GENDER-RELATED EFFECTS OF ADVANCED PLACEMENT COMPUTER SCIENCE COURSES ON SELF-EFFICACY, BELONGINGNESS, AND PERSISTENCE

By

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ABSTRACT

GENDER-RELATED EFFECTS OF ADVANCED PLACEMENT COMPUTER SCIENCE COURSES ON SELF-EFFICACY, BELONGINGNESS, AND PERSISTENCE

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The underrepresentation of women in computer science has been a concern of educators for multiple decades. The low representation of women in the computer science is a pattern from K-12 schools through the university level and profession. One of the purposes of the introduction of the Advanced Placement Computer Science Principles (APCS-P) course in 2016 was to help broaden participation in computer science at the high school level. The design of APCS-P allowed teachers to present computer science from a broad perspective, allowing students to pursue problems of personal significance, and allowing for computing projects to take a variety of forms. The nationwide enrollment statistics for Advanced Placement Computer Science Principles in 2017 had a higher proportion of female students (30.7%) than Advanced Placement Computer Science A (23.6%) courses. However, it is unknown to what degree enrollment in these courses was related to students' plans to enroll in future computer science courses.

This correlational study examined how students' enrollment in Advanced Placement Computer Science courses, along with student gender, predicted students' sense of computing self-efficacy, belongingness, and expected persistence in computer science. A nationwide sample of 263 students from 10 APCS-P and 10 APCS-A courses participated in the study. Students completed pre and post surveys at the beginning and end of their Fall 2017 semester regarding their computing self-efficacy, belongingness, and plans to continue in computer science studies. Using hierarchical linear modeling analysis due to the nested nature of the data

within class sections, the researcher found that the APCS course type was not predictive of self-efficacy, belongingness, or expectations to persist in computer science. The results suggested that female students' self-efficacy declined over the course of the study. However, gender was not predictive of belongingness or expectations to persist in computer science. Students were found to have entered into both courses with high a sense of self-efficacy, belongingness, and expectation to persist in computer science.

The results from this suggests that students enrolled in both Advanced Placement Computer Science courses are already likely to pursue computer science. I also found that the type of APCS course in which students enroll does not relate to students' interest in computer science. This suggests that educators should look beyond AP courses as a method of exposing students to computer science, possibly through efforts such as computational thinking and cross-curricular uses of computer science concepts and practices. Educators and administrators should also continue to examine whether there are structural biases in how students are directed to computer science courses. As for the drop in self-efficacy related to gender, this in alignment with previous research suggesting that educators should carefully scaffold students' initial experiences in the course to not negatively influence their self-efficacy. Further research should examine how specific pedagogical practices could influence students' persistence, as the designation and curriculum of APCS-A or APCS-P alone may not capture the myriad of ways in which teachers may be addressing gender inequity in their classrooms. Research can also examine how student interest in computer science is affected at an earlier age, as the APCS courses may be reaching students after they have already formed their opinions about computer science as a field.

This dissertation is dedicated to Maria, Greyson, and Genny—the center of everything I love.

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CHAPTER 1 : INTRODUCTION

1.1 Background

Within the United States of America and across the globe, computer science education is enjoying a renaissance in interest from both the general public and policymakers (Code.org, 2017; Obama, 2016; Partovi, 2013; Trump, 2017). This resurgence in interest in computer science education is bolstered by a combination of factors, such as the increasing focus on STEM (Science Technology Engineering Mathematics) education, a shortage of programmers, and computer science being perceived as a path for economic advancement (Google Inc. & Gallup Inc., 2015). While the overall enrollment numbers in CS are increasing, the share of female students earning bachelor degrees in CS has fallen from a high of 37% in 1984, to 17.5% in 2015 (U.S. Department of Education, 2017). Women now earn 57% of all bachelor's degrees, and roughly half of science and engineering degrees as defined by the National Science Board (2016). Within this range of science and mathematics majors, though, a few majors continue to produce a low proportion of female graduates: computer science, engineering, mathematics, and statistics.

The number of female students participating in computer science at the K-12 level also remains abysmal. In 2016, female students in the United States only accounted for 23.2% of students taking the high-school course Advanced Placement Computer Science A (APCSA) exam (The College Board, 2016b). In Mississippi and Montana, no female students took the APCSA exam in 2016. Enrollment of women in APCSA is abysmal when compared to another AP course such as AP Calculus AB, which has comparable demands and preparatory courses; female students comprised 49.4% of students taking the AP Calculus AB exam in 2016 (Ericson, 2014; The College Board, 2016b). These trends of low participation of women in computer science reverberates in the workforce, where the culture of computing does not always provide women with a sense of belongingness (Aspray, 2016; DuBow, Kaminsky, & Weidler-Lewis, 2017; Margolis, 2013; Margolis & Fisher, 2003). DuBow, Kaminsky, and Weidler-Lewis (2017) found that women find that receiving respect, encouragement, and support from classmates and colleagues is a significant factor in helping them persist within the computing field.

All students need to be provided equal opportunity and support to enter and persist in computer science. On a macro-economic level, the need to have gender equity is highlighted by the fact that countries and industries with a gender imbalance in the workplace suffer an economic cost to their efficiency and overall production (Dollar & Gatti, 1999; Plantenga, 2015). On a micro level, computer scientists and software developers bring their own experiences and perspectives to the design of software and hardware, often testing the products themselves and trying to anticipate what a user needs or will do. A largely male workforce often develops products that appeal to male consumers and continues to perpetuate the male-dominated environment (Crowell, 2016; Oudshoorn, Rommes, & Stienstra, 2004; Rommes, Oost, & Oudshoorn, 1999). Oushoorn, Rommes, & Stienstra (2004) provided a case study of an online community, which used primarily male designers, and as a result the hardware and software design choices led to further gender bias in participation. For these reasons, and for social justice concerns, we should be working to increase the proportion of women in CS programs. One way to do this is to engage female students in computing within K-12 classrooms with the intent to both recruit and retain female students that currently are not persisting in computer science fields. As scholars have tried to address the problem of gender equity within computer science education, they have pursued multiple approaches.

One approach that educators have taken to broaden the appeal of computer science to female students is to present how computer science plays a role in multiple disciplines, focus on non-computing application of computer science principles, and encourage pedagogical strategies shown to support gender equity (Goode, 2008; Kafai & Burke, 2014; Margolis & Fisher, 2003; Ryoo, Goode, & Margolis, 2015; Yadav, Gretter, & Good, 2017). In an example of one such effort to increase the number of female students in computer science, College Board recently introduced the Advanced Placement Computer Science Principles (APCS-P) course that portrays computer science as a broader discipline. College Board developed the APCS-P in an effort to "appeal to a broader audience, including those often underrepresented in computing" (The College Board, 2016a, p. 4). In contrast with APCSA, which is largely a traditional programming course with programming lab assignments and assessments in a single language, the APCSP framework allows teachers to decide on which language to use for the course, encourages students to submit projects more physical in nature, and focuses on the overall "big ideas" of computer science. While the number of students taking the AP exams in 2017 show an increase in the percentage of female students in APCSP (30.7% female, 69.3% male) when compared to APCSA (23.6% female, 76.4% male) (College Board, 2017; The College Board, 2016b), this is only the first step in increasing gender equity within computer science. Until future enrollment and attrition rates in undergraduate CS programs become available, we will not have a direct measure of whether enrollment in the APCSP course will result in sustained interest in computer science at the college level and beyond. What can be done in the interim to gain insight into whether these curricular efforts are likely to show promise in addressing the gender equity issues within the computer science field?

1.2 Theoretical Framework

1.2.1 Persistence of Female Students in Computer Science

While recruiting female students into computer science remains a major area of focus, we also need to examine how their experience in CS might influence their persistence. Even if efforts to increase female students' enrollment in computer science achieve equal parity with male students, their experiences have to be meaningful and rewarding for female students to want to persist (Google Inc. & Gallup Inc., 2014; Kafai & Burke, 2014; Margolis & Fisher, 2003). Historically attrition of female undergraduates from CS is higher than that for male students and a significant factor in the lower number of degrees awarded to women (Chen, 2013; Cohoon & Lord, 2006; Hamilton et al., 2016). Prior work in other academic subjects has suggested that belongingness and self-efficacy are significant predictors of persistence (Beyer, 2014; Good, Rattan, & Dweck, 2012; Lent, Brown, & Larkin, 1986).

1.3 Belongingness

Baumeister and Leary (1995) framed belongingness as "human beings have a pervasive drive to form and maintain at least a minimum quantity of lasting, positive, and significant interpersonal relationships" (p. 497). Deci and Ryan (2000a), within the framework of self-determination theory, described belongingness as a component of an individual's fundamental psychological needs to guide them toward more competent and socially integrated behavior. Good, Rattan, and Dweck (2012) examined belongingness in students' study of mathematics, how it evolved over time, and affected persistence in the discipline. They found that while male students' sense of belongingness remained similar over time, women's sense of belongingness was eroded when exposed to an environment that reinforces negative stereotypes about female mathematicians (e.g. women are not good mathematicians) or the belief mathematic ability is a fixed trait.

Similarly, Lewis et al. (2016) found that female students' sense of belongingness in physics was more impactful for women with STEM careers than men. If a student continues to encounter situations that reinforce existing negative stereotypes, the probability of experiencing "domain disidentification" rises in which the student has a reduced sense of belonging and likelihood to pursue further studies in the field (Cundiff, Vescio, Loken, & Lo, 2013; Steele, 1997). Within computer science education, Cheryan et al. (2009) found that removing stereotypically male-identified objects from a computer science classroom—such as Star Trek posters and video games—resulted in a high sense of belongingness for female students while having little to no effect on male students. While there has been some research on how CS classroom environment can influence students' belongingness, there is limited research on how their sense of belongingness influences their self-efficacy in CS as well as their persistence in CS.

1.4 Self-Efficacy

Bandura (1997) described self-efficacy as "beliefs in one's capabilities to organize and execute the courses of action required to produce given attainments" (p. 3). Considerable research has been done on the relationship between self-efficacy and student learning outcomes and academic performance (Bandura, 1977, 1986, 2002; Lent, Brown, & Hackett, 1994; Lent et al., 1986). Research has also suggested that self-efficacy's predictive value holds across cultures and domain self-efficacy is predictive of career choice (Bandura, 2002). Lent and colleagues (1994, 1986; 2002) incorporated Bandura's general social cognitive theory into the social cognitive career framework and argued that domain self-efficacy was a main predictor of career choice and persistence across multiple fields of work. Pajares and Valiante (1997) found that writing self-efficacy contributed to fifth-grade students' essay writing performance, playing a mediating role for existing writing ability, and thus suggested that teachers should pay close attention to not only students' performance, but also students' beliefs about their performance as these are predictive of future academic choices. Within computer science and related fields, the same relationship can often be found in the literature with self-efficacy being tied to higher performance, persistence, choice of academic majors, and career aspirations (Beyer, 2014; Blaney & Stout, 2017; Cohoon & Lord, 2006; Lishinski, Yadav, Good, & Enbody, 2016). Thus, self-efficacy becomes a useful indicator for predicting not only academic performance, but also of the students' persistence in the field.

Prior work in computer science education has examined the role of physical classroom space as well as participation in introductory computer science courses on students' belongingness and self-efficacy (Beyer, 2014; Cheryan et al., 2009; Lishinski et al., 2016). However, there is limited research on how presenting computers science as being applicable to larger problem solving, across multiple disciplines, has an effect of self-efficacy and belongingness, especially at the K-12 level.

1.5 Positionality Statement

I am a researcher of computer science education with a focus on equity, having formerly worked as a teacher and technology coordinator in PreK-12 settings. My personal and professional background both limits and informs my work in computer science education and provides a lens I bring to equity issues. I worked at two private and independent schools over the span of 12 years in Virginia and Ohio. As a result, I worked with students with financial means, with some students from middle and lower income families, who were provided financial aid to be able to attend the school. The school in Virginia was a rural boarding school, grades 8-12, with both boarding and daily commuting students. The technology classes at this school often had all male students, or extremely low (e.g., 15:1) ratios of male to female students. I also found the classes to be overwhelming populated by white males and male international students from eastern Asia. The other school I taught at in Ohio was an all-female day school, located in an affluent suburb.

Both schools led me to question the gender and racial composition of the schools, along with how gender and racial imbalance appeared exacerbated in my computer science and technology classes. Being a white male, I bring my own biases in what I noticed and did within a classroom. Particularly at the school in Ohio, which to its credit had a strong focus on issues of social justice, I noticed how the contrast in gender balance between the two schools seemed to influence how students engaged with the subjects. I had also now had two children of my own and became increasingly aware of sexist assumptions in my own daily life and work that troubled me. I adjusted my teaching methods to attempt to address some of these issues, but found the recommendations given to me sometimes conflicting or confusing. The engagement I saw in my female students encouraged me, particularly because it contrasted with the narratives I was hearing from other schools regarding female students and technology. The students were excited to engage with the difficult technical problems of robotics and programming, appeared to be comfortable displaying technical proficiency, and openly rejected the idea of technology being a domain they were discouraged from entering.

Having the background and experiences as a teacher informed my selection of research topics in computational thinking, computer science education, and related efforts in gender equity in K-12. I recognize the limitations of my own experiences, particularly being male and white, and how those limitations influence conducting research that includes perspectives beyond my own. I carry the preconceptions that come from my background, social status, and privilege in these systems. Similar to my examining of my own teaching while in the K-12 environment, I struggle to examine how my research methods may have overlooked other perspectives . My hope is that my research, through these acknowledgements and resulting adjustments, will provide some insight for researchers, teachers, and students of varied backgrounds to address equity issues in computer science.

1.6 Purpose Statement

The purpose of this study was to examine how enrollment in two different Advanced Placement Computer Science (APCSA vs APCS-P) courses relate to high school students' sense of belongingness, self-efficacy, and persistence within computer science, and how student gender may interact with that relationship. These variables of interest were chosen for their relationship to the likelihood of a student choosing to pursue computer science in the future, including at the undergraduate level as well as persist within the field.

CHAPTER 2 : LITERATURE REVIEW

While recruiting females into computer science remains a major area of focus in the computer science education field, we also need to examine how students' experiences influence their persistence in CS. If we want to increase female student enrollment in computer science to parity with male students, we need to provide meaningful and rewarding experiences for female students to want to persist (Good et al., 2012; Google Inc. & Gallup Inc., 2014; Kafai & Burke, 2014; Margolis & Fisher, 2003). Historically, attrition of female undergraduates from CS is higher than that for male students and a significant factor in the lower number of degrees awarded to women (Chen, 2013; Cohoon & Lord, 2006; Hamilton et al., 2016). Prior work has suggested that belongingness and self-efficacy are significant predictors of persistence and academic achievement, in general (Goodenow, 1993; Hausmann, Schofield, & Woods, 2007; Pittman & Richmond, 2007) as well as in computer science (Lishinski et al., 2016). Understanding what influences both belongingness and self-efficacy in computer science classrooms, and how computer science educators may create an environment that bolsters students' sense of both, can possibly aid in the retention and persistence in computer science.

2.1 Belongingness

Baumeister and Leary (1995) stated that the need for belonging has two criteria: frequent, pleasant interactions, and a stable context of concern for each other's welfare. Deci and Ryan (2000b) presented the need for belongingness as a motivational basis for learning, with belongingness aiding in the transfer of group knowledge to the individual. Picket, Gardner, and Knowles (2004) found that belongingness developed through verbal and visual social cues, and could affect basic cognitive functions. Good, Rattan and Dweck (2012) examined belongingness in the context of mathematics education, how it evolved over time, and affected student persistence in the discipline. The authors used a measure of belonging with five factors (Membership, Acceptance, Affect, Desire to Fade, and Trust) to examine college students' sense of belongingness while enrolled in a calculus course. They found while both male and female students' plans to persist in mathematics were significantly predicted by their sense of belongingness, women's sense of belongingness eroded when exposed to an environment that reinforces negative stereotypes about female mathematicians (e.g. statements that women are not good mathematicians) or the belief that mathematic ability is a fixed trait. Lewis et al. (2016) provided practical recommendations for addressing gender equity for physics educators based upon review of empirical studies on female students' sense of belongingness in physics. They suggested instructors: (1) temper the use of cultural references that reinforce a "geek culture" within the field, (2) focus on and reward hard work over "natural talent", (3) explicitly state to students that feelings of not belonging in the domain are normal at first and fade over time, (4) use cooperative pedagogical strategies, such as a jigsaw activity model, to encourage meaningful social interaction within the classrooms, and (5) and to tie the course content to a larger social context outside of the classroom to help affirm the value of what is being learned.

