to Social Cognitive Career Theory (SCCT), a positive change in one's social support predicts a positive change in that person's attitudes toward a field or a career (Lent et al., 1994). In the context of CS education, parental support is measured as a student's perception of the support that their mother and father show in their learning of CS.

Linking Self-efficacy, Interest, and Parental Support

Exploring the relationship between students' perceived parental support, self-efficacy, and interest offers insights into fostering positive attitudes and effective teaching approaches for computer programming.

As described above, prior research found that self-efficacy is a predictor of one's interest in a field or a career (Lent & Brown, 2008; Lent et al., 1994), and self-efficacy in learning to program is correlated with interest in programming (Leifheit et al., 2019). Parental support is a form of social support that strongly predicts career interest and aspiration (Jodl et al., 2001; Palmer & Cochran, 1988; Paloş & Drobot, 2010; Turner & Lapan, 2002), and perceived parental support in CS is correlated to an increase in CS interest (Clarke-Midura et al., 2018; Denner, 2011). Students' perceived support is also linked to increases in self-efficacy (Bandura, 1997). A parent's interest in their child's education has also shown to significantly impact their attitude and in turn their persistence (Simpson, 2003).

Research underscores a positive correlation between parental involvement and students' achievement motivation and attitudes (Gonzalez-DeHass et al., 2005). Lent et al. (Lent et al., 1994) suggested that both parental resources and support influence their child's learning experiences, subsequently shaping self-efficacy and outcome expectations. However, the diverse factors associated with a child's parents can have distinct effects on student affect, with some exerting a pronounced influence (Fan & Williams, 2010).

In this study, we specifically focus on parental encouragement to pursue programming, and the expression of confidence in a child's abilities. Fisher (Fisher & Padmawidjaja, 1999) found that parental encouragement plays a significant role in students' career decision-making. Additionally, children's intrinsic motivation improves when parents are consistently informed about their progress and are provided guidance on how to support their children at home (Ames et al., 1995; Fan & Williams, 2010). Such motivation is further heightened when parents react positively to their children's academic achievements (Fan & Williams, 2010). Furthermore, when parents project confidence in their children's potential, it paves the way for a smoother and less stressful transition to college life (Cutrona et al., 1994). Lent and Brown (Lent & Brown, 1996) suggest that individuals are more likely to translate their career interests into actionable goals when they experience supportive environments, such as receiving encouraging feedback at home.

However, many of these studies at the primary school level have been done outside the formal CS education context, leaving the relationship between the constructs of students' perceived parental support, students' interest in computer programming, and self-efficacy in computer programming an understudied area. For example, a previous study in an informal learning context (Clarke-Midura et al., 2018), analyzed the effect of parental support on students' interest in and perceived value of CS, but the analysis did not include self-efficacy measures in the model. In a different study (Clarke-Midura et al., 2019), the changes in students' interest, self-efficacy, and perceived parental support were reported but the relationships between the three constructs were not explored.

Bresnihan et al. (2021) found that parents who engage in creative programming tasks with their children gain computing confidence, develop a positive attitude towards computing, and show increased involvement in their children's CS learning. On the other hand, understanding the impact that parental support can have on students' affect towards computer programming has implications for the design of CS curricula. Specifically, it underlines the importance of including elements aimed at influencing students' perceived parental support into instructional designs. For example, Harackiewicz et al. (Harackiewicz et al., 2012) sent home educational brochures about the science and mathematics activities carried out in a 15-month-long unit. Children whose parents were sent the brochures were more likely to subsequently take advanced STEM courses. In the context of CS education, two studies describe students taking projects home so that they could show them to their parents (Clarke-Midura et al., 2019; Sabin et al., 2017) to encourage conversations about CS and careers in CS between students and their parents.

Student interview data in one of the studies revealed that some students were praised by their parents for their skills in CS, some engaged with their parents in conversations about CS skills and careers, and some reported spending quality time together while playing with programming projects (Clarke-Midura et al., 2019). The other study (Sabin et al., 2017) also reported positive effects of sending students' final projects home. Others have tested the effect of parental involvement on academic achievement (Gonida & Cortina, 2014; Johnson & Hull, 2014; Moroni et al., 2015) and on student absenteeism and drop-outs (Bajar & Bajar, 2019; Robinson et al., 2018).

The above findings show how students' perceived parental support can influence their self-efficacy and interest in programming. However, to our knowledge, none of these studies looked at the interdependence between self-efficacy, interest, and parent support. Furthermore, a recent literature review (Shehzad, Recker, et al., 2023) found no conclusive findings

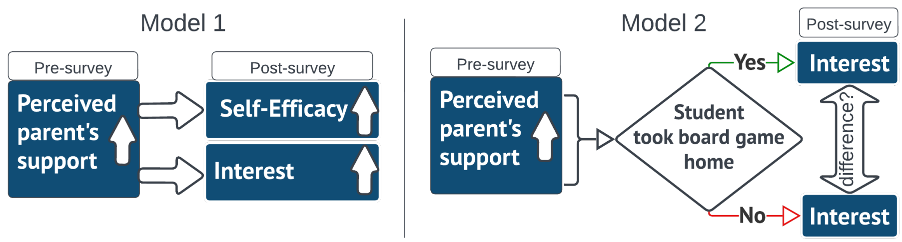


Figure 2.1

Model 1 examines whether higher parental support (pre-survey) is associated with a higher self-efficacy and interest (post-survey). Model 2 examines whether interest is mediated by the action of taking the board game home.

on what instructional design features were effective in improving self-efficacy and interest in programming.

Research Questions, Aims, and Objectives

To investigate mechanisms through which students' interest in programming, self-efficacy, and parental support are related, we address the following two research questions:

1. *Does students' perceived mother and father support predict students' self-efficacy to pursue computer programming and their interest in computer programming?*

2. *Does students' perceived mother and father support affect students' interest in computer programming indirectly through their action of taking the board game home?*

While the first research question explored the interplay between students' perceptions of parental support, their self-efficacy, and their interest, the second question examined whether a key design feature of the instructional unit (enabling students to take the board game used in CS activities home) affected students' interest in computer programming (see Figure 2.1).

First, we explored whether students' perceived parental support as self-reported on a pre-survey predicted students' self-reported self-efficacy and interest in programming. Subsequently, we examined whether the effect of parental support (as self-reported in the pre-survey) on students' interest was mediated by the action of taking the CS board game home and (possibly) talking about it with their parents. Overall, the present study addressed the importance of out-of-school factors by examining the predictive relationship between parental support, students' self-efficacy, and interest in computer programming. The present study also explored whether involving families by sending a CS artifact (in this case, a board game) home with students predicted an increase in students' interest in programming.

Method

Participants

This study was conducted in a rural region of the Western United States. Fifth grade students (N=170) in two schools that assented to participate and returned the parental consent form participated in the research. In total, 96 fifth grade students (46 girls and 50 boys) across three classrooms from one primary school and 74 fifth graders (35 girls and 39 boys) across three classrooms from another primary school participated in the study. 44% of the students in school 1 and 45% in school 2 qualify for free or reduced-price lunches as per data provided by the school district.

The instructional unit was taught to all the students in the schools, regardless of whether they participated in the research. The study was reviewed and approved by the university's institutional review board (IRB).

Research Context

The study integrated a commercial paper-based board game in the design of its instructional unit. Board games have been identified as computationally rich environments, capable of instantiating various computational concepts through game play, regardless of the players' awareness of their computational nature (Berland & Lee, 2011). Commercial board games vary in their designs, but can represent computer science (CS) through actions presented as written code, algorithmic sequences manifested as player moves, and solutions derived through the application of conditionals and Boolean logic.

After evaluating multiple options, we developed our instructional unit to use the commercial board game, //Code: On the Brink published by ThinkFun, as the initial entry point. The game consisted of various levels or puzzles for players to solve. Each level included a grid where players must program an agent (represented by a robot token) to move from a 'Start' square to a 'Finish' square. Players created procedures, allowing the robot token to execute commands and navigate from the starting space, as well as any subsequent grid spaces, until it eventually reached the 'Finish' square . To form these procedures, players used move cards (e.g., 'Move Forward', 'Turn Right', 'Do Nothing') placed on a control panel (see Figure 2.2). For instance, placing a 'Turn Right' in the first spot and a 'Move Forward' in the second spot of the control panel for blue would cause the robot to turn right and move forward one square each time it landed on a blue space.

The instructional unit was comprised of seven weekly lessons that encompassed both the classroom and the school library. The reason for this was that the partnering schools were exploring the possibility of utilizing the school library as a setting for implementing CS instruction. The design of our unit was an attempt to provide support to both the classroom teachers and school librarians in delivering CS instruction.

The typical lesson structure involved a classroom component led by the teacher, lasting up to 20 minutes, after which students proceeded to their scheduled weekly library time for 30 minutes of CS instruction. In the library, the school librarian introduced and assisted students working in pairs to: play the physical board game; play a Scratch version of the same game; design their own game level on paper using colored paper pieces and pencils; and program their level in Scratch for their peers to attempt (see Figure 2.2).