Within computer science education, Cheryan et al. (2009) conducted a series of four studies examining female undergraduate students' sense of belongingness in computer science and their classroom environments. In the first study, the authors developed a list of objects likely to be found in the office of a stereotypical computer scientist from two separate groups of undergraduate students. The researchers then decorated three classrooms, one with stereotypical objects (e.g. Star Trek posters), one with non-stereotypical object (e.g. nature posters), and one without decorative objects, where they conducted surveys of undergraduates about their likelihood to major in computer science. The researchers found that while male student interest in majoring in computer science did not vary across rooms, female students in the non-stereotypical room had a higher level of interest in majoring in computer science than females in the stereotypical and bare room. In their second study, the researchers described to undergraduate women two potential workplaces, both with similar salaries and an all-female team of coworkers, that differed only in the types of objects (stereotypical and non-stereotypical) found in their workplace. The students reported a lower sense of belonging in the stereotypical office than the non-stereotypical office, in spite of the presence of an all-female team. In the third study, undergraduate students of both genders were given descriptions of gender-balanced workplaces with similar salaries, one described using the stereotypical objects and one without. Male students were more likely than female students to choose the stereotypical workplace, however, overall males and females preferred the non-stereotypical workplace. Finally, the fourth study used a similar design to the third study, but the workplace was described as a web development company. The authors found that male students preferred the stereotypical environment over the non-stereotypical, while female students preferred the non-stereotypical environment. These findings point to not only the importance of environment in determining students' sense of belongingness, but how that environment can be a stronger influence that gender composition of the workplace, and how certain computing disciplines (e.g. web design) can convey gendered messages for students.

2.1.1 Belongingness and Stereotype Threat.

Belongingness is often intertwined with concerns about stereotype threat (Steele, 1997) in that both involve students being aware of how aspects of their own identity, such as race or gender, relate to their own conceptions of who does—or does not—become a member of a given field/domain. Steele described negative stereotypes as typecasting a group of people, such as “female students are not good mathematicians”. Stereotype threat is when a member of a negatively stereotyped group is faced with the “[predicament] that the existence of such a stereotype means that anything one does or any of one's features that conform to it make the stereotype more plausible as a self-characterization in the eyes of others, and perhaps even in one's own eyes.” (p. 797). Managing this predicament, while also completing the normal tasks required in that domain, such as completing homework or preparing for tests, can have a negative effect on one’s performance in comparison to peers without this burden. Their reduced performance is due to the mental energy spent upon trying to avoid being perceived as an example of a negative stereotype (Murphy, Steele, & Gross, 2007; Steele, 1997; Steele & Aronson, 1995). Stereotype threat appears to only negatively affect members of groups with a negative stereotype. While white males may be aware of a stereotype (e.g. “white males are the typical programmer”), they do not suffer the same detrimental effects of that stereotype as a woman or person of color might (Steele, 1997). Inzlicht and Ben-Zeev (2000) found that female undergraduate students assigned to both single gender and mixed gender three-person work groups performed better in mathematics and verbal assessments in all-female work groups. Inzlicht and Good (2005) suggested that the percentage of a student’s class that matches his/her gender, race, and ethnicity can affect the strength of stereotype threat, with its effects being more pronounced when students perceive themselves to be outnumbered in the classroom. This is further exacerbated when there is a mismatch between the teacher and student demographics in the classroom (Marx & Roman, 2002). The teacher may be perceived as another indicator of who works in a particular field or discipline, and thus can either reinforce or help counteract a negative stereotype. As a student continues to encounter situations that reinforce existing negative stereotypes, the probability of experiencing “domain disidentification” rises in which the student has a reduced sense of belonging and likelihood to pursue further studies in the field (Cundiff et al., 2013; Steele, 1997). Smith et al. (2015) similarly found that undergraduate female physics students identified greater stereotype threat than biology students, resulting in lower sense of identification with the field, and likelihood to continue in the field. Eccles et al. (1999) also showed that choice of major and courses at the university level can be affected for members of a group described by a negative stereotype. Tellhed et al. (2017) found that female high school students' lower interest in STEM careers, a field identified as more masculine, correlated with lower STEM self-efficacy and sense of belongingness. Meanwhile, male students' lower sense of belongingness in health and education careers, fields seen as more feminine, was also predictive of lower interest in entering those fields. While there has been some research on how CS classroom environment can influence students' belongingness, there is limited research on how their sense of belongingness influences their self-efficacy in CS as well as their persistence in CS.

2.2 Self-Efficacy

Bandura (1997) described self-efficacy as "beliefs in one's capabilities to organize and execute the courses of action required to produce given attainments" (p. 3). He proposed that there were several sources of self-efficacy including mastery experience, vicarious experience, persuasion, and arousal.

Mastery experience can be thought of as the successful completion of a task or challenge, leading to a heightened sense of self-efficacy in that particular task. For example, in a computer science context, this may be that a student successfully compiles their code without errors for the first time, and the positive experience with that task helps bolster their self-efficacy. Inversely, they could spend a significant amount of time searching for a syntax error that is preventing code from compiling, only to give up out of frustration. This could lead to a lessened sense of self-efficacy as a programmer and deter them from continuing their efforts.

Vicarious experience, learning from observing someone else complete the task, could also increase one's sense that they too could complete the task. For example, students may experience this by watching peers solve coding problems that they were unable to do independently. Using the syntax error example from above, a student may seek out assistance, watch how their peer uses a method to find the syntax error and as a result feel that they could also use this technique to solve the issue. Likewise, if they seek out help and their peers' methods for solving the problem is beyond the student's comprehension, this may reinforce the negative effect on their self-efficacy in programming.

Persuasion is the act of other persons encouraging you to complete a task, in a constructive manner, that bolsters self-efficacy to complete the task. For example, teachers may encourage a student to persevere in finding the syntax error that is frustrating them or congratulate them on successfully completing a difficult task. This persuasion may also come from peers that try to convince them that this is a difficult task, their level of effort is normal, and that they should keep working on the problem. Self-efficacy is again bolstered if the student receives these messages to persevere. In a negative example, a teacher or student could send a message that the tasks is exceedingly easy and that they should have finished earlier, and thus adding to the negative effect on the student's self-efficacy.

Finally, arousal is largely concerned with any physio-emotional state, such as nervousness or confidence, that results in changing the person's sense of self-efficacy regarding their ability to complete the task. For example, if a student experiences stress and frustration, it may be interpreted by the student as a sign of their lack of skill or ability, which could lead to lower self-efficacy. However, if a student is in a more positive emotional state, such as in a classroom that is devoid of distraction or negative imagery, they are more likely to have higher self-efficacy.

Of these four influences on self-efficacy, mastery experiences are often believed to be the most powerful (Bandura, 1977, 1986, 1997) as they are most authentically experienced by the subject. Considerable research has been done on the relationship between student self-efficacy and their academic performance (Bandura, 1977, 1986, 2002, Lent et al., 1994, 1986). Bandura's (1977, 1986) work on social cognitive theory suggested that self-efficacy was a strong predictor of performance on tasks of varying difficulty. Bandura (1977) described how adults with a fear of snakes watched a boa constrictor being handled by an assistant in various manners, while building up to handling the snake themselves. By surveying the participants' self-efficacy beliefs regarding the handling of snakes throughout the process, he found that the direct experiences where participants handled the snake themselves were more powerful in increasing their self-efficacy than watching the assistant handle the snakes. Research has also suggested that self-efficacy in a particular domain is predictive of career choice (Bandura, 2002).

Chemers and colleagues (2011) surveyed 665 undergraduates, graduate students, post-doctoral fellows, and recent graduates associated with a professional science organization for Chicano and Native American students. The researchers were investigating how personal psychological traits (e.g. self-efficacy, personal identity) mediated the influence of science support experiences on students' commitment to science careers. Results from the path analysis suggested that the effects of research experience, community involvement, and mentoring on a students' commitment to a science career was mediated by their science efficacy, leadership efficacy, and identity as a scientist. The mediating effects were present in both undergraduate and recent graduate, yet even stronger in the graduate and postdoctoral participants. This points to a need for instructors to understand more advanced students' sense of self-efficacy in order to ensure that support experiences (e.g. mentoring) are more effective in improving the retention of students within their field.

Pajares and Miller (1994) surveyed 350 undergraduate students regarding their mathematic self-efficacy, perceived usefulness of mathematics, mathematic anxiety, mathematic self-concept, and prior experience. Immediately after completing the survey, students then were asked to complete a mathematic problem instrument as a measure of performance. The researchers found that mathematic self-efficacy had the strongest effect on mathematic problem solving and also mediated the effect of gender and prior experience on mathematic self-concept, perceived usefulness of mathematics, and mathematic problem-solving performance. This points to self-efficacy as one possible influence to counteract any negative performance concerns related to student gender and experience.

In another study, Pajares and Valiante (1997) examined 518 fifth graders' self-efficacy as it related to their writing performance. Students completed a survey regarding their self-efficacy, perceived usefulness of writing, and writing apprehension in a single class period and then in another session completed a 30-minute essay writing task. Teachers were also asked to rate students' writing aptitude toward the end of the first semester, prior to students' completion of the essay task. The researchers found that writing self-efficacy contributed significantly to fifth-grade students' essay writing performance, had an effect in reducing writing apprehension, and increasing students' perception of usefulness of writing. Writing self-efficacy also partially mediated the effects of existing writing aptitude and student gender on students' writing apprehension, perceived usefulness of writing, and writing performance. These findings emphasize the significant role self-efficacy can play in a students' performance in the writing, leading to the researchers' suggestion that teachers should pay close attention to not only students' prior performance, but also students' beliefs about their performance as these beliefs mediate the predictive power of past performance on future performance.

Within computer science and related fields, similar relationship can be found with self-efficacy being tied to higher performance, persistence, choice of academic majors, and career aspirations (Beyer, 2014; Blaney & Stout, 2017; Cohoon & Lord, 2006; Lishinski et al., 2016). For example, Beyer (2014) surveyed 1319 first-year students of all majors across three years regarding their demographic information, stereotypes regarding CS, computer self-efficacy and experience, personality variables, and experience in CS courses. Student enrollment and grades in CS courses were tracked for their first year for 128 students, who enrolled in a CS course. The researchers found that first- year undergraduate male students had higher levels of computing self-efficacy than female students, female students rated their own CS ability lower than their male counterparts, and that female students were more likely than male students to believe that women have as much ability as men in CS. As for predicting the likelihood to enroll in a CS course, the strongest predictors were computer self-efficacy, high interest in CS, low family orientation, low openness to experiences, and low conscientiousness. Again, boosting computing self-efficacy could offer a manner in which to address disparities in whether a female student is likely to enroll in computer science courses.

Blaney and Stout (2017) collected data from 2184 undergraduate students enrolled in introductory computing courses across 65 universities regarding their computing self-efficacy, sense of belongingness in computing, and perceived instructor inclusivity. The researchers were primarily interested in how self-efficacy and belongingness may differ in these courses between first-generation college students and their peers, and how these differences appeared across gender. Students' sense of belongingness and self-efficacy had a positive correlation with their level of interaction with faculty in class and student perception of inclusivity. Female students reported less interaction with their instructors both inside and outside of class. The implications the researchers offered is that instructors must make an effort to provide interaction (e.g. group discussion) within their courses for all students, encourage students to attend office hours to introduce themselves, and use explicitly inclusive language in the classroom (e.g. she/he, him/her) as they describe working in computing.

Lishinksi et al. (2016) collected data from 346 undergraduate students enrolled in a CS1 course. The researchers' interest was in the relationship between students' self-efficacy to their programming performance, and how the relationship changed over the span of the semester. The authors found that while male and female students performed similarly in the course, female students adjusted their self-efficacy beliefs to more accurately match their performance earlier in the course than male students, possibly internalizing early failures, which further lowered their self-efficacy beliefs. Male students were slower to adjust their self-efficacy beliefs to match their performance, often overestimating their abilities before eventually reaching a higher correlation between self-efficacy and performance later in the course. The authors argued that differences in the way that male and female students adjust their self-efficacy beliefs can be especially impactful because self-efficacy beliefs can form a feedback loop with performance, where performance impacts self-efficacy, which further impacts future performance. One possible solution to this may be that instructors can examine their pedagogical choices to ensure students are not initially facing tasks that are too difficult or they run the risk of disproportionately lowering self-efficacy of female students over their male counterparts.

Considering the existing findings above (Beyer, 2014; Blaney & Stout, 2017; Cohoon & Lord, 2006; Lishinski et al., 2016), measuring self-efficacy becomes a useful measure for predicting not only academic performance, but point to the likelihood of a student continuing in their field.

2.3 Broadening Participation in Computer Science

Interest and research in gender equity within computer science over multiple decades has examined when we can best intervene in the educational pipeline, how we can remain aware of and address structural inequities in the existing school systems, and how we present computer science as a discipline to students. Given the importance of belongingness and self-efficacy in students' academic outcomes and persistence, it is important to examine how we can alter existing curriculum and classroom practice to better address gender inequality within computer science at the K-12 level.

2.3.1 Timing: Reach Students Before University

Prior work on increasing gender diversity in STEM fields has suggested that we need to engage women in high school and earlier (Google Inc. & Gallup Inc., 2014; Shapiro et al., 2015). Shapiro et al. (2015) surveyed 1189 (414 male, 775 female) middle school students to examine students' confidence, gender role beliefs, career aspirations, and exposure to STEM career options. Four hundred and seventy-five female students identified as girl scout members and 299 identified as not being girl scouts. The authors found that Girl Scouts had higher exposure to STEM career options than the non-Girl Scouts, along with being more likely to voice STEM career aspirations. The authors found that gendered notions of career paths had already been identified in the students' responses, with female students (both Girl Scouts and non-Girl Scouts) anticipating taking a break from their career to care for children, and boys being more likely to state that men are better at some professions than women. The researchers pointed to the higher exposure to STEM experiences as Girl Scouts as possibly counteracting the negative effect of gendered career beliefs on the students' career aspirations.

Google & Gallup (2014) surveyed 1600 participants (600 male, 1000 female) that included pre-college students, college students, and recent graduates. The respondents were 50% pre-college and 50% were currently attending or had recently graduated from college. Fifty percent of the all respondents were interested in or currently studying computer science or a related subject, while the remainder voiced no such interest. Results suggested that four factors accounted for 60.5% of the variance in female student's decision to major in CS. These factors - social encouragement, self-perception, academic exposure, and career perception - had largely been determined before female students entered the university and were less malleable after high school. Social encouragement was the strongest predictor of the decision to major in CS, accounting for 28.1% of the variance in the explainable factors. In addition, career perception of CS graduates was the second strongest predictor of students choosing to pursue a CS degree accounting for 27.5% of the variance in explainable factors. Results suggested that exposure to computer science courses in high school accounted for 22.4% of the variance in explainable factors. Lastly, Self-perception accounted for 17.1% of the variance in explainable factors affecting the decision to pursue a CS undergraduate degree.

Social encouragement included positive feedback from parents, teachers, and peers when pursuing an academic goal. Self-perception was comprised of both a female student' interest and perception of her proficiency in mathematics and problem-solving. Students exhibited this through a "passion for, an interest in … puzzles, problem-solving and tinkering" (Google Inc. & Gallup Inc., 2014, p. 5). Academic exposure referred to a student's opportunity to take a

Computer Science course in high school, the existence of computing in the high school curricula, or access to computing-related extracurricular activities. Female students who had completed an Advanced Placement Computer Science course were found to be 38% more likely to pursue a Computer Science degree. Lastly, career perception included having knowledge of the wide application of computer science beyond stereotypical views of CS as a solitary programming endeavor. Also included in career perception were the possible personal and professional benefits of a computing career. This was seen as not only combating media stereotypes of what a career in computing looks like, but also knowing that the work can have an effect on personal and social causes that relate to the student's interests. The Google & Gallup (2014) study also found that other factors, such as having a family member in the CS field, geography, early exposure to technology, and natural aptitude, had little or no influence on the likelihood for a student to enter into CS. With social encouragement, self-perception, academic exposure, and career perception being easier for teachers and parents to influence, these results were interpreted as a positive finding. The report suggested that these factors are malleable and recommended a number of steps for parents and educators.

Considering that students in the United States do not formally choose a specialization until they reach university presents an opportunity to reach them at the secondary level or even earlier. The more a student has the opportunity to experience success in mathematics and computer science in high school, the likelier they are to continue in computer science as an undergraduate (Google Inc. & Gallup Inc., 2014, p. 2014). While CS does not count towards high school graduation requirements in most states, twenty states have begun requiring schools to allow CS courses to count for some portion of students' math, science, or language graduation requirements (Zinth, 2016). A student's identification of computer science as a field of study, and possibly a career path, coincides with these first exposures in high school (A. Lee, 2015; McInerney, DiDonato, Giagnacova, & O'Donnell, 2006). This rise in support for CS as a college-preparatory course, coupled with research showing secondary level as the critical time for students to prepare for a CS pathway (Google Inc. & Gallup Inc., 2014, p. 2014; A. Lee, 2015; McInerney et al., 2006), makes it increasingly important to examine which of the current efforts show the greatest promise in increasing gender diversity in CS.