Data Collection

The study was designed as a one-group pre-post survey. The research team collected survey data at both the outset and completion of the instructional unit. All items were measured on a Likert scale ranging from 1 to 6, with "1" denoting "strongly disagree" and "6" indicating "strongly agree.

Figure 2.2

Instructional unit sequence

Measures and Covariates

The survey items were taken from a validated survey developed in another study (Clarke-Midura et al., 2019), which had adapted the survey for use in CS education from established and validated surveys for STEM, e.g., (Carrico & Tendhar, 2012; Fennema & Sherman, 1976; Vekiri & Chronaki, 2008). Based on our model described above, four constructs were included: 1) mother support (MS) and 2) father support (FS), which measured students' perception of the encouragement, confidence, and importance shown by their mothers and fathers in the students' ability to program; 3) self-efficacy (SE) or students' belief in their ability to learn to program and become a proficient coder; 4) interest in programming (IP), which measured students' interest in computer programming (see Table 2.1). We also identified students who voluntarily took the board games home and reported it on the post-survey. Coded as a binary yes/no item, the TakeHome variable served to measure whether taking the board game home acted as a mediator between students' perceived parental support and their interest.

Building on the premise that self-efficacy is an important factor in students' interest in programming, the SE items in our survey were framed as inquiries about how students saw themselves in relation to computer programming (see Table 2.1). For the variable of interest, Hidi and Renninger's four-stage model of interest (Hidi & Renninger, 2006) was adapted in the study that developed the survey (Clarke-Midura et al., 2019). In discussing the different types of interest (e.g., situational interest vs. individual interest; see (Clarke-Midura et al., 2020)), (Clarke-Midura et al., 2019) underlined the difficulty in differentiating these different types in practice as no precise measurements have been developed (Renninger

& Hidi, 2011). Therefore, they adapted measures widely used in the motivation literature to measure students' interest in and enjoyment of computer programming (Clarke-Midura et al., 2019). While we agree that interest takes time to develop (Hidi & Renninger, 2006) and that a seven-week instructional unit may not be able to change students' individual interest, we hoped that by increasing their self-efficacy in programming we would trigger their interest, and thus students would develop further interest in programming that would grow over time.

As described earlier, the present study included multiple survey items for measuring students' perceived mother's support and father's support (see Table 2.1). We also gave students the option to take the CS-themed tabletop board game home with them. The idea was that students would show the board game to and perhaps play with their parents, leading to conversations about CS and programming skills and careers. Students were thus asked on the post-survey if they took the board game home.

Psychometrics

In the present study, we used a survey instrument developed and validated by (Clarke-Midura et al., 2019). We performed two separate explanatory factor analyses (EFA) (Lawley & Maxwell, 1971) with varimax rotation (Kaiser, 1958) to explore the underlying structures of the measured constructs. For each EFA, Parallel analyses (Humphreys & Montanelli Jr, 1975) were performed to calculate the optimum number of factors that represented the underlying constructs. Note that these exploratory factor analyses are performed to ensure validity of separate constructs and do not make inferences about relationships between parental support, self-efficacy, and interest. Thus, a confirmatory factor analyses was subsequently performed that examined the relationships between these constructs, which is presented in the results section.

EFA 1: Parental Support

We performed an EFA that included mother's support and father's support variables. The EFA revealed that survey items underlying the two constructs loaded strongly onto

Table 2.1

Survey items, their labels and constructs

Construct	Question	Label
Interest in Programming	Computer programming sounds fun.	IP_fun
	I think computer programming is interesting.	IP_interest
	I think computer programming is boring.	IP_bore
Mother's Support	My mother has encouraged me to learn computer programming.	MS_Encourage
	My mother thinks I could be a good computer programmer.	MS_Confidence
	My mother thinks I'll need to learn computer programming for the future.	MS_Need
	My mother has shown no interest in whether I learn computer programming.	MS_Interest
Father's Support	My father has encouraged me to learn computer programming.	FS_Encourage
	My father thinks I could be a good computer programmer.	FS_Confidence
	My father thinks I'll need to learn computer programming for the future.	FS_Need
	My father has shown no interest in whether I learn computer programming.	FS_Interest
Self-Efficacy	If I took a class on computer programming, I could do well.	SE_Future
	If I wanted to, I could be a computer programmer in the future.	SE_Career
	I think I could do more challenging computer programming.	SE_Challenge
	I can learn to do computer programming.	SE_Learn
	I am a good computer programmer.	SE_Now
	I am confident in my ability to program	SE_Confidence
	I can program computers well.	SE_Ability

Table 2.2

Descriptive statistics of survey items at two time points. All items were measured on a Likert scale, ranging from 1-6 with "1" denoting "strongly disagree" and "6" denoting "strongly agree."

	Pre-survey			Post-survey		
	N	Mean	SD	N	Mean	SD
IP_Fun	156	4.70	1.58	164	4.30	1.71
IP_Interest	156	4.40	1.71	164	4.15	1.85
IP_Bore	156	4.70	1.57	164	4.40	1.66
MS_Encourage	151	3.15	1.69	164	2.60	1.55
MS_Confidence	151	3.88	1.65	164	3.44	1.68
MS_Need	151	3.22	1.68	164	2.93	1.73
FS_Encourage	151	3.23	1.63	164	2.94	1.62
FS_Confidence	151	2.95	1.67	164	2.72	1.71
FS_Need	152	3.70	1.65	163	3.29	1.70
SE_Future	156	4.45	1.38	164	4.21	1.36
SE_Career	154	4.12	1.59	164	4.02	1.68
SE_Challenge	156	3.71	1.68	164	3.66	1.77
SE_Learn	156	4.66	1.44	164	4.41	1.68
SE_Ability	156	3.95	1.62	164	3.85	1.60
SE_Confidence	156	4.19	1.57	164	3.93	1.68
SE_Now	156	3.53	1.56	164	3.57	1.67

one factor see Table 2.3. As can be seen, items related to mother's and father's interest did not load strongly onto factor 1, whereas other items did, thus the mother's and father's interest items were dropped from the analyses. Since all mother's and father's support items loaded strongly onto factor 1, they were combined into one construct of parental support. The Cronbach's alpha value for the parental support construct was calculated to be 0.89, an improvement over the Cronbach's alpha of 0.76 reported by (Clarke-Midura et al., 2019) for either mother's support and father's support, suggesting strong construct validity. However, combining the mother's support and father's support variables into a single construct removed our ability to examine the independent effects of mother's support and father's support on students' interest (Bahar & Adiguzel, 2016; Clarke-Midura et al., 2018; Otto, 2000) within the structural equation modeling (SEM) framework.

Table 2.3

EFA performed on mother's and father's support survey items

	Factor1	Factor2
FS_need_pre	0.75	
MS_Need_pre	0.71	
FS_Encourage_pre	0.79	
MS_Encourage_pre	0.80	
FS_Confidence_pre	0.74	
MS_Confidence_pre	0.70	
FS_Interest_pre		0.76
MS_Interest_pre		0.88

Note: Factor values smaller than 0.4
are not shown in the table.

EFA 2: Self-efficacy and interest

We also performed an EFA on items of self-efficacy and interest (see Table 2.4). As the items for the two constructs loaded onto two separate factors, interest and self-efficacy were treated as separate latent constructs in subsequent analyses. The Cronbach's alpha values for self-efficacy (0.92) and interest (0.87) showed strong reliability.

A total of 17 survey items were used in the final analyses, including the single item that asked students if they took the board game home with them.

Table 2.4

EFA performed on Self-efficacy and Interest items

	Factor1	Factor2
SE_Future_pre	0.60	
SE_Career_pre	0.54	0.51
SE_Challenge_pre	0.77	
SE_Learn_pre	0.47	0.56
SE_Ability_pre	0.85	
SE_Confidence_pre	0.66	0.44
SE_Now_pre	0.82	
IP_interest_pre		0.78
IP_fun_pre	0.40	0.80
IP_bore_pre		0.75

Note: Factor values smaller than 0.4
are not shown in the table.

Data Diagnostics

Data collected from the surveys were modeled using structural equation modeling. Statistical models were built in R (Team, 2023) using the sem( ) function in the Lavaan package (Rosseel, 2012). Since all of the variables in the model are measured on a Likert scale, frequency distributions were created to check normality assumptions (Rhemtulla et al., 2012). In cases where assumptions were violated, they were treated as ordered pairs. To address the asymptotic non-normality of the relatively small dataset, robust maximum likelihood (MLR) estimates were used for the model that used continuous items, and weighted least squares estimators with mean and variance adjustment (WLSMV) were used for the mediator model as it used the dichotomous TakeHome variable.

Analytic Strategy

We used confirmatory structural equation modeling (SEM), which allowed us to test a set of directional relationships between multiple variables (Ullman & Bentler, 2012) and thus, an appropriate method for addressing our research questions.

Examining the effect of parental support on self-efficacy and programming interest

The first research question examined the effect of students' perceived parental support on students' self-efficacy and interest in computer programming. We posit that students' perception of parental support can predict the change in self-efficacy as well as their interest in computer programming. In a confirmatory factor analysis (see 2.3), we tested whether the perceived mother's support and perceived father's support combined (PS_1) as measured on the pre-survey had an effect on the students' self-efficacy (SE_2) as well as students' interest (I_2) on the post-survey while controlling for pre-survey measures (SE_1 and I_1).

Note that mother's support and father's support variables were combined in the SEM approach to avoid the problem of multicollinearity.

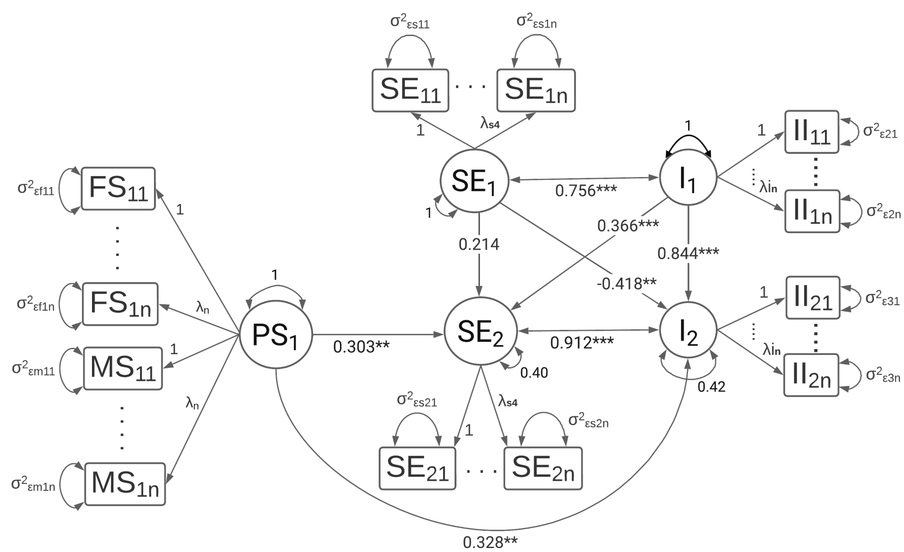


Figure 2.3

*Perceived parental support (PS_1) on pre-survey significantly predicted self-efficacy (SE_2) and interest (I_2) on post-survey while controlling for self-efficacy and interest on pre-survey (where ** p< .01; *** p<.001) (SE=Self-Efficacy ; I=interest in Programming; PS=Parental support)*

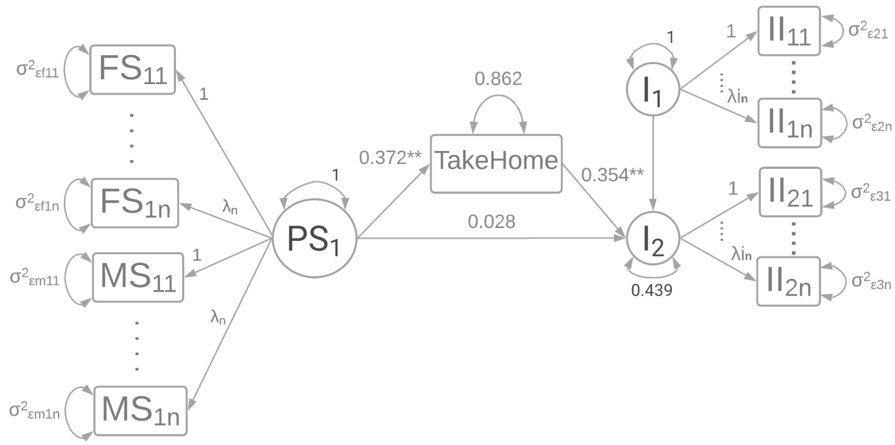


Figure 2.4

Perceived parent's support (PS_1) on the pre-survey significantly predicted student's interest (I_2) on post-survey. This effect was mediated by students' action of taking the board game home.

Single mediation models to test the effects of taking the board game home

For the second research question, we tested the mediation effect (MacKinnon et al., 2007) of taking the board game home (see Figure 2.4) between students' perceived parental support in the pre-survey (PS_1) and students' interest in programming (post-survey) (I_2) controlling for pre-survey (I_1). The outcome of this model provides insights for creating instructional designs that can affect students' interest in computer programming.

The mediator variable (TakeHome) was treated as dichotomous in the models. Furthermore, estimates of indirect effects were calculated via bootstrapping method (Hayes, 2009) for 5000 samples with replacement for the calculation of 95% and 99% confidence intervals in R. Just like in the previous model, mother's support and father's support variables were combined in the SEM approach.

Results

Statistics and Data Analysis

Nine students from the first school and seven students from the second school had missing data for the pre and post surveys (see Table 2.2) characterized as missing at random (MAR) (RUBIN, 1976). Full Information Maximum Likelihood (FIML) strategy was used to address missing patterns (Enders, 2001; Henk & Castro-Schilo, 2016) .

Since structural equation modeling assumes asymptotic normality, the distribution of the items was plotted and skewness and kurtosis measures were calculated. All of the skewness values fell between -3 and +3 and all of the kurtosis values fell between the values of -10 and +10, considered acceptable for structural equation modeling (Brown, 2015).

The chi-square test, Tucker-Lewis index (TLI) (Bentler & Bonett, 1980), root mean square error of approximation (RMSEA) (Browne & Cudeck, 1992; Steiger & Lind, 1980), and comparative fit index (CFI) (Bentler, 1990), were calculated as model fit measures. For the first model in Figure 2.3 ($PS_1 \rightarrow SE_2$ & $PS_1 \rightarrow I_2$), the model fit statistics were calculated as: χ^2 (289, N = 170) = 537.7, p < .001; CFI = 0.935; TLI = 0.927; RMSEA = 0.062, SRMR = 0.058). For the mediation model in Figure 2.4 ($PS_1 \rightarrow TakeHome \rightarrow I_2$), the model fit statistics were calculated as: χ^2 (66, N = 170) = 85.84, p = .051; CFI = 0.914; TLI = 0.90; RMSEA = 0.042, SRMR = 0.055). Although TLI and CFI values of 0.95 or higher are generally considered acceptable, Kline (Kline, 2016) suggests that these values can be too strict when the model is too complex or uses a small sample size. For such models, they suggest the threshold values of TLI> 0.90; CFI > 0.90; RMSEA <.08, SRMR < .08, which both of our models meet.

How parental support influences self-efficacy and interest

The regression results from the first model ($PS_1 \rightarrow SE_2 \rightarrow I_2$; see 2.3) revealed that the students' perceived parental support measured at the start of the unit (PS_1) predicted students' self-efficacy (SE_2 controlling for SE_1) (B = 0.366, SE = 0.10, p <. 001). This means that for a one standard deviation increase in the latent variable PS_1, the SE_2 increased by 0.366 standard deviations while controlling for pre-survey measures of SE_1 and I_1. The model also showed that parental support (PS_1) also predicted students' interest

(I_2) (B = 0.328, SE = 0.134, p < .003) while controlling for pre-survey measures of SE_1 and I_1. Stated differently, for one standard deviation increase in the latent variable PS_1, the I_2 increased by 0.394 standard deviations. This means that students' perceived parental support predicted a change in students' self-efficacy and their interest in programming. See Table 2.5) for factor loadings.

Table 2.5

Factor loadings (standardized) of survey items on their respective latent variables for model in Figure 2.3

	Pre-survey measures			Post-survey measures		
Construct	Indicator	Std. B	Std. Err	Indicator	Std. B	Std. Err
Interest	IP_Fun	0.93	0.00	IP_Fun	0.87	0.00
	IP_Interest	0.84	0.07	IP_Interest	0.94	0.07
	IP_Bore	0.73	0.09	IP_Bore	0.76	0.08
Self-efficacy	SE_Future	0.71	0.08	SE_Future	0.78	0.06
	SE_Career	0.73	0.07	SE_Career	0.80	0.06
	SE_Challenge	0.81	0.06	SE_Challenge	0.82	0.05
	SE_Learn	0.70	0.08	SE_Learn	0.74	0.09
	SE_Ability	0.87	0.00	SE_Ability	0.85	0.00
	SE_Confidence	0.80	0.09	SE_Confidence	0.88	0.06
	SE_Now	0.85	0.04	SE_Now	0.83	0.06
Parental Support	MS_Encourage	0.81	0.08			
	MS_Confidence	0.71	0.10			
	MS_Need	0.74	0.00			
	FS_Encourage	0.79	0.10			
	FS_Confidence	0.73	0.10			
	FS_Need	0.75	0.08			

To better visualize this, data is plotted in Figure 2.6 which shows that composite means for mother's support and father's support were both similarly correlated to the composite means of self-efficacy and interest, as our model suggests.