High school is often one of the first settings in which students may take a course devoted entirely to the study of computer science, but many primary and middle schools are introducing programs such as the Hour of Code and Computer Science Unplugged to reach younger students (CS Education Research Group, 2014). For example, Project Lead the Way has successfully offered professional development and curriculum for K-8 teachers, thus preparing students for the program's AP Computer Science courses that are offered later in high school (Brown, 2015). These efforts prior to high school are part of an overall strategy in addressing inequity in CS, and provide an area for further study, yet this study is focused on the high school level due to the immediate availability of consistent CS curricula across a wide set of participating high schools.

2.4 Structural Barriers for Equity

In addition to research discussed above on engaging female students in computer science, significant work has been done to understand how structural issues, such as disparate funding across educational systems, varied access to technology in the home, and prevalent gendered beliefs, result in lack of access to STEM and CS offerings for historically marginalized groups (Goode, 2008; Goode, Margolis, & Chapman, 2014; Margolis, 2008, 2013). Margolis (2008) examined three schools with varied resources and demographics in California to discover the root causes for differing gender, racial, and ethnic inequality in CS enrollment. The three schools varied in the number of computing courses offered, the depth of the computing curriculum, and the computing resources available to students during non-class times. With funding disparities across the different schools, the authors found that computing courses were vulnerable to cuts as they were not a graduation requirement, the quality of computing equipment varied, and students had access to resources for longer hours in the more affluent schools. The authors also identified problems with teachers' perceptions of innate student ability and teaching approaches that privileged students with prior experience with technology. The teachers' initial perception of innate student ability, whether students had a predisposed talent for computer programming, was especially problematic in that it appeared to be influenced by gender, race, and ethnicity of the students. The researchers also found that teachers would often privilege the knowledge and classroom interaction of students that already had prior experiences with technology, allowing their needs and questions to steer class discussion, thereby not giving all students equal opportunities and support to construct their own understanding of the material. Students also had unequal access to computers at home and stated their own racial and gendered beliefs regarding the typical "coder". The authors also identified gender inequity as female students encountered sexist interactions with classmates in CS courses, teacher and student beliefs that male students had more inherent coding ability, and a lack of other female students to form a support network. The authors also found that the lack of computer science as a required course, such as mathematics or science, put the impetus upon teachers and students to recruit and maintain enrollment within computing courses. Some students and teachers were still successful in recruiting female students, yet this was arguably limited by students' and teachers' personalities and resources.

In another study, Margolis and Fisher (2003) found that while both female and male students were motivated to major in CS as a result of enjoying programming, female students were also motivated by how computer science was applicable to other fields such as, science and math. This points to the need for CS curriculum to make these connections to other disciplines and computing as part of addressing gender equity. Despite efforts to increase female students' participation in computer science, there is limited research on what specific psychological factors, such as belongingness, influence female students to pursue computing disciplines. Given the existing declines in overall enrollment of female students (U.S. Department of Education, 2017; Zweben, 2013; Zweben & Bizot, 2016), additional research is needed to identify factors likely to influence female students' participation in CS.

2.4.1 Representations of Computing Disciplines

In addition to the efforts discussed previously to broaden participation in CS, a growing body of work has also examined how CS curriculum can be more inclusive and showcase multiple ways in which computer scientists choose to work (Kafai & Burke, 2014; Kafai, Fields, & Searle, 2014; Searle, Fields, Lui, & Kafai, 2014; Turkle, 1997). Turkle (1997) interviewed multiple female programmers and found that traditional approaches to teach programming, reflected by a focus on linear problem solving and defining a program, were not reflective of the full range of programming styles. She argued that these traditional methods were a reflection of a male-dominated field. Turkle and Papert (1990, 1992) proposed the concept of programmers using a form of bricolage, which was not linear and required the programmer to pull from various resources and media, much like an artist; yet still resulting in the end with a program as valid as any other. The programmers using this method reported a somewhat chaotic process, not always driven by a clear plan, in which they jumped around to work on code in various parts of a program until they were satisfied with the overall result. This new type of work was between what one would call traditional programming, with a text editor and compiler, and design work previously done in an analog fashion. Part of this bricolage approach was that the contexts in which computing was applied were more than just on the screen, producing physical artifacts or products that were integrated with the computing technology. The authors saw this approach to computing as a pathway to making the topic more relevant to students (Turkle & Papert, 1992).

Similar to Turkle and Papert's interest in the non-traditional contexts for applying computing, Kafai and colleagues (Kafai & Burke, 2014, 2015; Kafai, Lee, et al., 2014; Kafai, Peppler, & Chapman, 2009) have done extensive work with physical computing involving textiles and circuitry, often with a focus on extending the appeal of CS to female and historically marginalized students. Students are exposed to new contexts for using computing skills by working with these physical projects, engaging in the social experience of programming, and expanding their conceptions of who can be a computer scientist. The rise of maker education (Blikstein, 2013; Dougherty, 2012; Halverson & Sheridan, 2014; Sheridan et al., 2014) has also introduced students to computing ideas from a broader perspective. The results from these alternative approaches to learning and defining CS have pointed to greater participation and collaboration (Kafai, Fields, et al., 2014), increased interest in computing (Searle et al., 2014) among female and underrepresented minority students, and the development of computational thinking skills as a result of engaging in making (Wagh, Gravel, & Tucker-Raymond, 2017)

Kafai et al. (2014) conducted a qualitative study with 15 high school students (7 female, 8 male) in a 10-week physical computing module integrated into an existing computer science course. This module was comprised of lessons that used LilyPad Arduino circuits, a popular platform for programming that controls and interacts with sensors, lights, and other electronics.

These electronic components were integrated into working with textiles to create an artifact that was presented at the conclusion of the module. The researchers reported that students found an increased sense of relevance for their computing skills, an increased ability to envision themselves as computer scientists, and an expanded idea of what computing tasks can include as valid work. The researchers also noted that girls and boys that were not typically attracted to computing were equally participating in the projects, while the use of a non-competitive format for exhibiting final projects also increased engagement with computing concepts.

Searle and Kafai (2015) also conducted a qualitative study looking at a three-week unit delivered as part of a female-only Native Studies course for American Indian girls aged 12-14 at a tribal charter school. The course focused on student-driven textile projects that integrated circuitry with clothing (hoodies) that were shared at the end of the session. Students were encouraged to take the projects home with them to gain advice regarding sewing and crafting from knowledgeable friends and family. The researchers found that the focus on community and crafting of decorative clothing resonated with the cultural norms of the American Indians girls, increased their interest in computing, and gave them an expanded sense of their own capabilities.

Wagh et al. (2017) provided a case study of four 11th and 12th grade students (3 female, 1 male) engaged in making an interactive water fountain that reacted to musical tones with various lighting effects. The project was integrated with the use of Arduino circuit boards and LEDs, along with typical crafting supplies. Over the course of three weeks, the researchers repeatedly interviewed the participants in situ and documented the progression of the project via photographs and field notes. The team identified instances where the students had naturally engaged in, and further developed, the computational thinking skills of problem decomposition, debugging, troubleshooting, and sense making. The researchers pointed to how the use of a project personally important to students, the collaborative nature of the project, and the instant feedback from code to LEDs allowed students to more effectively develop and use these computational thinking skills.

These findings suggest that incorporating more of these non-traditional computing activities and approaches that go beyond typical programming courses into the CS curricula may help attract and retain students in computer science. This is supported by other research arguing that how we represent CS (Yadav et al., 2017) and student misconceptions about CS (Grover, Pea, & Cooper, 2014) has the potential to influence who participates in the field. It is important that we represent the computer science discipline in a way that broadens participation of traditionally underrepresented groups, including female students.

2.5 Context of the Study

Computer science curriculum efforts in K-12 are varied and difficult to match across schools, states, or regions. In an effort to establish a more consistent curriculum across geographical and pedagogical divides, we chose to use the existing Advanced Placement Computer Science courses as a context for both curricular structure and sampling of students.

2.5.1 Advanced Placement Computer Science

The AP Computer Science courses (AP Computer Science Principles and AP Computer Science A) are a set of courses offered in high schools throughout the United States which culminate in students taking a standardized test for each course. The College Board developed these courses with the input of both high school teachers and university faculty. The AP CS frameworks include a progression of topics and activities that teachers can rely upon. Considering the variation in how various states enact other computer science standards, the AP courses offer an opportunity to sample students across geographical settings. Currently, there are two AP CS courses –Advanced Placement Computer Science A (APCS-A) and Advanced Placement Computer Science Principles (APCS-P). The two courses reflect two differing approaches to the teaching of computer science – the APCS-A course focuses primarily on Java programming while the APCS-P course takes a broad view of computing. This provides an opportunity for us to examine how a broad view of computer science influences student outcomes in CS. While specifics regarding our sample and location are covered in the methodology section, it is first important to understand the form and history of these two courses.

2.5.1.1 Advanced Placement Computer Science A

The College Board has offered APCS-A in some form since 1984. This course has historically been conceptualized and organized as a traditional programming course, with a focus on one specific language, programming lab exercises, and paper-based classroom tests. The style of work is largely individual in nature, although certainly instructors provide students the opportunity to work together at times. The course description provided by the College Board (2014) organizes the curriculum by programming constructs such as variables, methods, iteration, and classes. This course was intended to be the equivalent of an undergraduate introductory CS course (CS101) taken during the first semester (The College Board, 2014), although APCS-A typically is done over the course of the entire academic year. The programming language, currently Java, is chosen by the College Board, with all official AP exams and materials reflecting only this language. The final APCS-A exam consists of questions regarding programming concepts and typical code-centric tasks, again in Java.

2.5.1.2 Advanced Placement Computer Science Principles

The College Board recently introduced the APCS-P course, partially in an effort to "appeal to a broader audience, including those often underrepresented in computing" (The College Board, 2016a, p. 4). This course was developed with the intent to broaden the appeal of computer science by focusing on seven big ideas of computing, including exposing students to computational thinking concepts and practices, and allowing students to examine how computing affects the world they live in (The College Board, 2016a). The Seven Big Ideas of computing are creativity, abstraction, data and information, algorithms, programming, the internet, and global impact. The APCS-P curricular framework uses computational thinking throughout the course using six CT practices: connecting computing, creating computational artifacts, abstracting, analyzing problems and artifacts, communicating, and collaborating.

APCS-P was first officially offered to high school students in the 2016-2017 academic year. Similar to APCS-A, the APCS-P course was intended to be the equivalent of a first semester computing course at the undergraduate level. While the APCS-A course has also made some changes over the years to appeal to a larger audience of students, the APCS-P course was intended to be fundamentally different from APCS-A in its approach. Its content is not only new but contains more flexibility in its implementation and format than the APCS-A course. The instructor can choose the language they prefer to use, with activities and exams being "language agnostic". Programming is still used to varying degrees in the course, but activities have been added that differ from the traditional, solitary programming lab assignments. APCS-P provides non-programming exercises in the form of reports and group discussions about social issues tied to computing, such as conducting data collection of consumers and the larger implications of doing so. Possibly the largest change, though, is that students are expected to create two projects of their own design: an “Explore Performance Task” and a “Create Performance Task”.

The *explore performance task* involves researching a computing innovation of the student’s choice (i.e. virtual reality), producing a “computational artifact” that explains the innovation and its impact, and replying in written form to a series of prompts regarding their chosen topic. The artifact must be documented and submitted as part of the AP exam. The *create performance task* involves the student creating a program to solve a problem of their own choosing. Students are heavily encouraged to work collaboratively with other students, and must use advanced logical and mathematical capabilities of their chosen programming language. The *create performance task* must be documented with video of the program running, written responses to prompts regarding their project, and submission of the final materials in an online AP digital portfolio. These tasks are completed over the duration of the course and not intended as an end-of-course assessment.

There is still a traditional end-of-course AP exam, but in place of using a prescribed language (e.g. Java), only *pseudocode* is provided so the student is not dependent on learning a specific language. Pseudocode is a term used to describe draft versions of a program written in natural language, not restricted to a formal programming language syntax, and used to describe the logical flow of a program without being concerned with exact structure and syntax. The remaining questions on the test are presented as traditional multiple choice word problems related to computer science principles and the relationship between computing and the world .

In determining the final AP score for the course, which is graded on a 1 to 5 scale, the “explore performance task” accounts for 16% of the score, the “create performance task” accounts for 24% of the score, and end-of-course exam accounts for 60% of the score. The reduced emphasis on the final exam and the lack of a prescribed programming language are a reflection of the purpose of the course to broaden representations and contexts for the use of computer science. This expansion of the course content beyond only programming constructs, along with the expanded form of assessment beyond paper tests, is what distinguishes the APCS Principles course from the more traditional APCS-A course.

The College Board intends for the Principles course to aid with efforts to broaden participation in CS (The College Board, 2016a). This is not the only goal of the Principles course, but a significant claim in College Board materials and related popular press (Anderson, 2018; The College Board, 2016a). The course was chosen by the researchers as a setting not only for these claims, but more importantly for the curricular choices available in APCS-P that are tied to the research addressing gender inequity. The APCS-P framework requires students to apply computer science to authentic problems, outside of the context of a computer science classroom, which matches with research showing this increases students' engagement and sense of belonging in a computing classroom (Blaney & Stout, 2017; Searle et al., 2014; Searle & Kafai, 2015). The use of computational thinking concepts adds to this cross-disciplinary reach of computer science, allowing for students to see the relevance of CS ideas to solving problems in other fields. While APCS-P is not an all-inclusive representation of all the efforts to address gender inequity through curriculum, the inclusion of computational thinking, a broad representation of computer science, and addressing personally relevant problems are significant enough components to reasonably expect changes in students' self-efficacy and belongingness.

2.6 Research Purpose

Considering the two Advanced Placement Computer Science courses and the intended purpose of APCS-P to broaden participation in computer science, this study addressed the following research questions:

1.) *How do Advanced Placement Computer Science A and Advanced Placement Computer Science Principles courses associate with students' sense of belongingness, self-efficacy, and persistence?*

    1b.) *How does student gender interact with the associations between course type and students' sense of belongingness, self-efficacy, and persistence?*

2.) *How do classroom gender proportions, and teacher gender in AP computer science courses associate with students' sense of belongingness, self-efficacy, and persistence?*

CHAPTER 3 : METHODS

This chapter provides a summary of the methodology used for this study, including the sampling, participants, measures, procedures, and statistical analysis. The study was conducted with a correlational, predictive design (Creswell, 2008), using cross-sectional survey methodology. The purpose of this design choice was to examine the correlation between students' belongingness, self-efficacy, and belongingness with their APCS course taken and their gender

3.1 Sampling

Students enrolled in APCS-A and APCS-P were recruited through teachers who belonged to professional Computer Science organizations such as the Computer Science Teachers Association (CSTA), Michigan Association for Computer Users in Learning (MACUL), social media groups for AP CS instructors, and personal contacts. Both teachers and students were expected to participate in the study for a class section to be included in the analysis. Participants were spread across a diverse range of locations within the United States. The initial email to the teachers included a request to complete a preliminary survey about their teaching experience and eligibility of classes to take part in the study. As this study included minors, teachers served as the primary conduit through which students were recruited, assent/consent materials collected, and survey links distributed. Using the recommendation from Kreft and de Leeuw (1998) regarding proper sample sizes for hierarchical linear modeling analysis, the researcher recruited at least 20 classes to participate in the study.

Forty-eight teachers responded to the initial recruitment survey, of which 39 were eligible to take part in the study. Teachers were sent paper consent and assent forms for both the teachers (N=39) and the students (N=981) enrolled in their APCS classes. An additional 15 teachers and their classes were dropped from the study for various reasons (withdrawal, non-response to emails, lack of consent, school policies), resulting in a total of 24 teachers (male = 12, female = 12). Concerns about including smaller class sizes for hierarchical linear modeling as described by Maas and Hox (2004) led to the removal of classes with less than five students, with a final total of 17 teachers (8 male, 9 Female) and 20 class sections (10 APCS-A, 10 APCS-P).

Of the 17 total teachers, 7 teachers taught APCS-A only, 7 teachers taught APCS-P only, and 3 teachers taught sections of both APCS courses concurrently. Specific number of student participants by gender for course sections are reflected in Table 1. Note that these are only study participants and do not reflect the total enrollment for each of the class sections.