The effect of taking the board game home

As shown in Figure 2.4, we tested if the effect of students' perceived parental support before the unit (PS_1) on students' interest in programming after the unit (I_2) was mediated

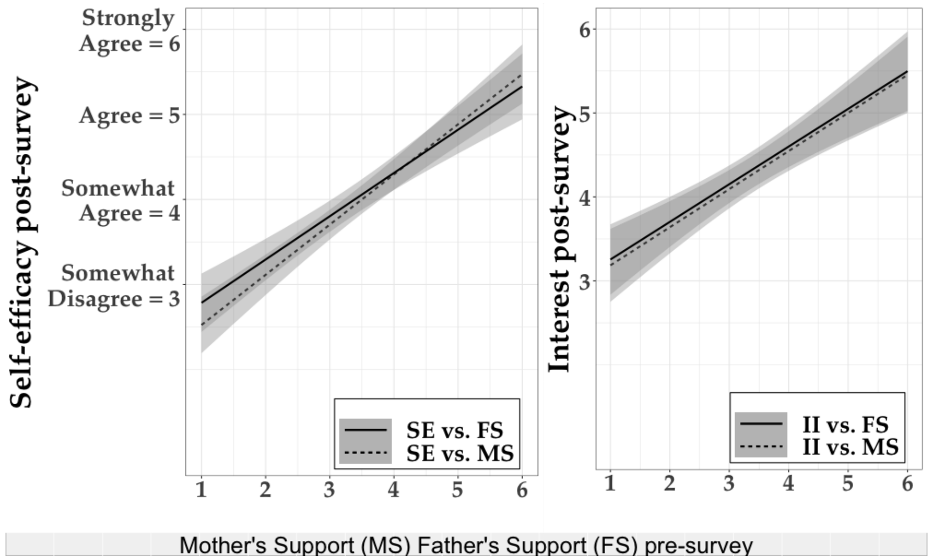


Figure 2.5

Higher mother's and father's support (MS and FS) scores on pre-survey are correlated with higher self-efficacy and interest on post-survey

by the action of taking the board game home (TakeHome variable). Using the indirect effects approach (Hayes, 2009) with the percentile bootstrap method with 5000 iterations, we found that 95% CI and 99% CI did not include a 0, which indicated a significant indirect effect through the TakeHome variable (Std B = 0.132, 95% CI [0.039, 0.399], 99% CI [0.017, 0.542]), confirming that perceived mother's support indirectly affected students' interest through the effect of taking the board game home.

Students who reported voluntarily taking the board games home also reported an increase in interest in computer programming, and this increase was significantly different from students that did not take the board game home. This suggests that the instructional design feature of allowing students to take a CS artifact home (here, a board game) is related to an increase in interest in programming (see Figure 2.6).

The composite means of mother's and father's supports are plotted against composite means of programming interest in Figure 2.4. Based on our mediation analysis (see Table 2.6), we conclude that the combined effect of mother's support and father's support on students' interest is mediated by students' action of taking the board game home and

Table 2.6

Factor loadings of survey items on their respective latent variables for mediation model in Figure 2.4

Construct	Indicator	Std. B	SE	Construct	Indicator2	Std B	SE
Interest_pre	IP_Fun	0.91	0.00	Parental Support pre	MS_Encourage	0.78	0.15
	IP_Interest	0.90	0.10		MS_Confidence	0.72	0.14
	IP_Bore	0.71	0.09		MS Need	0.75	0.00
Interest_post	IP_Fun	0.91	0.00		FS Encourage	0.78	0.17
	IP_Interest	0.92	0.10		FS Confidence	0.71	0.17
	IP_Bore	0.75	0.09		FS Need	0.75	0.15

that mother's support and father's support variables both have a similar influence on the mediation.

Discussion and Limitations

Addressing Research Questions

The present study set out to explore the relationship between perceived parental support, self-efficacy, and interest in computer programming. Our findings suggest that perceived parental support played a role in students' belief about their ability to program as well as their interest in programming.

Parental Support, Self-Efficacy, and Interest

Our results show that perceived parental support (PS_1) predicted self-efficacy (SE_2) and student interest in programming (I_2). The present research builds on our current understanding by relating the two constructs (perceived parental support and self-efficacy) to the construct of interest in programming. We also found that perceived parental support measured in the pre-survey (PS_1) influenced interest in programming (I_2) mediated by students' action of taking the board game home.

The present study is unique in its use of structural equation modeling in a formal

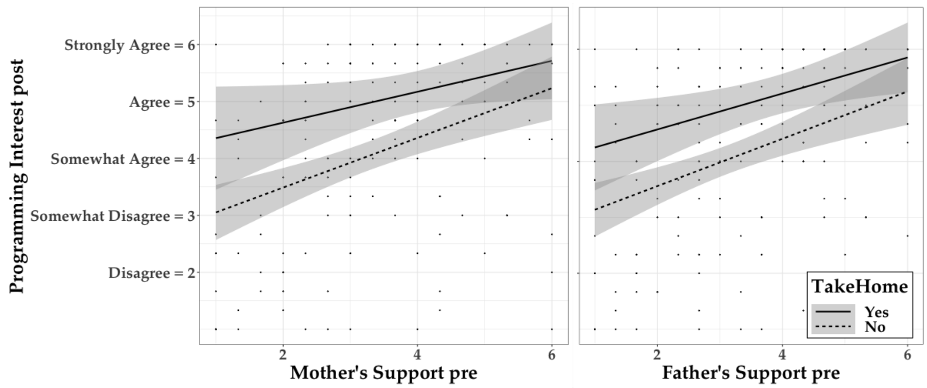


Figure 2.6

Students who took the board game home have a higher interest on post-survey compared to their peers who didn't but had similar mother's and father's support (MS and FS) scores on the pre-survey

K-12 school setting for the examination of affective constructs. Although it is difficult to relate students' self-efficacy in programming in primary education directly to the choice of a computing career later in their lives, the self-efficacy survey items in our study included questions about the students' beliefs in their ability to learn to program and become proficient coders in the future. We hoped that framing self-efficacy items in this way would help us draw connections between our findings and the existing literature on students' orientation towards a computing career. In the present study, we discovered that perceived parental support significantly predicted students' self-efficacy in computer programming.

Interest can lead to persistence (Lent & Brown, 2008) thus, interest in programming can be an important indicator of positive orientation towards a computing career. Despite its importance, there are many examples in the CS education literature where interest was measured but no significant change in interest was found (Clarke-Midura et al., 2020; Sabin et al., 2017; Starrett et al., 2015; Webb & Rosson, 2011). Some studies that showed a change in interest did not adequately explain what factors affected it (AlSulaiman & Horn, 2015; Chen et al., 2019). In the present study, we used interest in programming (I_2) as an outcome variable (see Figures 2.3 and 2.4). In the first of these models, the change in self-efficacy was highly correlated with interest at both timepoints. This is in line with the previous research which suggests that self-efficacy and interest have a reciprocal relationship (Lent et al., 1994; Nauta et al., 2002). Perceived parental support also predicted interest, which is similar to one of our previous findings in which we found that parents' support in their children's pursuit of CS affects children's beliefs about the usefulness of CS, and these beliefs affect to what extent they are interested in CS (Clarke-Midura et al., 2018). We found that mother's support and father's support have a combined effect that is significant. We hope that the present study will help fill gaps in the understanding of the relationship between perceived parental support, self-efficacy, and interest in programming.

Sharing Artifacts from School at Home

Our findings based on the single mediator model (see Figure 2.4) have implications for how we design classroom instruction for computer science. In particular, it showed the importance of finding ways to make connections between students' home and school lives. There is a dearth of research that explores how sharing computer programming related materials with parents affect students' interest in programming. In a previous literature review (Clarke-Midura et al., 2020), no conclusive findings were found on what instructional design features are effective in improving self-efficacy and interest in programming.

In the present study, we studied the effects of enabling students to take the board game used in CS classroom activities home to their parents. The idea behind enabling students to take the board games home was that students may show board games to their parents, leading to conversations about computer programming and careers in CS. Such conversations may in turn influence students' perception of support from their parents and or their interest in computer programming. Our results indeed showed that taking the board game home had a significant mediation effect between perceived parental support reported in the pre-survey and in students' interest in programming in the post-survey and the action of taking the board game home mediated this effect. We hope that this finding will encourage other research that will further examine ways to make connections between youth's school and home lives by sharing computing materials. Such research should explore methods of influencing parents' involvement in student learning and its effects on students' subsequent interest in and career aspirations toward computing.

LIMITATIONS

The present study has several limitations that should be acknowledged:

1. Lack of qualitative data: Qualitative data, such as interviews or observations, could have provided richer insights into the experiences of students and their parents, and helped to contextualize the findings.

2. Unavailability of demographic data: As the schools were located in a mostly white rural district, the study did not collect information on students' race or other demographic characteristics, which limits our understanding of how these factors might influence the relationships among perceived parental support, self-efficacy, and interest in programming. Student gender data was collected but were not used in the analyses. Future research should consider incorporating demographic variables to explore potential differences across different populations.

3. Household arrangements: The study used variables for mother's and father's support. This may not reflect the experiences of students from other household types like single parents, same-gender parents, or other guardians. We chose these variables based on their strong theoretical foundation. Including more family arrangements would lead to smaller sample sizes for those categories, potentially affecting statistical validity. Future research should use a larger, diverse sample to better represent different family structures and provide a more comprehensive measure of parental support.

4. Self-reported take-home variable: The TakeHome variable, which measured whether students took the board game home, was self-reported on the post-survey. This measure did not provide information about the duration for which the board game was taken home or whether students actually played the game with their parents or engaged in conversations about programming, as intended. The reliance on self-report data could have introduced biases and limited the accuracy of this measure. It is

also possible that spending more time with the board game resulted in the increase in their interest. Future research should consider using other ways to assess students' engagement with programming-related materials at home and the extent of parental involvement in these activities.

In addition, there are limitations related to the statistical models used in the study. The first limitation is related to our parent support model. In the SEM framework, we could not examine the differences in how perceived mother and father support influence interest and self-efficacy in the same model owing to a high degree of correlation between the two variables. While an alternative approach to SEM, such as multiple linear regression (MLR) analysis, to test significance for mother's support and father's support separately could be used, SEM is considered a more robust and accurate approach for several reasons (Bollen, 1989; Kline, 2016). SEM allows for the simultaneous estimation of multiple relationships in a single model, providing a more comprehensive understanding of the inter-dependencies among variables. MLR, conversely, is limited to examining a single dependent variable at a time (e.g., either self-efficacy or interest), which may lead to a fragmented understanding of the relationships in the data.

A limitation of the SEM model (see Figure 2.3) is that the self-efficacy ($SE_1 \& SE_2$) and interest ($I_1 \& I_2$) were measured at the same times (on pre-survey and post-survey respectively). Thus, the relationship between SE_1, I_1 and SE_2, I_2 is reciprocal and not predictive.

Finally, we note that circumstances where the independent variables cannot be manipulated, are not ideal for a mediation analysis (Vanderweele & Vansteelandt, 2009). This posed a threat to the validity of the mediation results since students' perceived mother's support and father's support variables were not manipulated, instead, they were simply observed. Despite this threat, we think that demonstrating the effect of taking the board game home can provide useful implications for instructional design practices.

CONCLUSIONS

The growing demand for computer programming skills brings along with it a critical need to improve student participation in computer science education. Since the curriculum is predicated on the idea that a board game based instructional unit avoids the barriers associated with the conventional screen based media, it may help broaden participation of underrepresented and under-served students. In the context of this approach, we found that students' perceived mother support and students' perceived father support affected students' interest in programming and students' self-efficacy to program (see Figures 2.3 & 2.4).

The affective constructs explored in this study are grounded in the widely recognized theory of socio cognitive career theory (SCCT). Studying the predictive effects of parental support on students' attitude in programming and examining the mediation effect of sending CS artifacts home is an important contribution to the field, as it reveals implications about out-of-school factors that should be considered in the design and implementation of any primary-level computing unit. These results have implications for research on broadening participation in CS education as well as in the design of CS instruction. For the former, studying the influence of out-of-school factors such as parental support can provide ways to understand and mitigate the effects of inequities that persist in computing education. Likewise, our findings inform the design of CS instructional activities. Interest-driven CS learning often fails to take these external factors into account as the instructional design is mostly aimed at improving in-activity interest. In the present study, we gave students the option to take a CS artifact home to see if it affected students' interest. Designers and researchers should examine other ways of building connections between school and home activities as means of influencing social supports that impact important constructs such as interest and self-efficacy.

CHAPTER 3
ADVANCING THE VALIDITY ARGUMENT OF PRACTICAL MEASURES IN ELEMENTARY COMPUTER SCIENCE

Introduction

The traditional methods used in educational research, which we term outcome measures, are typically used for measuring student performance for informing accountability and advancing theoretical constructs (Yeager et al., 2013). Although these measures serve a crucial function, they were not conceived with the explicit intention of enhancing and informing instructional practice. This shortcoming of outcome measures has catalyzed the emergence of what are called practical measures, measures that are intimately linked with the processes of teaching and learning, and capable of predicting outcomes relating to these practices (Penuel et al., 2018).

Practical measures diverge from their outcome counterparts primarily in their applicability. While outcome measures are summative, focusing on end results, practical measures adopt a formative approach, offering immediate feedback that can shape ongoing teaching and instructional practices. Practical measures hone in on actionable aspects of the learning and teaching experience. They serve as indicators of the instructional practices and remain closely linked to routine classroom activities.

Covering a range of methods, from casual teacher observations to concise student surveys and quizzes (Penuel et al., 2018), practical measures offer invaluable insights into the effectiveness of specific instructional decisions. They shed light on what's working, what's not, and where immediate adjustments are necessary, making them an indispensable tool for educators striving for continuous refinement. Moreover, they are designed to be quick and easy to administer, thereby preserving valuable instructional time.

At the heart of practical measures lies their ability to tap into the ”in-the-moment” context of learning and teaching. They are designed to capture subtle shifts in understanding and attitudes that may elude more summative measures, delivering insights into micro-level changes in the learning process. This immediate and direct linkage to instructional activities equips educators to discern effective components of their teaching and those requiring alteration. Ultimately, these measures may facilitate a more contextualized, nuanced comprehension of the learning process, fueling continuous improvement of instructional practices.

On the flip side, summative measures—valuable for exploring cognitive, affective, and behavioral constructs—often fail to capture the subtleties of computing education at the elementary level. This stems from their dependency on recall, a challenging task especially for younger learners lacking the self-awareness or linguistic ability to accurately articulate their experiences (Duckworth & Yeager, 2015). Therefore, such measures may fall short in encapsulating the immediate, fluctuating cognitive and emotional journey (Anderman, 2020) that young students navigate while learning computing concepts and skills (See Table 3.1 for a comparison of the advantages of the two approaches). Moreover, summative measures remain skewed towards informing research and theory development, rather than directly influencing pragmatic instructional nuances (Yeager et al., 2013).

Table 3.1

A Comparison of Different Advantages of Practical Measures and Outcome Measures

Practical Measures Advantages	**Outcome Measures Advantages**
Informs practice decisions	Assesses change over time
Less time consuming to administer	More in-depth examination of learning
Geared toward improvement	Parses out influences of overlapping constructs
Can be administered frequently	Targets long-term change
Experience is measured	Users answer by recalling and reflecting on a collection of experiences

Practical measures can bridge these gaps by connecting with the unique tasks and challenges embedded within instructional situations. By capturing changes close to the time of instruction, they can provide immediate, contextually relevant insights that supplement the broader perspectives offered by summative outcome measures, which instead track changes over extended periods and supply a longitudinal understanding of cognitive, affective, and behavioral constructs.

The objective of this research is to build on the validity argument of practical measures as articulated by (Penuel et al., 2018), while addressing the challenges associated with their validation.

Literature Review

Affective Measures Used in Education

The field of education heavily relies on constructs originating from motivational literature, many of which are geared towards determining an individual's affect or attitude towards a particular topic or field. An important application of these constructs lies in their potential to measure students' attitudes towards computing.

The motivational literature commonly utilizes a variety of affective measures. Prominent among these are self-efficacy (Bandura, 1977), self-concept of abilities (J. Eccles, 1983), as well as intrinsic and extrinsic motivation (Ryan & Deci, 2000), and interest (Hidi & Renninger, 2006), etc. These constructs, while distinct in their origin, often share various similarities.

Such affective measures have found considerable usage in the computing literature for measuring students' attitudes. For instance, self-efficacy has been explored in multiple studies in computing education context (Aivaloglou & Hermans, 2019; Chen et al., 2019; Mork et al., 2020; Wei et al., 2021). Other constructs employed include interest (Hébert & Jenson, 2020; Pierson et al., 2020), self-concept of ability (Hug et al., 2017), subject task value (Jormanainen & Tukiainen, 2020; Zhong et al., 2017), and expectancies for success. While their usage is wide, these constructs are not without overlaps and shared properties. Self-efficacy and self-concept of ability, for example, are significantly similar (Anderman, 2020; J. S. Eccles & Wigfield, 2020), and both also share commonalities with intrinsic motivation, intrinsic value, and expectancies for success, particularly in how they are measured (Koenka, 2020). Understanding the similarities and differences between these constructs in the motivational literature is an important research endeavor in establishing their theoretical grounds. However, the multiplicity of constructs and their shared characteristics can make it challenging for researchers to choose the appropriate measures for their specific contexts. Moreover, while these differences are meaningful for academic discourse, they can confuse practitioners and policymakers, contributing to possible misconceptions (Anderman, 2020). Hence, it becomes necessary to prioritize practicality over precision in measuring outcomes. Thus, the complexity of distinguishing these constructs in practice necessitates the prioritization of utility over

Practical Measures

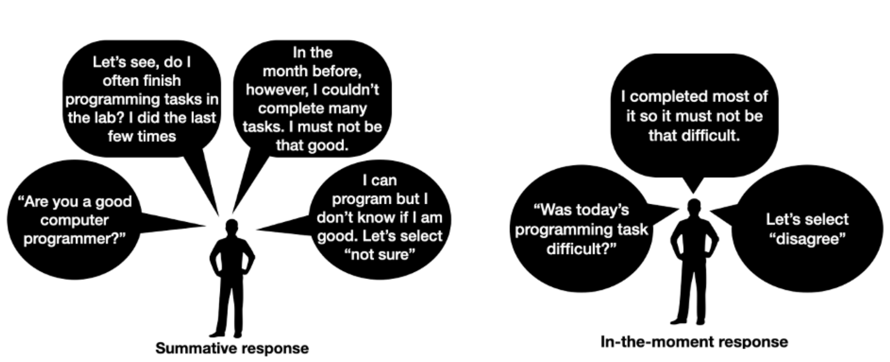
Despite the extensive use of outcome measures in educational research, these approaches come with limitations. For instance, they often require a large number of items to discern non-shared variances among constructs, making them time-consuming to administer and potentially reducing instructional time. Additionally, these measures often rely on respondents recalling their emotional states in specific past or future situations, leading to inaccuracies as learners frequently perceive their beliefs as consistent over time and struggle to evaluate their changes in beliefs ((Bowman, 2010; Duckworth & Yeager, 2015). This can undermine the ability of these measures to capture the cumulative and recursive changes in learners' cognitive and behavioral states (See Figure 3.1) that naturally occur over the course of learning (J. S. Eccles & Wigfield, 2020; Graham, 2020).