Table 1: Student Participant Summary by Class

Class ID	Teacher ID	Course	Total Participants	Male Participants	Female Participants
1	1	APCS-A	5	3	2
2	2	APCS-A	10	6	4
3	2	APCS-P	27	19	8
4	3	APCS-A	11	7	4
5	4	APCS-P	6	3	3
6	5	APCS-A	8	8	0
7	6	APCS-A	7	2	5
8	7	APCS-A	19	14	5
9	7	APCS-P	14	8	6
10	8	APCS-P	14	10	4
11	9	APCS-P	9	7	2
12	10	APCS-A	5	5	0
13	11	APCS-A	22	17	5
14	11	APCS-P	48	37	11
15	12	APCS-P	5	5	0
16	13	APCS-P	12	4	8
17	14	APCS-A	10	8	2
18	15	APCS-P	17	10	7
19	16	APCS-A	6	6	0
20	17	APCS-P	8	6	2
Total			263	185	78

3.2 Participants

Data was collected from a nationwide sample of 547 responses to the initial student survey. Participants were mostly from the Midwest region of the United States, with students from Arizona, Illinois, Indiana, Maryland, Michigan, New York, Ohio, Oklahoma, Pennsylvania, South Carolina, Texas, Vermont and Wisconsin taking part in the initial surveys. However, 242 responses were removed due to duplicate entries, attrition, lack of consent/assent, lack of a post-survey, enrollment in both CSA and CSP concurrently, and withdrawal. An additional 37 students were removed from analysis due to less than five participants within their respective individual class sections (Maas & Hox, 2004). Given the focus of research on gender differences, five students who did not provide their gender were also removed from the analysis. Final sample included 263 students with 185 male students and 78 female students. Students taking either of the two APCS course ranged from being in 9th to 12th grade, but the majority were in 11th or 12th grade, as are students in AP courses nationally (see Table 2 for detailed demographics on participants).

Racial demographics of the students (see Table 3) who self-identified were 189 White, 27 Asian, 22 multi-racial, 17 Black or African American, 2 Native American or Native Alaskan, and 6 as Other. There were 103 students in APCSA course (27 females and 76 males) and 160 students in APCSP course (51 females and 109 males).

Table 2: Student Participant Summary by Gender and Grade Level

Courses	Grade 9 Male	Grade 9 Female	Grade 10 Male	Grade 10 Female	Grade 11 Male	Grade 11 Female	Grade 12 Male	Grade 12 Female	Total
APCSA Only	9	2	6	1	34	13	27	11	103
APCSP Only	2	0	20	8	28	13	59	30	160
Total	11	2	26	9	62	26	86	41	263

Table 3: Student Participant Summary by Race and Course

Race	All	Total APCS A	Total APCSP	Male APCS A	Female APCS A	Male APCS P	Female APCS P
White	189	79	110	60	19	69	41
Asian	27	6	21	6	0	16	5
Multiple Race	22	6	16	2	4	12	4
Black or African American	17	8	9	5	3	8	1
Native American or Alaska Native	2	2	0	2	0	0	0
Other	6	2	4	1	1	4	0
Total	263	103	160	76	27	109	51

3.3 Measures

3.3.1 Student Surveys

A survey was used to collect data on student (Appendix A) demographic information, sense of belongingness in computer science, self-efficacy in computer science, and persistence within computer science. Teachers also completed a survey (Appendix B) regarding demographics, computer science courses offered at their school, courses they were currently teaching, and APCS class gender composition.

Belongingness

I measured students' sense of belongingness in computer science using an adapted version of the Math Sense of Belongingness Scale (Good et al., 2012). The adapted survey included 28 items on an 7-point Likert-type scale (Strongly Agree to Strongly Disagree), which were adapted for this study by changing item text portions from "mathematics" or "math" to "computer science". The scale was also adapted from Good et al. (2012) original 8-point scale to a 7-point scale to ensure all of the measures had consistent scales, intended to avoid response error. Good et al. (2012) found five factors related to students' sense of belongingness in mathematics: Membership (e.g., "I feel like I belong to the math community"); Acceptance (e.g., "I feel accepted"); Affect (e.g., "I feel comfortable"); Trust (e.g., "I trust my instructors to be committed to helping me learn"); and Desire to Fade (e.g., "I wish I could fade into the background and not be noticed"). The belongingness composite score used in subsequent analysis was calculated by taking the mean of all five factors' respective means.   Good et al. (2012) achieved a Cronbach's alpha of 0.81 for the composite belongingness score. For this study, the composite belongingness score achieved a Cronbach's alpha of 0.85.   For the five subscales, Good et al. (2012) achieved a Cronbach's alpha ranging from 0.78 to 0.95. For this study, the subscale alpha ranged from 0.77 to 0.94 (see Table 4).

Table 4: Cronbach's Alpha for Belongingness Scale

Factor	Good et al. (2012)	Current Study
Membership	0.95	0.92
Acceptance	0.91	0.94
Affect	0.91	0.94
Desire to Fade	0.78	0.88
Trust	0.81	0.77
Composite Belongingness	0.81	0.85

Self-efficacy

The Self-Efficacy for Learning and Performance Scale, a component of the Motivated Strategies for Learning Questionnaire (MSLQ) (Pintrich, Smith, Garcia, & McKeachie, 1991) was used to assess students' self-efficacy for the course. The self-efficacy scale was comprised of eight items on a 7-point Likert-type scale (see Appendix A), of which a mean of the responses was calculated to derive a self-efficacy composite score. Previously reported analysis of this survey had excellent internal consistency reliability as measured by Cronbach's alpha of(α = 0.93) (Pintrich et al., 1991). The scale has been used for assessing student self-efficacy in prior computer science education studies (Lishinski et al., 2016). For this study internal validity was assessed with Cronbach's alpha ($\alpha = 0.96$).

Persistence

In order to measure students' persistence in computer science, I adapted a measure from Yadav et al. (2014), which examined students' interest and engagement in computing. The original scale from Yadav et al (2014) was a four-point Likert-type scale, which I adapted to a seven-point Likert-type scale for the purposes of this study to be consistent with other items in student survey. The eleven items in the persistence section are Likert-type scale items that were adapted to examine students' interest in continuing to study computer science topics, the value they place upon computer science in relation to their future career, and their interest in pursuing a career related to computer science. For this study internal validity of persistence scale was assessed with Cronbach's alpha ($\alpha = 0.96$).

Prior Grades

Collecting students' prior grades directly from the school systems was considered unlikely and a source of further bias due to differing school records and GPA calculations for students. As a measure of prior academic achievement, we adapted a self-reporting scale from the National Education Longitudinal Study of 1988 (Ingels, 1990; NCES, 1988). Research has established similar self-reported measures of academic achievement as acceptable and highly correlated with actual student grades (Frucgt & Cook, 1994; Kuncel, Credé, & Thomas, 2005)

3.3.2 Teacher Surveys

An initial background survey was completed by teachers with items regarding their gender, race/ethnicity, courses offered at their school, courses they were expected to teach, and the gender composition of the CS course. A follow-up survey was completed after the semester had finished to verify that they taught specific courses as initially expected, if any students had dropped the course, and any reasons students may have given for dropping the course. The first survey was composed of 17 items, while the second survey was composed of 8 items (see Appendix B).

3.4 Procedures

Teachers were contacted via an email list for APCS-A and APCS-P instructors, personal contacts of the researcher, and social media posts for APCS teachers asking for their participation and that of their students. Teachers completed an online recruitment survey to ensure that they were teaching at least one APCS course, expected class enrollment totals, and would start teaching the course in the fall semester. Teachers were compensated for taking part in the study. Students were compensated through a random drawing for Amazon gift cards if they completed all the forms and steps of the study. To avoid any concerns regarding coercion, students that chose to not take part in the study, yet returned a consent form stating so, were also included in the drawing pool for compensation. Compensation was sent directly to teachers, along with gift cards for students that were selected in the drawing.

At the beginning of their fall semester, teachers that were teaching at least one APCS course in the fall semester were sent a collection of paper consent forms for their students to complete. Teachers were expected to collect and return these forms within the first two weeks of their course. As their courses began and consent forms were gathered, teachers were then emailed a link to both the student pre-survey and initial teacher surveys. The teachers were encouraged to have students complete these surveys in a class setting to improve completion rate by early-September at the latest. Due to significant weather events (multiple hurricanes) that disrupted multiple schools, the deadline was extended to mid-September for all schools. The schools varied in their start dates for fall semester, from late July to early September, so priority was given to schools starting earlier when sending out the consent forms and links to surveys, with an effort to have each school receive these within the first week of class. The student pre-surveys gathered student background information, belongingness, self-efficacy, and persistence. In order to examine any possible changes in students' belongingness, self-efficacy, and persistence, post-surveys were sent out in early December with a completion deadline of before holiday break. Due to unforeseen school schedule changes, weather, and unique school events, the deadline was extended into mid-January for these surveys as well.

It is important to note that students were only halfway through their AP courses at the time when the post surveys were taken. They likely had enough experiences to see the influence of the curriculum on their belongingness and self-efficacy, as previous studies have shown (Cheryan et al., 2009; Lent et al., 1986; Lishinski et al., 2016; Master, Cheryan, & Meltzoff, 2016; Walton, Logel, Peach, Spencer, & Zanna, 2015). Cheryan et al. (2009) and Master et al. (2016) both found that women's sense of belongingness fell after only a brief intervention in which classroom or workplace décor was altered to be stereotypically male in nature. Lent et al. (1986) found difference in participants self-efficacy and vocational interest across a 10-week course. These studies all point to the likelihood that any changes in self-efficacy and belongingness in this study can reasonably be expected to take hold within one semester.

During both the pre-survey and post-survey phases of the process, teachers were contacted via email to make them aware of how many students had completed their respective surveys, which consent forms had been returned, and if their own teacher surveys were not yet complete. After the deadline for students' post-survey had passed in mid-January, preliminary analysis was conducted, and summary rosters sent to teachers for confirmation. Teachers replied when necessary with any rosters inaccuracies, such as a student choosing the incorrect course they were enrolled in, and any updates to course gender enrollment totals.

3.5 Analysis

Both APCS courses were likely affected by each class' pedagogical, demographic, and environment variables. This presented class sections as a possible contextual variable, with it being likely that the sample of students would not be independent of each other and thus would have student outcomes correlating within their class section. With students nested within each class section in the current study, three separate hierarchical linear modeling (HLM) analyses were used on the data to examine whether the predictive powers of APCS course and student gender on belongingness, self-efficacy, and persistence (each as an outcome in the model) varied between classes. The use of HLM accounts for the within-group variance for each class section, allowing for a more appropriate estimate of the effect of each variable than a simple multiple regression on the entire collection of data would have provided. Intra-class correlation was calculated to determine if HLM was the appropriate statistical method to use for the study data. ICC could be interpreted as a percentage of the overall variance explained by the variance within the class sections, with recommendations from 0.02 to 0.10 being common thresholds to begin considering the use of HLM (Finch, 2014) over other methods. Multilevel analysis was conducted for two levels: variables related to the individual student (Level 1) and variables related to the class section (Level 2). The major analysis of the study was based on comparing student outcomes (belongingness, self-efficacy, and persistence) between APCS-A and APCS-P, while adjusting for differences between clusters on Level-1 (individual student) and Level-2 (class section) covariate characteristics. Level-1 covariates included student's pre-test levels of belongingness, self-efficacy, and persistence, along with student gender, and self-reported prior academic performance. Level-2 covariates included teacher gender and class gender balance percentages.

CHAPTER 4 : RESULTS

This chapter describes the analysis and results conducted on the resulting data from the student and teacher surveys described in Chapter 3.

4.1 Descriptive Statistics

Summary statistics (Table 5) and correlations (Table 6) for self-efficacy, belongingness, persistence, and student prior grades can be found below.

Table 5: Descriptive Statistics for Self-Efficacy, Belongingness, Persistence, and Student Prior Grades

	Self Efficacy Pre	Self Efficacy Post	Belong. Pre	Belong. Post	Persist. Pre	Persist. Post	Student Grades
N	263	263	263	263	263	263	263
Median	5.88	5.88	5.45	5.50	5.55	5.64	6.00
Mean	5.71	5.62	5.43	5.46	5.47	5.41	5.67
SD	1.08	1.15	0.86	0.88	1.16	1.25	0.62
Minimum	2.00	1.38	3.33	2.85	1.64	1.36	1.00
Max	7.00	7.00	7.00	7.00	7.00	7.00	6.00

Pearson correlations provide a preliminary indicator of how the pre and post scores for self-efficacy, belongingness, and self-efficacy may be related. As such, the reader should note that subsequent analysis using hierarchical linear modeling will provide more accurate results of each variable's influence. Results suggested that pre self-efficacy had positive correlations with post self-efficacy (r=0.68, $p<0.001$) and student self-reported prior grades (r=0.20, $p<0.01$). Post self-efficacy had a positive correlation with student self-reported prior grades (r=0.14, $p<0.05$). Pre belongingness had a positive relationship with post belongingness (r=0.64, $p<0.001$). Results suggested that pre persistence had a positive correlation with post persistence (r=0.73, $p<0.001$).

Table 6: Self-Efficacy, Belongingness, Persistence, and Student Prior Grades Correlations

	Self Efficacy Pre	Self Efficacy Post	Belong. Pre	Belong. Post	Persist. Pre	Persist. Post
Self Eff. Pre						
Self Eff. Post	0.68***					
Belong. Pre	0.64***	0.46***				
Belong. Post	0.45***	0.60***	0.64***			
Persist. Pre	0.40***	0.30***	0.47***	0.32***		
Persist. Post	0.30***	0.40***	0.32***	0.49***	0.73***	
Student Grades	0.20**	0.14*	0.02	-0.01	0.06	0.07

Notes * $p<0.05$ ** $p<0.01$ *** $p<0.001$

As shown in Table 7, APCS-P courses had a higher proportion of female participants (female = 31.9%, male = 68.1%) than APCS-A courses (female = 26.2%, male = 72.8%). A chi squared test of independence was conducted to examine whether there was a relationship between the course taken and student gender. The relationship between these variables was not significant ($\chi^2(1) = 0.71$, $p=0.40$). It is important to keep in mind that these percentages are for total participants in the study, which is distinct from the class gender percentages reported by teachers which included both study participants and non-participants.

Table 7: Frequency of Student Participants by Course and Gender

	Female Students	Male Students
APCS-A	27 (26.2%)	76 (72.8%)
APCS-P	51 (31.9%)	109 (68.1%)
Total	78 (29.7%)	185 (70.3%)

As shown in Table 8, participants from APCS-P courses were more likely to have a female teacher (female = 52.5%, male = 47.5%) than APCS-A courses (female = 32.0%, male = 70.0%). A chi squared test of independence was conducted to examine whether there was a relationship between the course taken and teacher gender. The relationship between these variables was significant ($\chi^2(1) = 9.8$, p=0.002), with students in APCS-P being more likely to have a female teacher than students in APCS-A.

Table 8: Frequency of Teacher Gender by Course

	Students with Female Teacher	Students with Male Teachers
APCS-A	33 (32.0%)	70 (68.0%)
APCS-P	84 (52.5%)	76 (47.5%)
Total	117 44.5%)	146 (55.5%)

As shown in Table 9, APCS-P classes had a higher proportion of female teachers (female = 60.0%, male = 40.0%) than APCS-A courses (female = 40.0%, male = 60.0%). A chi squared test of independence was conducted to examine whether there was a relationship between the course taken and teacher gender. The relationship between these variables was not found to be significant ($\chi^2(1) = 0.2$, p=0.655).

Table 9: Frequency of Teacher Gender for Each Class Section by Course Type

	Class Sections with Female Teacher	Class Sections with Male Teachers
APCS-A	4 (40.0%)	6 (60.0%)
APCS-P	6 (60.0%)	4 (40.0%)
Total	10 (50.0%)	10 (50.0%)

4.2 Outcome Variable Change

To analyze pre-post changes in each outcome variable, I calculated a pre-post change for self-efficacy, belongingness, and persistence. This was calculated by subtracting pre scores from post scores for each of the three outcome variables.

Table 10 (see below) offers a summary of the self-efficacy post scores by student gender, course taken, and teacher gender to give an overview of how the different factors of interest compare. Of note is the relatively small mean change in self-efficacy for all participants (M=-0.10, SD=0.89). Female (M=-0.19, SD=0.96) and male (M=-0.05, SD=0.86) students both showed a minor decrease in self-efficacy. APCS-A students show a minor increase in self-efficacy (M=0.02, SD=1.01), while APCS-P students show a minor decrease in self-efficacy (M=-0.17, SD=0.79). Students with both female teachers (M=-0.08, SD=0.86) and male teachers (M=-0.11, SD=0.91) showed a decrease in self-efficacy.

Table 10: Descriptive Statistics for Self-Efficacy by Student Gender, Course, and Teacher Gender

	N	Self-Efficacy Pre		Self-Efficacy Post		Self-Efficacy Change	
		Mean	SD	Mean	SD	Mean	SD
Student Gender							
Female	78	5.31	1.12	5.12	1.32	-0.19	0.96
Male	185	5.88	1.02	5.83	1.00	-0.05	0.86
Course							
APCS-A	103	5.43	1.18	5.46	1.25	0.02	1.01
APCS-P	160	5.89	0.98	5.72	1.07	-0.17	0.79
Teacher Gender							
Female	117	5.63	0.97	5.55	1.10	-0.08	0.86
Male	146	5.77	1.16	5.67	1.19	-0.11	0.91
Total	263	5.71	1.08	5.62	1.15	-0.10	0.89

Table 11 (see below) offers a summary of the Belongingness post scores by student gender, course taken, and teacher gender to give an overview of how the different factors of interest compare. Of note is the relatively small mean change in belongingness for all participants (M=0.02, SD=0.74). Both female (M=0.04, SD=0.63) and male (M=0.02, SD=0.78) students experienced a minor increase in belongingness. APCS-A students showed a minor gain in belongingness (M=0.12, SD=0.76) while APCS-P students showed a minor decrease (M=-0.04, SD=0.72). Students in classes with female teachers experienced a very minor decrease in belongingness (M=-0.01, SD=0.69), while those in classes with male teachers showed a minor increase (M=0.02, SD=0.748.