In response to these limitations and the increasing need for informing day-to-day classroom practices in computing education research, the focus is shifting towards the use of practical measures. These measures are tailored to assist practitioners in prioritizing their efforts and are typically less time-and-effort-intensive to administer, allowing for more frequent data collection (Bryk et al., 2015; Yeager et al., 2013).

However, practical measures present their own challenges. Given their primary role in

Figure 3.1

The process by which students respond to summative and in-the-moment surveys (Duckworth & Yeager, 2015)



informing practice rather than measuring outcomes, establishing the validity of practical measures is a challenging task due to the typically small number of items they contain (Bryk et al., 2015; Penuel et al., 2018; Yeager et al., 2013). This leads to difficulties in establishing internal reliability, resulting in scarce research on testing their validity.

Given the importance of establishing validity for practical measures in educational research, Penuel et al. (2018) and other scholars have developed specific criteria for evaluating the validity of practical measures:

1. **Focus on improving practice:** The chosen measures should center on enhancing educational practices. To achieve this, they need to be fundamentally linked to the underlying issues encountered during the learning process. This connection ensures that these measures serve to directly address and overcome challenges experienced by learners (Yeager et al., 2013).

2. **Ability to predict student outcomes:** The second criterion stresses the predictive capacity of these measures. This means that the measures selected should be capable of predicting specific student outcomes (Bryk et al., 2015; Yeager et al., 2013). Furthermore, establishing the hypothesized relationships through measurement equivalence across times (Kosovich et al., 2015) would validate these measures as early indicators of these outcome measures (Penuel et al., 2018).

3. **Embeddedness in the learning process:** Finally, these practical measures should be integrated within the learning process. They shouldn't function as isolated tools but should actively be a part of the educational activities, informing teachers about the students' progression of learning.

The current study seeks to adhere to these criteria in its approach. The broader research practice partnership project (Shehzad, Clarke-Midura, et al., 2023) echoes the intent of the first criterion. The overarching goal of this project is to improve instructional practices, emphasizing the significance of addressing problems faced during learning. As for the second criterion, this study employs a statistical model to analyze the predictive relationships between the exit tickets and students' affective outcomes. This methodology allows the research to explore the predictive capacity of exit ticket responses in relation to students' learning outcomes. The present study, as we shall see, involves administration of surveys embedded in the learning process, thus fulfills the third criterion.

In previous research, the outcomes in the Penuel et al. (2018) study were limited to an assessment task, the outcomes in the current study on the other hand encompasses learners' attitudes towards computing, measured in terms of self-efficacy, interest, and computer science identity.

Methods

Participants and Context

This study was conducted as a part of a larger research project in collaboration with Utah State University (USU) and a local school district that encompasses 17 elementary schools serving rural and small-town communities. Our research team collaborated with district content leaders and educators to co-design instructional units for Grade 5 that integrated mathematics and computer science (CS) concepts across instructional contexts, the regular classroom and the computer lab. The focal population for the present study comprises Grade 5 students studying in the partnering school district. Across all 17 schools, these students participated in math-integrated CS lessons in the computer lab and CS-integrated math lessons in their regular classrooms.

Expansive framing (Engle et al., 2012) is an instructional theory that aims to support the transfer of learning across contexts. It suggests that by presenting content across diverse settings, students can apply what they learn in one setting to another. This approach underscores the importance of interconnecting subjects to enhance transfer. In our approach, we utilized expansive framing to inform the design integrated CS-math lessons. CS concepts were interwoven into math lessons, while math principles were highlighted during computer lab sessions, mutually reinforcing math and programming concepts. The use of expansive framing as a theory is gaining traction in many instructional approaches (Grover et al., 2014). This paper focuses on students' learning during the computer lab lessons.

Research Instruments

Affect Outcome measures

The outcome measures used in this study include constructs identified in the literature that relate to students' attitudes towards computing. It incorporates items from previous works (Clarke-Midura et al., 2019; Hulleman, 2007) and its design prioritizes practicality over precision. This is evident in the fact that it includes a total of only 9 items related to self-efficacy, interest, and computer science identity (see Table 3.2).

While these affective constructs provide valuable insights into students' attitudes towards computing, they also come with limitations associated with outcome measures. The next section, therefore, delves into practical measures designed for this study. These practical measures aim to address limitations associated with outcome measures and offer a more immediate, "in-the-moment" perspective on student motivation and engagement.

Student Exit Tickets

One form of practical measures used in educational research is student exit tickets. Penuel et al. (2018) defined student exit tickets as short surveys administered at the end of

Table 3.2

Student Affect Survey Items Measured On A 5-point Likert Scale (1 = Strongly Disagree to 5 = Strongly Agree) and Respective Constructs

Survey Item	**Construct**
I could become a computer programmer one day.	CS Identity
I can be a computer programmer.	CS Identity
The programming we are learning in the computer lab is interesting.	Interest
Computer programming is boring.	Interest
I am interested in computer programming outside of the computer lab.	Interest
Computer programming is interesting.	Interest
I am a good computer programmer.	Self-Efficacy
I could do more challenging computer programming.	Self-Efficacy
I can program computers well.	Self-Efficacy

each instructional unit, providing educators with insights to inform their ongoing instructional practices. These practical measures, used recurrently, are not just informative but can also be predictive of essential educational outcomes (Yeager et al., 2013). In the current study, we used exit tickets to measure students' experiences.

In selecting the most suitable exit ticket measures, we adhered to three key criteria set forth by Penuel et al. (2018) and others.

1. **Enjoyment:** The value that students find in a task often depends on enjoyment (J. S. Eccles & Wigfield, 2020). A positive learning context can foster a favorable attitude and heighten self-assessed ability (Koenka, 2020). In the field of CS education, higher enjoyment has been linked to increased self-efficacy (Kinnunen & Simon, 2011). The exit ticket item assessing enjoyment utilized a Likert scale, where students rated their agreement with the statement: "I enjoyed programming in today's class."

2. **Perceived Difficulty/Ease:** Perceptions of task difficulty can shape students' expectations for success and their intrinsic interest in the task (J. S. Eccles & Wigfield, 2020). A high level of perceived difficulty can adversely affect (Rattan et al., 2012) and incite frustration (Graham, 2020). However, overcoming challenging tasks can stimulate positive emotions like pride (Weiner, 2010) as some studies found that higher difficulty of programming tasks to be correlated with higher learning (Durak et al.,

2019; Von Wangenheim et al., 2017). Thus, the perceived difficulty is an important variable influencing students' affective outcomes one way or the other. The corresponding exit ticket item asked students to rate their agreement on a Likert scale with the statement: "Today's programming task was difficult". The scale was reversed for this item during the analysis.

3. **Perceived Connection between Computer Science and Math:** The recent literature review by Shehzad, Recker, et al. (2023) underscores the importance of explicitly linking computer science and math in education, a finding grounded in the works of Israel and Lash (2020), Weintrop et al. (2016), and Wong and Cheung (2020). This explicit linkage is crucial for fostering a meaningful math-integrated computer science experience, a key objective of this study. The significance of this approach stems from the concept of Expansive Framing (Engle et al., 2012) - the idea that broad contextual framing of concepts, such as math and computer science, encourages students to take ownership and engage in authorship. The corresponding exit ticket item asked students the following question: " Today's class was related to what I do in math class."

The chosen exit ticket items (See Figure 3.2) adhere to the defined selection criteria as follows. They are fundamentally linked to the issues encountered during learning (Criterion 1), possess predictive capacity towards specific student outcomes (Criterion 2), and are integrated within the learning process (Criterion 3). This study seeks to examine relationships between these constructs and their impacts on student outcomes, thereby adding to our understanding of the mechanisms of learning.

Data Collection

The exit tickets (see Figure 3.2), which were designed to serve as practical measures embedded within the learning process, were administered in the computer lab twice in an academic year, once after the lesson implementation in the fall and then in the spring during the same school year. We administered the affect outcome survey (see Table 3.2) before

Figure 3.2

Student exit tickets on a 5-point Likert scale

	Strongly Disagree	Disagree	Not Sure	Agree	Strongly Agree
I enjoyed doing the math in today's class.					
Today's math lesson was difficult.					
I worked with other kids in my class today.					
Today's class was related to what I do in the computer lab.					

and after the two-lesson implementation. Table 3.3 shows the number of students, classes, and schools that participated in the surveys and exit tickets.