Table 11: Summary Statistics for Belongingness by Student Gender, Course, and Teacher Gender

	N	Belongingness Pre		Belongingness Post		Belongingness Change	
		Mean	SD	Mean	SD	Mean	SD
Student Gender							
Female	78	5.16	0.84	5.20	0.9	0.04	0.63
Male	185	5.54	0.85	5.56	0.84	0.02	0.78
Course							
APCS-A	103	5.27	0.91	5.39	0.94	0.12	0.76
APCS-P	160	5.54	0.81	5.50	0.83	-0.04	0.72
Teacher Gender							
Female	117	5.34	0.86	5.34	0.89	-0.01	0.69
Male	146	5.50	0.86	5.55	0.85	0.05	0.78
Total	263	5.43	0.86	5.46	0.88	0.02	0.74

Table 12 (see below) offers a summary of the Persistence post scores by student gender, course taken, and teacher gender to give an overview of how the different factors of interest compare. Of note is the relatively small mean change (M = -0.06, SD = 0.90) in persistence for all participants. Female students showed a minor positive change in persistence (M = 0.02, SD = 0.78) while male students showed a minor decrease (M = -0.10, SD = 0.94). APCS-A students also showed a minor increase in persistence (M=0.02, SD=0.72) while APCS-P students showed a minor decrease (M=-0.10, SD=0.99). There was a minor decrease for students in classes with both female teachers (M=-0.08, SD=0.73) and male teachers (M=-0.05, SD=1.01).

Table 12: Summary Statistics for Persistence by Student Gender, Course, and Teacher Gender

	N	Persistence Pre		Persistence Post		Persistence Change	
		Mean	SD	Mean	SD	Mean	SD
Student Gender							
Female	78	5.14	1.26	5.17	1.34	0.02	0.78
Male	185	5.61	1.09	5.51	1.20	-0.10	0.94
Course							
APCS-A	103	5.54	1.19	5.55	1.19	0.02	0.72
APCS-P	160	5.43	1.14	5.32	1.29	-0.11	0.99
Teacher Gender							
Female	117	5.22	1.20	5.15	1.32	-0.08	0.73
Male	146	5.67	1.09	5.62	1.16	-0.05	1.01
Total	263	5.47	1.16	5.41	1.25	-0.06	0.90

4.3 Normality of Outcome Variables

An area of concern was the normality of the outcome variables, an assumption of the use of hierarchical linear modeling. As seen in Table 13, the calculated standardized skewness statistics for Self Efficacy Post (-6.215), Belongingness Post (-2.923), and Persistence Post (-5.506) showed notable negative skew. This negative skew reflected the scores having been consistently recorded toward the upper end of the 7-point Likert-type scales for each of the measures for self-efficacy, belongingness, and persistence. A square transformation was performed to bring the outcome variables within more acceptable ranges for analysis.

Table 13: Outcome Variable Skew and Kurtosis

	Self-Efficacy Post	Belong. Post	Persist. Post	Self-Efficacy Post Squared	Belong. Post Squared	Persist. Post Squared
N	263	263	263	263	263	263
Skewness	-0.934	-0.439	-0.827	-0.349	-0.028	-0.260
SE of Skewness	0.150	0.150	0.150	0.150	0.150	0.150
Kurtosis	0.894	-0.045	0.406	-0.661	-0.549	-0.867
SE of Kurtosis	0.299	0.299	0.299	0.299	0.299	0.299
Skew Std.	-6.215	-2.923	-5.506	-2.326	-0.186	-1.728
Kurtosis Std.	2.987	-0.151	1.357	-2.208	-1.834	-2.897

4.4 Analysis and Results

The analyses for the effects of student gender and course type (APCS-A vs. APCS-P) on self-efficacy, belongingness, and persistence, using hierarchical linear modeling, are covered in this section. A separate analysis was conducted for each of the outcome variables: self-efficacy, belongingness, and persistence.

4.4.1 Self-Efficacy Analysis and Results

A null model with self-efficacy post scores, with intercepts allowed to vary by class section, was examined to determine if hierarchical linear modeling (HLM) was necessary for analysis. The intraclass correlation (ICC) was found to be 0.079, which suggested that 7.9% of the variance in self-efficacy was between class sections. An ICC of this amount in hierarchical data is considered sufficient to justify using hierarchical linear modeling methods(Niehaus, Campbell, & Inkelas, 2014).

Level One variables were self-efficacy pre scores, student gender, and student prior grades. Level Two variables were teacher gender, APCS course taken, and percentage of male students in the class.

Self-efficacy pre scores, student prior grades, and class percentage of male students were centered and standardized to reduce any possible issues with multicollinearity (Finch, 2014), using grand mean centering due to the course type (Level Two) variable being of primary interest (Field, Miles, & Field, 2012). All models used maximum likelihood method for generating parameter estimates. In step two of our analysis, the model was further developed by individually adding the Level One predictors (self-efficacy pre scores, student gender, student prior grades) as fixed effects. The addition of both self-efficacy pre scores ($\chi2$ (1) = 160.42, $p < 0.001$) and student gender ($\chi2$ (1) = 6.007, $p < 0.05$) showed significant improvement in the model. However, the additional of students' prior grades to the model did not show a significant improvement in model fit, yet was retained in the model as theoretically important as a covariate. In step three, each of the Level Two variables (teacher gender, APCS course taken, and percentage of male student in the class) were added as static slope, with none of the variables significantly improving the fit of the model. Similar to how the Level One variables were retained, the Level Two variables were retained as they were theoretically important for the research questions and did not significantly worsen the model fit. In step four, each of the Level One variables (self-efficacy pre scores, student gender, student prior grades) were tested individually as a random slope, yet none of the variables produced a statistically significant improvement to the model fit. Testing these variables as a random slope allowed me to test whether the model is improved by allowing the variable to have a different slope value for each of the class sections. As a result of the lack of model improvement, all the Level One variables remained as fixed slope variables in the model. In step five, each Level Two variable was tested as a random slope, just as the Level One variables were, yet none of the variables produced a statistically significant improvement to the model fit. As a result, all the Level Two variables remained as fixed slope variables in the model. In the final step, an interaction effect was tested between student gender and teacher gender, with the model at this point being unable to converge. The inability of the model to converge suggests that this model was uninterpretable and unusable model. The resulting best fit model from this process used only fixed slopes for the predictor variables, but did allow the intercept to be random across classes. The model was as follows,

Final Self-Efficacy HLM Model:

Level 1: $Y_{ij} = \beta_{0j} + \beta_1 j(\text{SelfEffPre}) + \beta_{2j}(\text{StudentGender}) + \beta_{3j}(\text{StudentGrades}) + \varepsilon ij$

Level 2: $\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{TeacherGender}) + \gamma_{02}(\text{APCSCourse}) + \gamma_{03}(\text{PercentMale}) + u_{0j}$

Mixed Model: $Y_{ij} = \gamma_{00} + \gamma_{01}(\text{TeacherGender}) + \gamma_{02}(\text{APCSCourse}) + \gamma_{03}(\text{PercentMale}) +$

$\gamma_{10}(\text{SelfEffPre}) + \gamma_{20}(\text{StudentGender}) + y_{30}(\text{StudentGrades}) + u_{0j} + u_{2j}(\text{Class}) + \varepsilon ij$

Effects found include a positive relationship for self-efficacy post scores with self-efficacy pre scores ($\beta = 0.65$, $p < .001$, ES = 0.67) and a negative relationship with student gender ($\beta = -0.11$, $p = 0.02$, ES = 0.02). This suggests a medium to large effect size for the self-efficacy pre scores on the self-efficacy post score. A significant effect from student gender on self-efficacy post-scores can be interpreted as female students experiencing a decline in self-efficacy over the course of the study. The model failed to show any significance for students' prior grades, teacher gender, APCS course taken, and class percentage of male students. The resulting statistics are shown in Table 14.

Table 14: Self-Efficacy Hierarchical Linear Model Analysis

	Self-Efficacy Post			
	B	*std. Beta*	*SE*	*p*
Fixed Parts				
(Intercept)	34.30			**<.001**
Self-Efficacy Pre	7.64	0.65	0.05	**<.001**
Female Student	-2.89	-0.11	0.05	**.020**
Student Grades	0.41	0.03	0.05	.490
Female Teacher	-0.18	-0.01	0.06	.900
APCS-Principles	-0.44	-0.02	0.06	.775
Class % Male	0.19	0.02	0.06	.792
Random Parts				
σ^2	70.232			
$\tau_{00,\ \text{classID}}$	2.808			
N_{classID}	20			
ICC_{classID}	0.038			
Observations	263			
R^2 / Ω_0^2	.510 / .509			

4.4.2 Belongingness Analysis and Results

A null model with belongingness post scores with intercepts allowed to vary by class section, was examined to determine if hierarchical linear modeling (HLM) was necessary for analysis. The intraclass correlation (ICC) was found to be 0.026, suggesting that 2.6% of the variance in belongingness was between class sections. An ICC of this amount in hierarchical data is considered sufficient to justify using hierarchical linear modeling methods (Niehaus et al., 2014)

Level One variables were belongingness pre scores, student gender, and student prior grades. Level Two variables were teacher gender, APCS course taken, and percentage of male students in the class.

Belongingness pre scores, student prior grades, and class percentage of male students were centered and standardized to reduce any possible issues with multicollinearity (Finch, 2014), using grand mean centering due to the course type (Level Two) variable being of primary interest (Field et al., 2012). All models used maximum likelihood method for generating parameter estimates. In step two of our analysis, the model was further developed by adding the Level One predictors (belongingness pre scores, student gender, student prior grades) as fixed effects, with the addition of only belongingness pre scores showing a significant difference ($\chi2$ (3) = 153.07, $p < 0.001$) from the previous model. Student gender and students' prior grades reported did not show a significant change in the model fit, but were retained in the model as theoretically important. In step three, each of the Level Two variables (teacher gender, APCS course taken, and percentage of male student in the class) were added as static slope, with none of the variables significantly improving the fit of the model. Similarly to how the Level One variables were retained, the Level Two variables were retained as they were theoretically important for the research questions and did not significantly worsen the model fit. In step four, each Level One variable was tested as a random slope, with the finding that allowing student gender to be random produced a statistically significant improvement to the model fit ($\chi2$ (2) = 6.1923, $p < 0.032$). However, the correlation of the random slope of student gender (-1.00) denoted a possible problem with an overfit model, providing a model that was too closely tied to the data collected to be generalized to other data sets. Testing for singularity confirmed the overfit fit model, so student gender was not made random and all Level One predictors remained static. In step five, each Level Two variable was tested as a random slope, yet none of the variables produced a statistically significant improvement to the model fit. As a result, all the Level Two variables remained as fixed slope variables in the model. In the final step, an interaction effect was tested between student gender and teacher gender, but failed to find a significant difference. The resulting best fit model from this process used fixed slopes for all of the predictor variables except student gender, which along with the intercept was allowed to be random across classes. The model was as follows:

Final Belongingness HLM Model:

Level 1: $Y_{ij} = \beta_{0j} + \beta_1 j(\text{BelongPre}) + \beta_{2j}(\text{StudentGender}) + \beta_{3j}(\text{StudentGrades}) + \varepsilon ij$

Level 2: $\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{TeacherGender}) + \gamma_{02}(\text{APCSCourse}) + \gamma_{03}(\text{PercentMale}) + u_{0j}$

Mixed Model: $Y_{ij} = \gamma_{00} + \gamma_{01}(\text{TeacherGender}) + \gamma_{02}(\text{APCSCourse}) + \gamma_{03}(\text{PercentMale}) + \gamma_{10}(\text{BelongPre}) + \gamma_{20}(\text{StudentGender}) + y_{30}(\text{StudentGrades}) + u_{0j} + u_{2j}(\text{Class}) + \varepsilon ij$

Effects found include a positive relationship for belongingness pre scores with belongingness post scores (β=0.66, $p < .001$, ES = 0.70). This suggests a medium to large effect size for the belongingness pre scores on the belongingness post score. The model failed to show any significance for student gender, students' prior grades, teacher gender, APCS course taken, and class percentage of male students. The resulting statistics are shown in Table 15.

Table 15: Belongingness Hierarchical Linear Model Analysis

	Belongingness Post			
	B	*std. Beta*	*SE*	*p*
Fixed Parts				
(Intercept)	31.44			**<.001**
Belongingness Pre	6.08	0.66	0.05	**<.001**
Female Student	-0.60	-0.03	0.05	.539
Student Grades	-0.17	-0.02	0.05	.707
Female Teacher	-0.77	-0.04	0.06	.520
APCS-Principles	-0.84	-0.04	0.07	.507
Class % Male	0.47	0.05	0.06	.446
Random Parts				
σ^2	45.550			
$\tau_{00,\ \mathrm{classID}}$	2.331			
N_{classID}	20			
ICC_{classID}	0.049			
Observations	263			
R^2 / Ω_0^2	.483 / .483			

4.4.3 Persistence Analysis and Results

As the first step of analysis, a null model with persistence post scores with intercepts allowed to vary by class section, was examined to determine if hierarchical linear modeling (HLM) was necessary for analysis. The intra class correlation (ICC) was found to be 0.149, suggesting that 14.9% of the variance in persistence was between class sections. An ICC of this amount in hierarchical data is considered sufficient to justify using hierarchical linear modeling methods (Niehaus et al., 2014).

Level One variables were persistence pre scores, student gender, and student prior grades. Level Two variables were teacher gender, APCS course taken, and percentage of male students in the class.

Persistence pre scores, student prior grades, and class percentage of male students were centered and standardized to reduce any possible issues with multicollinearity (Finch, 2014), using grand mean centering due to the course type (Level Two) variable being of primary interest (Finch, 2014). All models used maximum likelihood method for generating parameter estimates. In step two of our analysis, the model was further developed by adding the Level One predictors (persistence pre scores, student gender, student prior grades) as fixed slopes, with the addition of only persistence pre scores showing to be significant difference ($\chi 2$ (3) = 191.5, $p < 0.001$) from the previous model. Student gender and students' prior grades reported did not show a significant change in the model fit, but were retained in the model as theoretically important. In step three, each of the Level Two variables (teacher gender, APCS course taken, and percentage of male student in the class) were added as static slope, with none of the variables significantly improving the fit of the model. Similarly to how the Level One variables were retained, the Level Two variables were retained as they are theoretically important for the research questions and did not significantly worsen the model fit. In step four, each Level One variable was tested as a random slope, yet none of the variables produced a statistically significant improvement to the model fit. As a result, all the Level One variables remained as fixed slope variables in the model. In step five, each Level Two each Level Two variable was tested as a random slope, yet none of the variables produced a statistically significant improvement to the model fit. As a result, all the Level Two variables remained as fixed slope variables in the model. In the final step, an interaction effect was tested between student gender and teacher gender but failed to find a significant difference. The resulting best fit model from this process used fixed slopes for all the predictor variables, while the intercept was allowed to be random across classes. The model was as follows:

Final Persistence HLM Model:

Level 1: $Y_{ij} = \beta_{0j} + \beta_1 j(\text{PersistPre}) + \beta_{2j}(\text{StudentGender}) + \beta_{3j}(\text{StudentGrades}) + \varepsilon ij$

Level 2: $\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{TeacherGender}) + \gamma_{02}(\text{APCSCourse}) + \gamma_{03}(\text{PercentMale}) + u_{0j}$

Mixed Model: $Y_{ij} = \gamma_{00} + \gamma_{01}(\text{TeacherGender}) + \gamma_{02}(\text{APCSCourse}) + \gamma_{03}(\text{PercentMale}) +$
$\gamma_{10}(\text{PersistPre}) + \gamma_{20}(\text{StudentGender}) + y_{30}(\text{StudentGrades}) + u_{0j} + u_{2j}(\text{Class}) + \varepsilon ij$

Effects found include a positive relationship for persistence pre scores with persistence post scores (β=0.72, $p < .001$, ES = 1.02). This suggests a large effect size for the persistence pre scores on the persistence post score. The model failed to show any significance for student gender, students' prior grades, teacher gender, APCS course taken, and class percentage of male students. The resulting statistics are shown in Table 16.

Table 16: Persistence Hierarchical Linear Model Analysis

	Persistence Post			
	B	*std. Beta*	*SE*	*p*
Fixed Parts				
(Intercept)	28.46			**<.001**
Persistence Pre	7.70	0.72	0.04	**<.001**
Female Student	0.76	0.03	0.04	.528
Student Grades	0.19	0.01	0.04	.824
Female Teacher	-0.92	-0.04	0.04	.398
APCS-Principles	-0.92	-0.04	0.04	.417
Class % Male	4.53	0.05	0.05	.264
Random Parts				
σ^2	70.039			
$\tau_{00,\ classID}$	0.000			
$N_{classID}$	20			
$ICC_{classID}$	0.000			
Observations	263			
R^2 / Ω_0^2	.545 / .545			

CHAPTER 5 : DISCUSSION

This study examined how two different Advanced Placement Computer Science courses, APCS-A and APCS-Principles, affect students' sense of self-efficacy, belongingness, and persistence within computer science, and how those relationships relate to student gender. The three outcome variables of self-efficacy, belongingness, and persistence were chosen as possible indicators of the likelihood of students to pursue computer science. The relationship between student gender and the two courses was examined due to the underrepresentation of women in computer science. Teachers and students from a nationwide sample of APCS courses completed multiple surveys to provide a rich data set. Hierarchical linear modeling analysis was conducted to account for the nested nature of the students within their respective class sections. Based upon prior literature, teacher gender, class section gender percentages, and students' prior grades were also included in the analysis. Hierarchical linear analysis was conducted with separate models for each of the outcome variables (self-efficacy, belongingness, and persistence).

Results suggested that students' pre self-efficacy scores and student gender significantly predicted post self-efficacy scores. The APCS course taken, students' prior grades, teacher gender, and class percentage of male students did not have a significant relationship with post self-efficacy scores. Student gender had a small, negative effect on post self-efficacy scores, which suggested that female students had a larger decrease in self-efficacy than male students over the course of the study. These results match with existing research, which has found that male students take longer than female students to match their self-efficacy beliefs with actual task performance (Beyer, 2014; Beyer, Rynes, Perrault, Hay, & Haller, 2003) and that students' self-efficacy is influenced by their performance in a CS course (Lishinski et al., 2016). Research has also suggested that even in typically female-majority courses such as biology, male students have a higher sense of confidence in their skills than female students with similar grades (Cooper, Krieg, & Brownell, 2018).

Findings suggest that only students' pre belongingness scores were significantly related to post belongingness post scores. APCS course taken, students' gender, prior grades, teacher gender, and class percentage of male students did not have a significant relationship with belongingness post scores. While the effect of course chosen and student gender are the main focus of this study, I found the lack of influence of two covariates (teacher gender and class gender percentages) on belongingness to be surprising. The lack of a change in belongingness, particularly in the APCS-P course, was surprising as this course was supposed to engage traditionally underrepresented students in computing ideas, including women, to broaden the participation of students in computer science. No difference was found by gender for belongingness, yet there are prevalent negative stereotypes associated with female students' abilities in computer science (Beyer, 2014; Cundiff et al., 2013; C. M. Lewis, Anderson, & Yasuhara, 2016; Master et al., 2016) and female students in this study were in minority in their classes. Results from prior research related to stereotype threat (Cheryan et al., 2009; Murphy et al., 2007; Steele, 1997) would suggest that teacher gender and class percentage of student gender would have a significant effect on student belongingness, particularly for female students.

In predicting student persistence post scores, only students' persistence pre-scores were found to have a statistically significant relationship. The APCS course taken, students' gender, prior grades, teacher gender, and class percentage of male students did not have a significant relationship with persistence post scores. Considering how exposure to computer science courses is shown in prior research to be a significant factor in whether students choose to major in computing fields (Google Inc. & Gallup Inc., 2014), and how APCS-Principles was intended to improve upon female students interest in continuing in CS, these results are surprising.

One possible explanation for the lack of APCS course predicting self-efficacy, belongingness, or persistence might be due to the enactment of the two APCS courses and inherent variability in how teachers implemented the curriculum. Only knowing the course designation does not provide information on whether the CS principles included a broad representation computer science and how computing is applicable within other disciplines. Prior research has suggested that female students are attracted to a broader view of computer science and how what they learn in CS can be used to solve problems in other disciplines (Margolis, Fisher, & Miller, 2000). Future work should examine how different instantiations of the APCS-P could influence students' self-efficacy, belonging, and persistence. Future work could also gather data describing the specific pedagogical strategies teachers used within the APCS-P and APCS-A classes and examine whether these had an effect on belongingness or self-efficacy in computer science. Within the range of possible instantiations and pedagogical practices used in APCS-A or APCS-P, there are likely examples that do influence students' beliefs. However, in its current form, the study did not capture these distinctions within the range of courses sampled. This examination of practices in the classroom should be done from both from a student and teacher perspective, as while teachers may fully intend to use different approaches, students may not receive or experience these efforts in the way it was intended.

The variability in teacher practices could also be a result of teachers' beliefs, practices, and pedagogical preferences. This study did not collect data related to the actual practices taking part in the classroom, or attempt to capture teacher beliefs that relate to their pedagogical choices. If these beliefs and choices were independent of which courses they taught, and thus affected both courses equally, it would explain why the results by course were so similar and no difference by course was found.

Another possible hypothesis for the lack of findings could be due to the diffusion of practices between APCS-A and APCP-P. The majority of participating APCS teachers had taught or were currently teaching other computer science courses, with a significant portion having taught both APCS-A and APCS-P. It is very likely that as they attended professional development workshops, reviewed professional teaching materials, and engaged with the CS teaching community, that teachers of both APCS-P and APCS-A integrated some of these recommended practices for making their courses more equitable. As a result, APCS-A students may have benefited from these equity efforts, and thus explain the lack of difference in results across courses. The inverse could also be true, in that newly learned practices related to equity were not fully enacted into either of the courses, with not enough difference to be found between APCS-A and APCS-P as a result. Again, we do not have enough information about what occurred within the classroom, particularly the pedagogical choices being made and the classroom social interactions, to be able to say how present or not these practices were.

Considering the lack of significant change in students' self-efficacy, belongingness, and persistence found in this study, a possible explanation is that students entering into the APCS courses have already formed their beliefs around their relationship to computer science. Participants were largely juniors and seniors in high school, which suggests we need to reach them before high school or even earlier to allow them to see relevance of CS to other fields. This aligns with suggestions by Grover et al. (2014) and Shapiro et al. (2015) that middle school aged and younger students may be a more appropriate age group to target for addressing gender inequity in computer science. Students have already received and are beginning to process messages regarding the gendered notions of computer science by middle school (Shapiro et al., 2015; Yadav et al., 2017). Research shows that primary and middle school students have successfully developed and used computational thinking concepts (Grover et al., 2014). While researchers focusing on younger age levels would lose the common curricular guidance of the AP programs, it is possible that other curricular efforts through existing organizations such as Project Lead the Way, Code.org, or Google could provide a similar consistent, national framework. In considering this shift to younger students, it bears considering that this focus on earlier grades does not release us as researchers and educators from our responsibility to continue addressing gender inequality in the upper grade levels.

Finally, the lack of change in self-efficacy, belongingness, and persistence may be that the measures adapted for this study were too general and not nuanced enough to measure constructs within computer science. The field of computer science is referred to broadly in these instruments, assuming students have a reasonable conception of what the term ‘computer science’ entails. Lishinski (2017) similarly hypothesized that these general measures are not detailed enough for the domain, and that instruments that relate to sub-concepts of computer science could be developed that could be better understood by students. Rather than make references to the “computer science community” or similar descriptions, the instruments could be adjusted with more approachable language for CS novices. Additionally, this is an area where a more detailed interview could provide a sense of what students’ conception of computer science is prior to and after working within the course.

5.1 Implications

The results found that the type of AP Computer Science course did not significantly influence students’ self-efficacy, belongingness, and persistence. As such, the implication is that the current implementation of APCS Principles course may not be associated with an increase in either male or female students' likelihood to persist in the field of computer science.

5.1.1 Implications for Practice

For those teaching computer science at the high school level, or involved in developing the APCS curriculum, these may not appear to be helpful results at first glance. Consider that female students accounted for only 23.6% of APCS-A enrollees during the 2016-2017 academic year, while in APCS-P female students accounted for 30.1% of APCS-P enrollees. While this shows an improvement in the recruitment of women into CS courses, this proportion is still very low and considerable work still needs to be done to achieve comparable gender proportions in computer science. This suggests a need to look beyond high school curriculum alone to address gender inequity, possibly examining structural barriers outside of the classroom that determine who is more likely to walk into the classroom door.

School administrators, counselors, and policymakers can help address structural barriers by looking for instances where students are not currently being directed toward computer science and asking why that is. While APCS-P was intended to address some of these issues, it is possible that we are still mostly bringing kids in the door that would have likely ended up in computer science anyway. Efforts like CSforAll, which are focusing on exposing all students to some computer science, without needing to be enrolled in a formal CS course, may help with the lack of CS experience. The integration of computational thinking approaches into non-CS courses may also aid in exposing students to the idea that they are already doing CS types of activities in their existing work (Benakli, Kostadinov, Satyanarayana, & Singh, 2017; Hambrusch, Hoffmann, Korb, Haugan, & Hosking, 2009; I. Lee, Martin, & Apone, 2014; Voogt, Fisser, Good, Mishra, & Yadav, 2015; Yadav, Hong, & Stephenson, 2016). This not only reaches students with CS while avoiding the need to be in a CS course, but can also provide authentic experiences for the applicability of CS concepts. These experiences could increase students' self-efficacy to pursue computer science and feel like they belong. In addition, introducing CS ideas by integrating in core subject areas could expose teachers and administrators to the range of possible applications of computer science, and adjust their conception of who would benefit from taking a course in computer science.

An additional consideration for future practice for administrators would be to examine whether they are assigning teachers of differing experiences to the different types of computing courses. It is possible that if there is a disparity in teaching experience, that disparity is detracting from possible benefits to be had from the existing curriculum. APCS-P by design is more approachable for novice students in programming (The College Board, 2016a) and that may result in teachers with less programming experience to be more commonly assigned to teach APCS-P courses. Future practice and research can examine the exact practices put into use by the teachers, whether the practices correlate with years of experience or other measures of teachers' content knowledge. There may also be biases present in which schools are able to offer more advanced computing courses, such as APCS-P and APCS-A, due to disparate funding and staffing (Margolis, 2008)

The results from this study also found that female students' self-efficacy was negatively affected to a larger degree than their male counterparts, similar to the findings of Lishinski et al. (2016). As suggested by Lishinski et al., educators should be carefully scaffolding students experiences to ensure that they are providing challenging enough challenges to build students' sense of self-efficacy, but not so challenging that they are discouraging students.

5.1.2 Implications for Future Research

A consideration for future research is developing measures that are applicable to computer science. We need to develop measures that are sensitive enough to measure self-efficacy, belongingness, and persistence within computer science. In addition, we also need to better understand how students conceive of computer science. Future research needs to examine how students' conceptions of computer science influence their self-efficacy, belongingness, persistence. We have little sense of how to interpret changes in student self-efficacy, belongingness, or persistence without knowing more about their reasons for their answers.

Future research could also examine how other variables such as gendered student perceptions of CS, as well as teachers beliefs about who can do CS, could also influence students' self-efficacy, belongingness, persistence. Shumow and Schmidt (2013) found that teacher beliefs in a science classroom can lead to higher levels of classroom interaction between male students and instructors, resulting in inequitable learning experiences for female students. Reigel-Crumb and Humphries (2012) in an analysis of nationwide data found that teacher's gendered beliefs regarding the mathematic ability was related to more negative evaluations of female students. Espinoza et al. (2014) found that mathematics teachers were more likely to attribute male students' success to ability and female students' success to effort. They also found that interventions could help address these beliefs and the influence on classroom practice. Future research could use examine similar phenomena in computer science settings, with classroom observation to see how teachers interact with students in the classroom and how their beliefs influence their pedagogical choices.

In addition to the effect of teacher beliefs, student beliefs in fixed ability traits, or student perceptions of the prevalence of ability beliefs among peers, could have an effect on belongingness. When female students perceive that teachers or peers believe that ability to learn a particular discipline is innate and fixed, there is a negative effect on their sense of belongingness (Good et al., 2012). Consider that a female student may enter a classroom and see a disproportionate number of male students, and then encounters statements about the need for innate talent in this field. This could arguably lead to her developing a lack of belonging in the discipline. Smith et al. (2013) found that female students in male dominated STEM fields often believed that they will have to work harder than their male counterparts, interpreted this as a lack of ability, and resulted in a lower level of motivation. We did not examine students' or teachers' ability beliefs in this study, and thus may have missed a significant predictor of existing belongingness beliefs. Future research can examine these beliefs in computer science classrooms, along with perceptions students have of others' beliefs.

As more time passes from the introduction of the APCS-P courses, we can more directly study the relationship between retention of female and other underrepresented students within computer science by examining college acceptance, dropout, and graduation rates for students that took the APCS courses in high school. However, this requires longitudinal studies to examine the impact of APCS-P on persistence in CS.

There also needs to be work on examining experiences of other underrepresented groups, including African-American and Latino students in computer science. However, typical low enrollment of these groups in APCS courses requires national sampling of participants. In addition, future research could also use qualitative approaches to complement our understanding of why students choose to persist (or not) within computer science, and the effect that courses like APCS have on them. Using qualitative methods to more fully understand the process by which students make their decisions, and the cultural and gendered messages they receive in relation to the course could also inform development of curriculum and pedagogical practices used to engage traditionally underrepresented groups in CS.

5.2 Limitations

The limitations for this study are largely the result of the chosen study methodology and design, participation rates, conceptualization of study variables, and demographic realities of secondary computer science education.

With a descriptive study such as this one, the immediate limitations we can point to are due to selection bias (Remler & Van Ryzin, 2011). In regards to self-selection bias, students have some control over which courses they enroll in in high school, with computer science often being an optional course not required for graduation (Zinth, 2016). This leads to a bias towards students who already have an interest in computer science, or have been encouraged to do so, and thus may already have a higher sense of self-efficacy, belongingness, and persistence in computer science than the overall student population.

The method of recruitment of students via their teacher introduced additional selection bias in gaining student participants. The expectation of teachers to conduct recruitment and collect study forms may have led to a lower participation rate and often resulted in entire classes of students not being recruited due to teacher participants deciding to withdraw. There are also issues with bias as students can be directed to courses by their counselors and teachers, who may have pre-existing notions of which students are best suited for computer science (Margolis, 2008). Finally, the decision of the students whether or not to participate in the study introduced yet another level of selection bias. Some of the selection bias was partially addressed through the use of covariates such as pre-existing levels of self-efficacy, belongingness, and persistence, along with students' prior academic performance.

Another limitation of this study would be that the participants were overwhelmingly identified as white or Asian and majority male. This limits the generalizations we can make from the results, as they do not fully reflect the experiences of students of color and intersections of other underrepresented groups of students (Vitores & Gil-Juárez, 2015). Particularly troubling is the underrepresentation of female students of color in this sample, which mirrors a national problem within computer science. This could be addressed by recruiting students from multiple ethnicities and racial groups, resulting in large enough subsets of data for historically marginalized populations. Interviewing students about their decision to enroll in APCS, and any intersections they found between their experiences in APCS and their gender, race, or ethnicity, could also provide insight. Presenting the range of experiences students describe across multiple settings, and finding similarities in such, would offer a more complete picture of APCS course experiences and speak to possible generalizable conclusions.

The limitations of self-reported data are present in this study, with the possibility that students are biased to provide answers they believe socially acceptable, skewed toward more recent experiences, or may have a limited interpretation of the survey questions. Any of these biases can threaten the validity of the measures and in some may play a role in the high mean scores for self-efficacy, belongingness, and persistence scores. One manner of addressing this could be through also complementing these self-reported measures with external measures that indicate similar constructs. For instance, while we do not have a method of externally measuring a student's sense of belongingness, we could record classroom interactions and analyze students' frequency of interaction or voicing of sense of belonging or feeling isolated. External measures such as these are imperfect as well, but when coupled with the self-report data could strengthen the validity of the data.

Another limitation I attempted to address in this study was the conceptualization of gender as dichotomous (Glasser & Smith, 2008). Gender was chosen as a variable rather than sex, due to the American Psychological Association (APA) guidance of gender being related to social groups, rather than sex which is often interpreted as being related to biological characteristics of students (2010). I was mostly interested in how the courses offered would appeal to students in their social interactions within their classrooms, having no relation to biological designations. I recognized that the APA guidance is imperfect (Glasser & Smith, 2008) in that researchers are still often conflating sex and gender, and are defaulting to a dichotomous definition of both. I attempted to address the range of possible gender identities by giving students a choice beyond male or female, a field "Other" with the ability to enter in any text desired and an option to not provide gender. The same choices were made available for teachers when they reported the overall class gender percentages. However, I received only male or female responses from students, except for some invalid student responses that were very likely reactionary in nature toward the non-binary gender option. While I had hoped this option offered space for non-binary and gender nonconforming students to self-identify for the study, I did not receive any such responses. In retrospect, the options I offered for gender designation of were not affirming enough to encourage students to fully share their information. A more appropriate solution for future research would be a more explicit inclusion of multiple gender identities, rather than trying to capture these under a vague and possibly dehumanizing category of "Other." In addition to the limitations of the survey responses, I also see structural problems where study design may have influenced student responses, as an impersonal survey where the privacy of the data is unknown, may not be the setting for a student to disclose this information.