Table 3.3

Frequencies of students, classes, and schools that took the survey

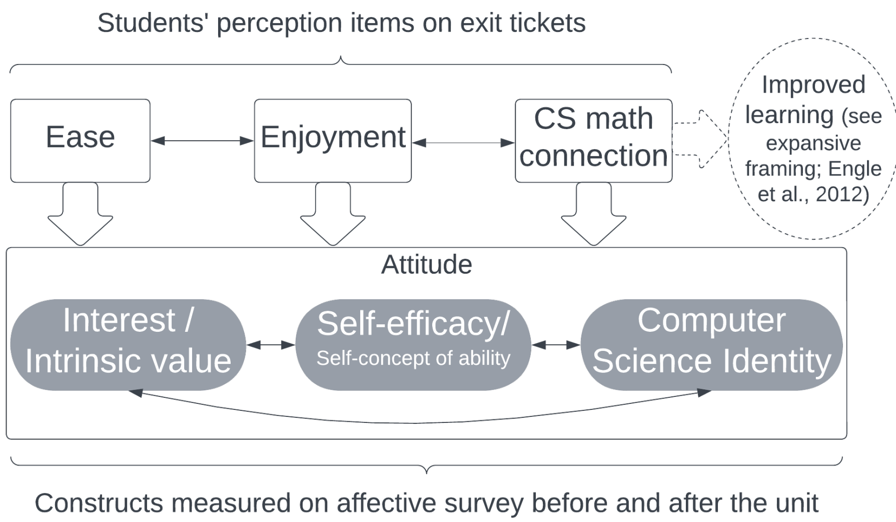
Instrument	# Schools	# Classes	'n' students
Pre-survey September 2022	17	49	1153
Post-survey March 2023	12	35	848
CS Exit Tickets Fall 2022	17	47	1067
CS Exit Tickets Spring 2023	15	45	929

Working theory

This study used both practical measures and affective outcome measures. These measures are interconnected within a working theory (See Figure 3.3), which hypothesizes how these observed outcomes are produced (Yeager et al., 2013). In particular, student responses to exit tickets are hypothesized to predict affective outcomes, thus equipping practitioners with valuable knowledge to evaluate and refine their instructional strategies. The ultimate goal is to understand the interconnectedness of students' perceptions of a computer science (CS) instructional context, and their attitudes toward computing.

Figure 3.3

Working theory connecting exit ticket items to outcome measures



Objectives and Contributions

Motivated by theoretical underpinnings and practical application, the present study aims to validate practical measures. The research uses statistical modeling to analyze predictive relationships between exit ticket responses and pre-post affect surveys linked to attitudes towards computing. Its objectives and corresponding research questions are thus structured around these goals.

Objective 1: Identify useful student experience measures that can be captured through exit tickets.

This first objective recognizes that affective constructs such as self-efficacy (Schunk & DiBenedetto, 2020), interest (Lent & Brown, 2008), and computer science identity, while related to learning outcomes, are usually measured through pre-and-post-implementation surveys, thus do not link student experiences to classroom instruction. The current study aims to identify valid exit ticket items that measure students' learning experiences and can be embedded within the learning process.

Research Question 1: What exit ticket items can be embedded in the learning process that are valid measures of students' learning experience?

Objective 2: Predict students' CS outcomes based on their reported experiences using exit tickets.

The second objective builds on the first, aiming to predict students' CS affective outcomes based on students' reported experiences using exit tickets. It seeks to validate the working theory underlying the use of these practical measures, moving beyond previous attempts that were either impractical due to length of practical measures (Kosovich et al., 2015) or unsuccessful in establishing a connection between student exit tickets and learning outcomes (Penuel et al., 2018). In this study, we collected student experiences in real-time and related them to students' affective outcomes.

- Research Question 2: How well can the lesson-specific exit ticket measures predict student affective outcomes?

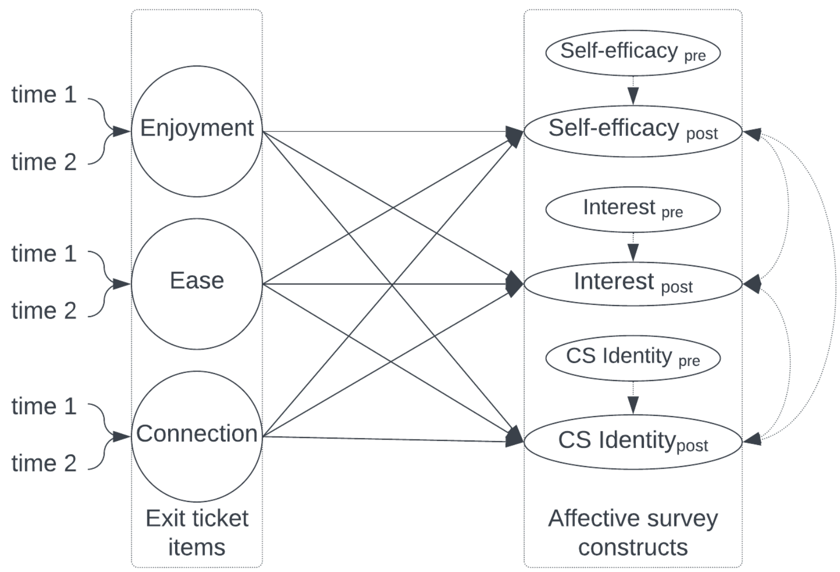
By identifying useful student experience measures, we seek to fill a noted gap in the motivational literature, which currently lacks methods for systematically capturing student emotions related to their learning experiences in real-time (Graham, 2020). Exit tickets are administered directly post-instruction, and can serve as a vehicle to record these momentary affective states, capturing their cumulative and recursive changes (J. S. Eccles & Wigfield, 2020). In predicting students' CS outcomes based on their reported experiences, this study aims to validate the working theory (see Figure 3.3) underpinning this research, lending empirical weight to its practical implications.

Analysis

For analysis, we chose to perform confirmatory factor analysis using Structural Equation Modeling (SEM) framework over analysis of variance (ANOVA) or regression due to its distinctive advantages. In contrast to ANOVA or regression, it allows for simultaneous estimation of multiple, interrelated relationships (Kline, 2016). Furthermore, SEM allows for the analysis of latent variables and measurement error, permitting a more precise and nuanced understanding of underlying constructs and relationships within the data. In addition, SEM supports the testing of complex, interrelated relationships between multiple variables simultaneously, hence providing a comprehensive view of the data landscape.

Figure 3.4

SEM model diagram based on working theory



Path diagram

Based on our working theory (see Figure 3.3), Figure 3.4 shows a path diagram demonstrating the hypothesized relationships between affect measures on the post-survey and student exit ticket measures. The two instances (fall and spring) of administering each exit ticket item were represented by a combined effect latent variable for the items of enjoyment and ease. We used the CS math connection item as an observed variable (an average of the two time points), a decision influenced by the issues of model convergence. The exit ticket items served as the independent variables, and the affective outcomes of interest, self-efficacy, and computer science identity functioned as dependent variables in our model.

Data Diagnostics

We performed an Exploratory Factor Analysis (EFA) with varimax rotation (Kaiser, 1958; Lawley & Maxwell, 1962) for the 9-item affect survey to establish the validity of the underlying constructs. The EFA results clearly demonstrated that the items of self-efficacy, interest, and computer science identity loaded effectively on their respective constructs (see Table 3.4).

We then checked the skewness and kurtosis values of the measures, ensuring that they were within the acceptable ranges of -2 and +2 for all the student response items recorded on the 5-point Likert scale.

Table 3.4

Results of the Exploratory Factor Analysis of Affective Survey Conducted for Establishing Construct Validity

	Factor1 (Interest)	**Factor2 (Self-Efficacy)**	**Factor3 (CS Identity)**
CS identity item 1			0.72
CS identity item 2			0.69
Interest Item 1	0.69		
Interest Item 2 (reversed)	0.66		
Interest Item 3	0.45		
Interest Item 4	0.79		
Self-efficacy item 1		0.63	
Self-efficacy item 2		0.59	
Self-efficacy item 3		0.71	

Note: Factor values smaller than 0.4 are hidden in the table.

Lastly, we tested the measurement invariance of our model across the two timepoints when the exit ticket data was collected. The test included data for the students who responded to exit tickets at both timepoints (n = 557). This step is crucial for establishing the statistical validity of practical measures (Kosovich et al., 2015).

Table 3.5 results indicate that none of the three comparisons were significant, thereby affirming strict measurement invariance across timepoints.