In addition to students' responses regarding their own gender, there is a possible problem with the teacher reported class gender ratios, as some students may not yet be publicly identifying as their gender or may not match the school records of student gender that teachers likely used as a data source. Similar to race and ethnicity, even if I had students identifying as non-binary or gender nonconforming, the sample needed for quantitative analysis would have to be substantial. This, along with the personal nature of students identifying their gender, lends itself toward more qualitative methods in which trust can be established over time and in which individual, detailed accounts can offer more a more complete picture of a student's experience within APCS.

5.3 Conclusion

Advanced Placement Computer Science courses are but one context in which we can examine our efforts to address gender inequity within computer science education. This study showed no significant differences in students' self-efficacy, belongingness, and persistence based solely upon the students' APCS course. The findings suggest that female students encountered a slight decrease in their computer science self-efficacy in these courses, which does bolster the case for a more detailed examination of how these courses are taught and how female students describe their classroom experiences. The results of this study should not be interpreted to say that these APCS courses are of no benefit to the students, only that we should be careful not to automatically predict increases in female enrollment in undergraduate CS majors based solely on the increases we see in APCS courses. Addressing gender inequity is not solely about these the outcome variables chosen for this study and more work needs to be done to use measures sensitive enough to capture nuances of student experience in computer science. The results from this study show that enrollment in courses designated as APCS-A or APCS-P does not predict any differences in female students' self-efficacy, belongingness, or likelihood of persisting within computer science. In summary, results suggest that more work needs to be done and we cannot just put our faith in one course as the answer to address inequities within CS.

APPENDICES

APPENDIX A Survey for Students

NOTE: Items that are in only one of the surveys are denoted as such

1.) First Name:

2.) Last Name:

3.) (PRE-TEST ONLY) Gender:
   a. Female
   b. Male
   c. Prefer not to say
   d. Other:____________

4.) (PRE-TEST ONLY) Are you Spanish, Hispanic, Latino or none of these?

5.) (PRE-TEST ONLY) Choose one or more races that you consider yourself to be:
   a. White
   b. Black or African American
   c. Native American or Alaska Native
   d. Asian
   e. Native Hawaiian or Pacific Island
   f. Other:____________

6.) Date of Birth:

7.) (PRE-TEST ONLY) What is your current grade level in school?

   a. Grade 9
   b. Grade 10
   c. Grade 11
   d. Grade 12
   e. Other: ____________

8.) School Name:

9.) School City:

10.) School State:

11.) Teacher Last Name:

Academic History

12.) Choose the statement that best describes your grades in high school up until now:

a. Mostly A's
b. Mostly B's
c. Mostly C's
d. Mostly D's
e. Mostly below D's
f. Does not apply to me

13.) Choose the statement that best describes your grades in SCIENCE courses in high school up until now:

a. Mostly A's
b. Mostly B's
c. Mostly C's
d. Mostly D's
e. Mostly below D's
f. Does not apply to me

14.) Choose the statement that best describes your grades in MATH courses in high school up until now:

a. Mostly A's
b. Mostly B's
c. Mostly C's
d. Mostly D's
e. Mostly below D's
f. Does not apply to me

15.) Which course(s) are you currently taking?

a. AP Computer Science A only
b. AP Computer Science Principles only
c. Both AP Computer Science A and AP Computer Science Principles
d. Neither AP Computer Science course

(PRE-TEST ONLY) Previous computer science courses (only completed by those answering A for question 15)

16.) (PRE-TEST ONLY) Have you previously taken the AP Computer Science Principles course? Y/N

17.) (PRE-TEST ONLY) Have you taken any non-AP Computer science courses before this course? Y/N/I don't know

(PRE-TEST ONLY) **Previous computer science courses** (only completed by those answering B for question 15)

16.) (PRE-TEST ONLY) Have you previously taken the AP Computer Science A course? Y/N

17.) (PRE-TEST ONLY) Have you taken a non-AP computer science courses before this semester? Y/N/I don't know

Belongingness

This next set of questions deals with your feeling of belonging in this course.

Today we have some questions we would like you to answer about your experience in your computer science courses and the computer science community. When we mention the computer science community, we are referring to the broad group of people involved in that field, including the students in a computer science course. We would like you to consider your membership in the computer science community. By virtue of taking a computer science course, you could consider yourself a member of the computer science community. Given this broad definition of belonging to the computer science community, please respond to the following statements based on how you feel about that group and your membership in it. There are no right or wrong answers to any of these statements; we are interested in your honest reactions and opinions. Please read each statement carefully and indicate the number that reflects your degree of agreement.

Level of Agreement

1 – Strongly disagree • 2 – Disagree • 3 – Somewhat disagree • 4 – Neither agree or disagree • 5 – Somewhat agree • 6 – Agree • 7 – Strongly agree

When I am in my computer science class…

1.) I feel that I belong to the computer science community.
1 2 3 4 5 6 7

2.) I consider myself a member of the computer science world.
1 2 3 4 5 6 7

3.) I feel like I am part of the computer science community.
1 2 3 4 5 6 7

4.) I feel a connection with the computer science community.
1 2 3 4 5 6 7

5.) I feel like an outsider.
1 2 3 4 5 6 7

6.) I feel accepted.
1 2 3 4 5 6 7

7.) I feel respected.
1 2 3 4 5 6 7

8.) I feel disregarded.
1 2 3 4 5 6 7

9.) I feel valued.
1 2 3 4 5 6 7

10.) I feel neglected.
1 2 3 4 5 6 7

11.) I feel appreciated.
1 2 3 4 5 6 7

12.) I feel excluded.
1 2 3 4 5 6 7

13.) I feel like I fit in.
1 2 3 4 5 6 7

14.) I feel insignificant.
1 2 3 4 5 6 7

15.) I feel at ease.
1 2 3 4 5 6 7

16.) I feel anxious.
1 2 3 4 5 6 7

17.) I feel comfortable.
1 2 3 4 5 6 7

18.) I feel tense.
1 2 3 4 5 6 7

19.) I feel nervous.
1 2 3 4 5 6 7

20.) I feel content.
1 2 3 4 5 6 7

21.) I feel calm.

1 2 3 4 5 6 7

22.) I feel inadequate.
1 2 3 4 5 6 7

23.) I wish I could fade into the background and not be noticed.
1 2 3 4 5 6 7

24.) I try to say as little as possible.
1 2 3 4 5 6 7

25.) I enjoy being an active participant.
1 2 3 4 5 6 7

26.) I wish I were invisible.
1 2 3 4 5 6 7

27.) I trust the testing materials to be unbiased.
1 2 3 4 5 6 7

28.) I have trust that I do not have to constantly prove myself.
1 2 3 4 5 6 7

29.) I trust my instructors to be committed to helping me learn.
1 2 3 4 5 6 7

30.) Even when I do poorly, I trust my instructors to have faith in my potential.
1 2 3 4 5 6 7

This next set of questions deals with how you believe you will perform in this course. There are no right or wrong answers to any of these statements; we are interested in your honest reactions and opinions. Please read each statement carefully, and indicate the number that reflects your degree of agreement

Level of Agreement
1 – Not at all true of me • 7 – Very true of me

31.) I believe I will receive an excellent grade in this class.
1 2 3 4 5 6 7

32.) I'm certain I can understand the most difficult material presented in the readings for this course.
1 2 3 4 5 6 7

33.) I'm confident I can understand the basic concepts taught in this course.

1 2 3 4 5 6 7

34.) I'm confident I can understand the most complex material presented by the instructor in this course.
1 2 3 4 5 6 7

35.) I'm confident I can do an excellent job on the assignment and tests in this course.
1 2 3 4 5 6 7

36.) I expect to do well in this class.
1 2 3 4 5 6 7

37.) I'm certain I can master the skills being taught in this class
1 2 3 4 5 6 7

38.) Considering the difficulty of this course, the teacher, and my skills, I think I will do well in this course.
1 2 3 4 5 6 7

This next set of questions deals with how you may use your computer science knowledge in the future.
There are no right or wrong answers to any of these statements; we are interested in your honest reactions and opinions. Please read each statement carefully, and indicate the number that reflects your degree of agreement

Level of Agreement:

1 – Strongly disagree • 2 – Disagree • 3 – Somewhat disagree • 4 – Neither agree or disagree • 5 – Somewhat agree • 6 – Agree • 7 – Strongly agree

39.) Knowledge of computer science will allow me to secure a better job
1 2 3 4 5 6 7

40.) My career goals do not require that I learn computer science skills
1 2 3 4 5 6 7

41.) I expect that learning computer science skills will help me to achieve my career goals
1 2 3 4 5 6 7

42.) I hope that my future career will require the use of computer science concepts

1 2 3 4 5 6 7

43.) Having background knowledge and understanding of computer science is valuable in and of itself

1 2 3 4 5 6 7

44.) I am interested in a career as a computer scientist

1 2 3 4 5 6 7

45.) I am interested in a career where knowledge of computer science would be useful.

1 2 3 4 5 6 7

46.) I plan to pursue a career that requires computer science skills

1 2 3 4 5 6 7

47.) I am interested in taking computer science courses in college.

1 2 3 4 5 6 7

48.) I am likely to teach myself computer science skills on my own.

1 2 3 4 5 6 7

49.) If given the opportunity, I would take more computer science courses

1 2 3 4 5 6 7

APPENDIX B Survey for Computer Science Teachers

Thank you for volunteering to take part in this study. We expect to distribute these surveys at the beginning and end of the fall semester for all students and teachers. Your participation and that of your students will contribute to research regarding students' sense of belongingness and self-efficacy within computer science, along with their desire to persist in the field.

1.) First Name:

2.) Last Name:

3.) (PRE-TEST ONLY) Gender:

    a. Female
    b. Male
    c. Prefer not to say
    d. Other: ___________

4.) (PRE-TEST ONLY) Are you Spanish, Hispanic, or Latino or none of these?

    a. Yes
    b. No

5.) (PRE-TEST ONLY) Choose one or more races that you consider yourself to be:

    a. White
    b. Asian
    c. Black or African American
    d. Native Hawaiian or Pacific Islander
    e. Native American or Alaska Native
    f. Other:____________

6.) (PRE-TEST ONLY) Date of Birth:

7.) School Name:

8.) School City

9.) School State

10.) I am currently teaching the course(s):

a. AP Computer Science A
b. AP Computer Science Principles

11.) My student in this (these) courses participated in the study:

a. AP Computer Science A
b. AP Computer Science Principles

12.) (PRE-TEST ONLY) What other computer science courses have you taught?

13.) (PRE-TEST ONLY) How many years, including the current academic year, have you taught AP Computer Science A

14.) (PRE-TEST ONLY) How many years, including the current academic year, have you taught AP Computer Science Principles?

15.) (PRE-TEST ONLY) How many years, including the current academic year have you taught computer science courses?

16.) (PRE-TEST ONLY) How many years have you taught in general?

17.) (PRE-TEST ONLY) How many students of the following genders are currently enrolled in this course (if multiple classes/sections, please denote student for each class/section)?

a. Male:____________
b. Female:___________
c. Other:_____________

18.) (PRE-TEST ONLY) Which computer science courses are available for students to take at your school?

a. Advanced Placement Computer Science A
b. Advanced Placement Computer Science Principle
c. Other:______________________

19.) (POST-TEST ONLY) If any students participating in the study withdrew from the class, please list their name(s): _________________________________

20.) (POST-TEST ONLY) If any students withdrew from the course, what reasons did the student(s) state for doing so? If multiple students listed, please state each with student's reason.

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REFERENCES

REFERENCES

American Psychological Association. (2010). *Publication manual of the American Psychological Association.* (6th ed.). Washington, DC: American Psychological Association.

Anderson, N. (2018, January 8). Expansion of AP computer science courses draws more girls and minorities. *Washington Post*. Retrieved from https://www.washingtonpost.com/local/education/expansion-of-ap-computer-science-draws-more-girls-and-minorities/2018/01/08/cd5932d8-e040-11e7-89e8-edec16379010_story.html

Aspray, W. (2016). Organizations That Help Women to Build Computing Careers. In *Women and Underrepresented Minorities in Computing* (pp. 165–203). Springer, Cham. Retrieved from https://link-springer-com.proxy1.cl.msu.edu/chapter/10.1007/978-3-319-24811-0_8

Bandura, A. (1977). Self-efficacy: Toward a Unifying Theory of Behavioral Change. *Psychological Review*, *84*(2), 191.

Bandura, A. (1986). The Explanatory and Predictive Scope of Self-Efficacy Theory. *Journal of Social and Clinical Psychology; New York*, *4*(3), 359–373. https://doi.org/http://dx.doi.org.proxy2.cl.msu.edu/10.1521/jscp.1986.4.3.359

Bandura, A. (1997). *Self-efficacy: the exercise of control*. New York: W.H. Freeman.

Bandura, A. (2002). Social cognitive theory in cultural context. *Applied Psychology*, *51*(2), 269–290.

Baumeister, R. F., & Leary, M. R. (1995). The need to belong: Desire for interpersonal attachments as a fundamental human motivation. *Psychological Bulletin*, *117*(3), 497–529. https://doi.org/10.1037/0033-2909.117.3.497

Benakli, N., Kostadinov, B., Satyanarayana, A., & Singh, S. (2017). Introducing computational thinking through hands-on projects using R with applications to calculus, probability and data analysis. *International Journal of Mathematical Education in Science and Technology*, *48*(3), 393–427. https://doi.org/10.1080/0020739X.2016.1254296

Beyer, S. (2014). Why are women underrepresented in Computer Science? Gender differences in stereotypes, self-efficacy, values, and interests and predictors of future CS course-taking and grades. *Computer Science Education*, *24*(2–3), 153–192. https://doi.org/10.1080/08993408.2014.963363

Beyer, S., Rynes, K., Perrault, J., Hay, K., & Haller, S. (2003). Gender differences in computer science students (p. 49). ACM Press. https://doi.org/10.1145/611892.611930

Blaney, J. M., & Stout, J. G. (2017). Examining the Relationship Between Introductory Computing Course Experiences, Self-Efficacy, and Belonging Among First-Generation College Women. In *Proceedings of the 2017 ACM SIGCSE Technical Symposium on Computer Science Education* (pp. 69–74). New York, NY, USA: ACM. https://doi.org/10.1145/3017680.3017751

Blikstein, P. (2013). Digital Fabrication and “Making” in Education: The Democratization of Invention. *FabLabs: Of Machines, Makers and Inventors*, 1–21.

Brown, B. (2015). Project and Problem Based Learning: PLTW and AP CS Principles. *Acm*, 52.

Chemers, M. M., Zurbriggen, E. L., Syed, M., Goza, B. K., & Bearman, S. (2011). The Role of Efficacy and Identity in Science Career Commitment Among Underrepresented Minority Students: Efficacy and Identity in Science Career Commitment. *Journal of Social Issues*, *67*(3), 469–491. https://doi.org/10.1111/j.1540-4560.2011.01710.x

Chen, X. (2013). STEM Attrition: College Students’ Paths into and out of STEM Fields. Statistical Analysis Report. NCES 2014-001. *National Center for Education Statistics*. Retrieved from http://eric.ed.gov/?id=ED544470

Cheryan, S., Plaut, V. C., Davies, P. G., & Steele, C. M. (2009). Ambient belonging: How stereotypical cues impact gender participation in computer science. *Journal of Personality and Social Psychology*, *97*(6), 1045–1060. https://doi.org/10.1037/a0016239

Code.org. (2017, March 27). University computer science finally surpasses its 2003 peak! Retrieved April 23, 2017, from https://medium.com/anybody-can-learn/university-computer-science-finally-surpasses-its-2003-peak-ecefa4c8d77d

Cohoon, J. M., & Lord, H. (2006). A faculty role in women’s participation in computing. In E. M. Trauth (Ed.), *Encyclopedia of gender and information technology* (pp. 297–303). Hershey, PA: Idea Group Reference.

College Board. (2017). *AP Program Participation and Performance Data 2017: Program Summary Report 2017*. Retrieved from https://secure-media.collegeboard.org/digitalServices/pdf/research/2017/Program-Summary-Report-2017.pdf

Cooper, K. M., Krieg, A., & Brownell, S. E. (2018). Who perceives they are smarter? Exploring the influence of student characteristics on student academic self-concept in physiology. *Advances in Physiology Education*, *42*(2), 200–208. https://doi.org/10.1152/advan.00085.2017

Creswell, J. W. (2008). *Educational Research: Planning, Conducting, and Evaluating Quantitative and Qualitative Research* (3 edition). Upper Saddle River, N.J: Prentice Hall.