Table 3.5

Chi-square Tests for Measurement Invariance Across Timepoints

Models compared	**DF**	χ^2	**p-val**
Variable factor loadings			
Restricted factor loadings	12	0.13	1
Restricted factor loadings			
Restricted factor loadings and intercepts	15	10.26	.803
Restricted factor loadings and intercepts			
Restricted factor loadings, intercepts, and error variances	21	1.34	1

Results

We conducted our analysis using the lavaan package (Rosseel, 2012) in R (Team, 2023) to specify the path model shown in Figure 3.4 as a structural equation model. The resulting model fit statistics were as follows: χ^2 (201, N = 1564) = 569.9, $p < .001$; CFI = 0.952; TLI = 0.945; RMSEA = 0.038, SRMR = 0.040. These metrics—CFI, SRMR, and RMSEA—indicate a good model fit as they reside within the acceptable ranges of CFI > 0.95; RMSEA <.08, SRMR < .08 prescribed Hu and Bentler (1999) more stringent cutoff thresholds.

The regression results of this model are reported in Table 3.6. Here, we present the predictive relationships between exit ticket items and post-survey measures of Self-efficacy, Interest, and CS Identity.

Table 3.6 illustrates:

- Perceived enjoyment, as reported in the exit tickets, significantly predicted post-survey measurements of self-efficacy (Std β = 0.34, SE = 0.14, p = .001), interest (Std β = 1.98, SE = 1.53, p = .05), and CS identity (Std β = 0.41, SE = 0.15, $p < .001$) —while controlling for the respective pre-survey measurements.

- Perceived ease, also recorded in the exit tickets, significantly predicted post-survey measurement of self-efficacy (Std β = 0.26, SE = 0.16, p = .013) while controlling for the pre-survey measurement of self-efficacy. The relationships with Interest and CS

Table 3.6

Results showing predictive relationship between student exit ticket items and post-survey Self-efficacy, Interest, and CS Identity

			Self-efficacy post-survey		**Interest post-survey**		**CS Identity post-survey**	
N = 848			# Items = 3		# Items = 4		# Items = 2	
Predictor	N	Type	Std β	SE	Std β	SE	Std β	SE
–	1153	Pre-survey	0.30***	0.07	-0.62	0.87	0.27***	0.06
Enjoyment	1062, 926	Exit Ticket	0.34**	0.14	1.98*	1.53	0.41***	0.15
Ease	1058, 926	Exit Ticket	0.26*	0.16	-0.79*	0.9	0.07	0.16
Connection	1056, 925	Exit Ticket	0.01	0.05	-0.39*	0.27	-0.01	0.05

*** p <. 001, ** p < .01, * p <.05
Note: Estimates are standardized

Identity were not significant while controlling for their respective pre-survey measurements.

- The perceived connection between math and CS, reported in the exit tickets, didn't significantly predict any of the affective constructs measured on the post-survey, when pre-survey measures were taken into account.

From the findings, we can conclude:

- Exit tickets are valid tools for capturing students' real-time perceptions of instructional activities. This validity is demonstrated by the invariance of measurements across two timepoints (Kosovich et al., 2015).
- Exit tickets can predict the summative measures of student affect outcomes.
- While the perceived connection between math and CS did not predict any of the affective constructs measured, it remains a valid measure that aligns with the overarching goals and theory of the research-practice partnership project. We might need to add additional outcome variables in future studies to understand the effects of students' perceptions of connections between math and CS instruction.

Lastly, Table 3.7 presents the standardized values of factor loadings.

Table 3.7

Standardized values of factor loadings

		Pre-survey		**Post-survey**	
Construct	Item	Std β	SE	Std β	SE
Self-Efficacy	item 1	0.75	0	0.84	0
Self-Efficacy	item 2	0.67***	0.05	0.73***	0.04
Self-Efficacy	item 3	0.72***	0.05	0.78***	0.03
Interest	item 1	0.71	0	0.84	0
Interest	item 2	0.68***	0.06	0.76***	0.04
Interest	item 3	0.65***	0.06	0.76***	0.04
Interest	item 4	0.87***	0.06	0.9***	0.03
CS Identity	item 1	0.74	0	0.87	0
CS Identity	item 2	0.87***	0.05	0.87***	0.03
Student exit tickets					
enjoyment	time 1	0.62	0	–	–
enjoyment	time 2	0.62***	0.08	–	–
ease	time 1	0.5	0	–	–
ease	time 2	0.53***	0.18	–	–

*** $p < .001$

Discussion

The current measures used in educational research often fall short when it comes to informing practical instructional strategy. Their long administration time often limits their frequency of use, and the measurements of student perceptions typically rely on recalling emotional states. Practical measures, on the other hand, address the immediate concerns of instructional practice. These measures can be easily and promptly administered, collected closer to the time of instruction, and thus, may capture cognitive and behavioral changes more accurately. However, it is often hard to test the construct validity of practical measures. The current study confirms the validity of student exit tickets, a form of practical measure, in accurately representing student experiences. These findings present a case for the use of exit tickets as tools to provide educators with immediate feedback about their instruction, thereby allowing them to make timely adjustments and improvements.

Interpretation of Findings

These findings confirm that student exit tickets can serve as reliable practical measures, capable of being embedded in the learning process to capture students' immediate learning experiences. The study revealed that items on exit tickets, specifically those regarding students' perceived enjoyment and difficulty of tasks, can accurately predict affective outcomes, thus demonstrating their predictive capacity and utility in educational practice. The findings also make a case for using exit tickets as a proxy for more time intensive measures of student affect.

When we compare our findings with existing literature on measures commonly used in computing education, we find that our study aligns with previous work. We found that enjoyment (as captured by the exit ticket) was found to predict self-efficacy, interest, and computer science identity in the present study. This is consistent with literature indicating a correlation between enjoyment and attitude toward computer programming (Cabada et al., 2018) and related constructs (J. S. Eccles & Wigfield, 2020; Kinnunen & Simon, 2011). Moreover, the 'ease' of a task (as perceived by students and assessed by the exit ticket) was found to predict self-efficacy on the post-survey. This finding aligns with previous research, which has shown that difficulty can adversely affect students' attitudes when measured as expectancies for success (Weiner, 2010), and motivation (Rattan et al., 2012), and can potentially lead to frustration (Graham, 2020).

Interestingly, our findings also show that ease did not significantly predict interest and was negatively correlated with it. The negative correlation is not an entirely new finding. For instance, Weiner (2010) suggested that when tasks are perceived as too easy, students might deem them as mundane, and conversely, the completion of challenging tasks may spark feelings of pride and other positive emotions. Moreover, some research has demonstrated that a higher level of difficulty in programming tasks can be associated with greater learning outcomes (Durak et al., 2019; Von Wangenheim et al., 2017). Therefore, the relationship between task difficulty and attitudes towards computing appears to be multifaceted, encompassing both advantages and disadvantages.

Implications for Practice

Given these findings, we recommend incorporating student exit tickets into instructional activities as they can be an effective means for capturing cognitive and emotional experiences in real-time. As shown in this study, exit tickets can reliably measure students' perceived enjoyment, difficulty levels, and to an extent, connection between subjects.

Moreover, student electronic exit tickets are easy to administer and don't take up valuable class time (Raza et al., 2021). Gathering this information immediately after instruction can allow educators to adapt their teaching strategies promptly, such as by introducing additional reinforcement for concepts perceived as difficult. On the other hand, if enjoyment levels are low, teachers might consider incorporating more engaging, hands-on activities. By integrating this feedback mechanism into teaching practices, educators can dynamically respond to the changing needs of their students, ultimately enhancing their learning outcomes.

Limitations and Directions for Future Research

Our study has several constraints to consider. One key limitation is the lack of direct assessment of student learning outcomes, limiting the analysis to exit ticket measures predicting affective outcomes only. Further research could address this by incorporating direct assessments of learning outcomes, thereby examining the predictive strength of exit tickets.

The administration of exit tickets was confined to two timepoints in our study, leaving room for the exploration of measurement consistency across multiple timepoints. We also attempted to test for measurement invariance across various student groups. It required dividing data among groups reducing the sample size, which was already impacted by a high number of missing data points. Thus, the model didn't converge. Future studies should consider a larger sample size or reduce missingness in data to test measurement invariance among different student groups more robustly.

The research setting, centered around Grade 5 students from 17 rural-serving elementary schools in the western US, might not reflect the wider population of elementary students. The generalizability of these findings could be expanded in future research by including different grades, school types, and geographical locations, thus testing the measures' robustness across various student populations. It would also be valuable to investigate the applicability of exit tickets in different subjects outside of computing education to establish their broader validity.

Additionally, the varying predictive power of different exit ticket items was observed, with the perception of a connection between math and CS not predicting any affective outcomes. This points to the potential need for more comprehensive measures, such as assessment measures, to understand its effects better.

To capture students' experiences more holistically, future research could look into validating additional practical measures. For example, measures capturing students' engagement, perceived relevance of the material, or their sense of belonging in the classroom might improve our understanding of student experiences. Further research should also consider how educators interpret and utilize the feedback provided by exit tickets and their subsequent effects on student learning and affective outcomes.

Conclusion

This study presents key insights on the potential of practical measures, like student exit tickets, in transforming instructional approaches within computing education and beyond. Our findings underscore the value of these measures in capturing students' real-time learning experiences, without need to administer time-consuming pre/post surveys. In practice, they can empower educators to make immediate adjustments based on these experiences, fostering a more responsive learning environment tailored to student needs. Furthermore, educators can use easy to administer exit tickets as proxies to measuring affect via surveys that typically take much longer to administer.

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