Crowell, R. (2016). Gender Bias and the Evaluation of Players: Voice and Gender in Narrated Gameplay Videos. *Dissertations and Theses*. https://doi.org/10.15760/etd.3150

CS Education Research Group. (2014). Computer Science Unplugged. Retrieved January 12, 2014, from http://csunplugged.org/

Cundiff, J. L., Vescio, T. K., Loken, E., & Lo, L. (2013). Do gender-science stereotypes predict science identification and science career aspirations among undergraduate science majors? *Social Psychology of Education : An International Journal; Dordrecht*, *16*(4), 541–554. https://doi.org/http://dx.doi.org.proxy2.cl.msu.edu/10.1007/s11218-013-9232-8

Deci, E. L., & Ryan, R. M. (2000a). The“ what” and“ why” of goal pursuits: Human needs and the self-determination of behavior. *Psychological Inquiry*, *11*(4), 227–268.

Deci, E. L., & Ryan, R. M. (2000b). The “What” and “Why” of Goal Pursuits: Human Needs and the Self-Determination of Behavior. *Psychological Inquiry*, *11*(4), 227–268.

Dollar, D., & Gatti, R. (1999). *Gender inequality, income, and growth: are good times good for women?* (Vol. 1). Development Research Group, The World Bank Washington, DC. Retrieved from http://darp.lse.ac.uk/frankweb/courses/EC501/DG.pdf

Dougherty, D. (2012). The maker movement. *Innovations*, *7*(3), 11–14.

DuBow, W., Kaminsky, A., & Weidler-Lewis, J. (2017). Multiple Factors Converge to Influence Women’s Persistence in Computing: A Qualitative Analysis. *Computing in Science & Engineering*, *19*(3), 30–39. https://doi.org/10.1109/MCSE.2017.42

Eccles, J. S., Barber, B., & Jozefowicz, D. (1999). Linking gender to educational, occupational, and recreational choices: Applying the Eccles et al. model of achievement-related choices. In *Sexism and stereotypes in modern society: The gender science of Janet Taylor Spence* (pp. 153–192). Washington, DC, US: American Psychological Association.

Ericson, B. (2014, January 1). Detailed AP CS 2013 Results: Unfortunately, much the same. Retrieved January 12, 2017, from https://computinged.wordpress.com/2014/01/01/detailed-ap-cs-2013-results-unfortunately-much-the-same/

Espinoza, P., Arêas Da Luz Fontes, A. B., & Arms-chavez, C. J. (2014). Attributional gender bias: teachers’ ability and effort explanations for students’ math performance. *Social Psychology of Education : An International Journal; Dordrecht*, *17*(1), 105–126. https://doi.org/http://dx.doi.org.proxy1.cl.msu.edu.proxy2.cl.msu.edu/10.1007/s11218-013-9226-6

Field, A. P., Miles, J., & Field, Z. (2012). *Discovering statistics using R*. London ; Thousand Oaks, Calif: Sage.

Finch, W. H. (2014). *Multilevel modeling using R*. Boca Raton, FL: CRC Press, Taylor & Francis Group.

Frucgt, V. G., & Cook, G. L. (1994). Further research on the accuracy of students' self-reported grade point averages, SAT scores, and course grades. *Perceptual and Motor Skills*, *79*(2), 743–746.

Glasser, H. M., & Smith, J. P. (2008). On the Vague Meaning of "Gender" in Education Research: The Problem, Its Sources, and Recommendations for Practice. *Educational Researcher*, *37*(6), 343–350. https://doi.org/10.3102/0013189X08323718

Good, C., Rattan, A., & Dweck, C. S. (2012). Why do women opt out? Sense of belonging and women's representation in mathematics. *Journal of Personality and Social Psychology; Washington*, *102*(4), 700.

Goode, J. (2008). Increasing diversity in k-12 computer science: strategies from the field. In *ACM SIGCSE Bulletin* (Vol. 40, pp. 362–366). ACM. Retrieved from http://dl.acm.org/citation.cfm?id=1352259

Goode, J., Margolis, J., & Chapman, G. (2014). Curriculum is not enough: the educational theory and research foundation of the exploring computer science professional development model (pp. 493–498). ACM Press. https://doi.org/10.1145/2538862.2538948

Goodenow, C. (1993). Classroom Belonging among Early Adolescent Students: Relationships to Motivation and Achievement. *The Journal of Early Adolescence*, *13*(1), 21–43. https://doi.org/10.1177/0272431693013001002

Google Inc. & Gallup Inc. (2014). Women Who Choose CS: What Really Matters. Google Inc. & Gallup Inc. Retrieved from https://goo.gl/rLX6ax

Google Inc. & Gallup Inc. (2015). Images of Computer Science: Perceptions Among Students, Parents and Educators in the U.S. Google Inc. & Gallup Inc. Retrieved from https://goo.gl/F3SSWH

Grover, S., Pea, R., & Cooper, S. (2014). Remedying Misperceptions of Computer Science Among Middle School Students. In *Proceedings of the 45th ACM Technical Symposium on Computer Science Education* (pp. 343–348). New York, NY, USA: ACM. https://doi.org/10.1145/2538862.2538934

Halverson, E. R., & Sheridan, K. M. (2014). The Maker Movement in Education. *Harvard Educational Review*, *84*(4), 495–504.

Hambrusch, S., Hoffmann, C., Korb, J. T., Haugan, M., & Hosking, A. L. (2009). A Multidisciplinary Approach Towards Computational Thinking for Science Majors. *ACM SIGCSE Bulletin*, *41*(1), 183–187.

Hamilton, M., Luxton-Reilly, A., Augar, N., Chiprianov, V., Gutierrez, E. C., Duarte, E. V., … Wong, E. (2016). Gender Equity in Computing: International Faculty Perceptions and Current Practices. In *Proceedings of the 2016 ITiCSE Working Group Reports* (pp. 81–102). New York, NY, USA: ACM. https://doi.org/10.1145/3024906.3024911

Hausmann, L. R. M., Schofield, J. W., & Woods, R. L. (2007). Sense of Belonging as a Predictor of Intentions to Persist Among African American and White First-Year College Students. *Research in Higher Education*, *48*(7), 803–839. https://doi.org/10.1007/s11162-007-9052-9

Ingels, S. J. (1990). *National Education Longitudinal Study of 1988 (NELS:88) - Student Component Data File User's Manual*. Retrieved from https://nces.ed.gov/surveys/nels88/

Inzlicht, M., & Ben-Zeev, T. (2000). A Threatening Intellectual Environment: Why Females Are Susceptible to Experiencing Problem-Solving Deficits in the Presence of Males. *Psychological Science*, *11*(5), 365–371. https://doi.org/10.1111/1467-9280.00272

Inzlicht, M., & Good, C. (2005). How environments can threaten academic performance, self-knowledge, and sense of belonging. In S. Levin & C. V. Laar (Eds.), *Stigma and Group Inequality: Social Psychological Perspectives*. Mahwah, NJ: Psychology Press.

Kafai, Y. B., & Burke, Q. (2014). Beyond Game Design for Broadening Participation: Building New Clubhouses of Computing for Girls. In *Proceedings of Gender and IT Appropriation. Science and Practice on Dialogue - Forum for Interdisciplinary Exchange* (p. 21). Siegen, Germany: European Society for Socially Embedded Technologies. Retrieved from http://dl.acm.org/citation.cfm?id=2670301

Kafai, Y. B., & Burke, Q. (2015). Constructionist Gaming: Understanding the Benefits of Making Games for Learning. *Educational Psychologist*, *50*(4), 313–334. https://doi.org/10.1080/00461520.2015.1124022

Kafai, Y. B., Fields, D., & Searle, K. (2014). Electronic Textiles as Disruptive Designs: Supporting and Challenging Maker Activities in Schools. *Harvard Educational Review*, *84*(4), 532–556.

Kafai, Y. B., Lee, E., Searle, K., Fields, D., Kaplan, E., & Lui, D. (2014). A Crafts-Oriented Approach to Computing in High School: Introducing Computational Concepts, Practices, and Perspectives with Electronic Textiles. *Trans. Comput. Educ.*, *14*(1), 1:1–1:20. https://doi.org/10.1145/2576874

Kafai, Y. B., Peppler, K. A., & Chapman, R. N. (2009). *The Computer Clubhouse: Constructionism and Creativity in Youth Communities* (50045th edition). New York: Teachers College Press.

Kreft, I., & Leeuw, J. de. (1998). *Introducing multilevel modeling*. London ; Thousand Oaks, Calif: Sage.

Kuncel, N. R., Credé, M., & Thomas, L. L. (2005). The Validity of Self-Reported Grade Point Averages, Class Ranks, and Test Scores: A Meta-Analysis and Review of the Literature. *Review of Educational Research; Washington*, *75*(1), 63–82.

Lee, A. (2015). Determining the effects of computer science education at the secondary level on STEM major choices in postsecondary institutions in the United States. *Computers & Education*, *88*, 241–255. https://doi.org/10.1016/j.compedu.2015.04.019

Lee, I., Martin, F., & Apone, K. (2014). Integrating Computational Thinking Across the K–8 Curriculum. *ACM Inroads*, *5*(4), 64–71. https://doi.org/10.1145/2684721.2684736

Lent, R. W., Brown, D., & Hackett, G. (2002). Social Cognitive Career Theory. In *Career choice and development* (4th ed, pp. 255–311). San Francisco, CA: Jossey-Bass.

Lent, R. W., Brown, S. D., & Hackett, G. (1994). Toward a Unifying Social Cognitive Theory of Career and Academic Interest, Choice, and Performance. *Journal of Vocational Behavior*, *45*(1), 79–122. https://doi.org/10.1006/jvbe.1994.1027

Lent, R. W., Brown, S. D., & Larkin, K. C. (1986). Self-Efficacy in the Prediction of Academic Performance and Perceived Career Options. *Journal of Counseling Psychology; Washington, D.C.*, *33*(3), 265.

Lewis, C. M., Anderson, R. E., & Yasuhara, K. (2016). “I Don’t Code All Day”: Fitting in Computer Science When the Stereotypes Don’t Fit (pp. 23–32). ACM Press. https://doi.org/10.1145/2960310.2960332

Lewis, K. L., Stout, J. G., Pollock, S. J., Finkelstein, N. D., & Ito, T. A. (2016). Fitting in or opting out: A review of key social-psychological factors influencing a sense of belonging for women in physics. *Physical Review Physics Education Research*, *12*(2). https://doi.org/10.1103/PhysRevPhysEducRes.12.020110

Lishinski, A. (2017). *Cognitive, Affective, and Dispositional Components of Learning to Program* (Doctoral Dissertation). Michigan State University.

Lishinski, A., Yadav, A., Good, J., & Enbody, R. (2016). Learning to Program: Gender Differences and Interactive Effects of Students’ Motivation, Goals, and Self-Efficacy on Performance. In *Proceedings of the 2016 ACM Conference on International Computing Education Research* (pp. 211–220). New York, NY, USA: ACM. https://doi.org/10.1145/2960310.2960329

Maas, C. J. M., & Hox, J. J. (2004). The influence of violations of assumptions on multilevel parameter estimates and their standard errors. *Computational Statistics & Data Analysis*, *46*(3), 427–440. https://doi.org/10.1016/j.csda.2003.08.006

Margolis, J. (2008). *Stuck in the shallow end: education, race, and computing*. Cambridge, Mass: MIT Press.

Margolis, J. (2013). Unlocking the clubhouse: a decade later and now what? In *Proceeding of the 44th ACM technical symposium on Computer science education* (pp. 9–10). ACM. Retrieved from http://dl.acm.org/citation.cfm?id=2445202

Margolis, J., & Fisher, A. (2003). *Unlocking the Clubhouse: Women in Computing*. Cambridge, Mass.: The MIT Press.

Margolis, J., Fisher, A., & Miller, F. (2000). The anatomy of interest: Women in undergraduate computer science. *Women's Studies Quarterly; Old Westbury, N.Y.*, *28*(1), 104–105.

Marx, D. M., & Roman, J. S. (2002). Female Role Models: Protecting Women's Math Test Performance. *Personality and Social Psychology Bulletin*, *28*(9), 1183–1193. https://doi.org/10.1177/01461672022812004

Master, A., Cheryan, S., & Meltzoff, A. N. (2016). Computing whether she belongs: Stereotypes undermine girls' interest and sense of belonging in computer science. *Journal of Educational Psychology*, *108*(3), 424–437. https://doi.org/10.1037/edu0000061

McInerney, C. R., DiDonato, N. C., Giagnacova, R., & O'Donnell, A. M. (2006). STUDENTS'CHOICE OF INFORMATION TECHNOLOGY MAJORS AND CAREERS: A QUALITATIVE STUDY. *Information Technology, Learning, and Performance Journal*, *24*(2), 35.

Murphy, M. C., Steele, C. M., & Gross, J. J. (2007). Signaling Threat: How Situational Cues Affect Women in Math, Science, and Engineering Settings. *Psychological Science*, *18*(10), 879–885. https://doi.org/10.1111/j.1467-9280.2007.01995.x

National Science Board. (2016). Science and Engineering Indicators 2016. Retrieved from https://www.nsf.gov/statistics/2016/nsb20161/#/

NCES. (1988). National Education Longitudinal Study of 1988 (NELS:88) - Overview. Retrieved June 22, 2018, from https://nces.ed.gov/surveys/nels88/

Niehaus, E., Campbell, C. M., & Inkelas, K. K. (2014). HLM Behind the Curtain: Unveiling Decisions Behind the Use and Interpretation of HLM in Higher Education Research. *Research in Higher Education*, *55*(1), 101–122.

Obama, B. H. (2016, January 12). Remarks of President Barack Obama – State of the Union Address As Delivered. Retrieved January 14, 2016, from https://www.whitehouse.gov/the-press-office/2016/01/12/remarks-president-barack-obama-%E2%80%93-prepared-delivery-state-union-address

Oudshoorn, N., Rommes, E., & Stienstra, M. (2004). Configuring the User as Everybody: Gender and Design Cultures in Information and Communication Technologies. *Science, Technology, & Human Values*, *29*(1), 30–63. https://doi.org/10.1177/0162243903259190

Pajares, F., & Miller, M. D. (1994). Role of Self-Efficacy and Self-Concept Beliefs in Mathematical Problem Solving: A Path Analysis. *Journal of Educational Psychology*, *86*(2), 193.

Pajares, F., & Valiante, G. (1997). Influence of Self-Efficacy on Elementary Students' Writing. *The Journal of Educational Research*, *90*(6), 353–360. https://doi.org/10.1080/00220671.1997.10544593

Partovi, H. (2013). With support from Obama to Shakira, Apple to Zuckerberg, the Hour of Code is Here. Retrieved March 24, 2014, from http://codeorg.tumblr.com/post/69469632752/hourofcodeishere

Pickett, C. L., Gardner, W. L., & Knowles, M. (2004). Getting a Cue: The Need to Belong and Enhanced Sensitivity to Social Cues. *Personality and Social Psychology Bulletin*, *30*(9), 1095–1107. https://doi.org/10.1177/0146167203262085

Pintrich, P. R., Smith, D. A. F., Garcia, T., & McKeachie, W. J. (1991). *A Manual for the Use of the Motivated Strategies for Learning Questionnaire (MSLQ)*. Retrieved from https://www.researchgate.net/publication/271429287_A_Manual_for_the_Use_of_the_Motivated_Strategies_for_Learning_Questionnaire_MSLQ

Pittman, L. D., & Richmond, A. (2007). Academic and Psychological Functioning in Late Adolescence: The Importance of School Belonging. *The Journal of Experimental Education*, *75*(4), 270–290. https://doi.org/10.3200/JEXE.75.4.270-292

Plantenga, J. (2015). *The economics of gender equality; a review of the literature in three propositions and two questions*. WWWforEurope Working Paper. Retrieved from https://www.econstor.eu/handle/10419/125759

Remler, D. K., & Van Ryzin, G. G. (2011). *Research Methods in Practice: Strategies for Description and Causation*. Thousand Oaks, Calif: SAGE Publications.

Riegel-Crumb, C., & Humphries, M. (2012). EXPLORING BIAS IN MATH TEACHERS' PERCEPTIONS OF STUDENTS' ABILITY BY GENDER AND RACE/ETHNICITY. *Gender and Society*, *26*(2), 290–322.

Rommes, E., Oost, E. V., & Oudshoorn, N. (1999). Gender in the Design of the Digital City of Amsterdam. *Information, Communication & Society*, *2*(4), 476–495. https://doi.org/10.1080/136911899359510

Ryoo, J., Goode, J., & Margolis, J. (2015). It takes a village: supporting inquiry- and equity-oriented computer science pedagogy through a professional learning community.

Computer Science Education, *25*(4), 351–370. https://doi.org/10.1080/08993408.2015.1130952

Searle, K. A., Fields, D. A., Lui, D. A., & Kafai, Y. B. (2014). Diversifying high school students' views about computing with electronic textiles (pp. 75–82). ACM Press. https://doi.org/10.1145/2632320.2632352

Searle, K. A., & Kafai, Y. B. (2015). Culturally Responsive Making with American Indian Girls: Bridging the Identity Gap in Crafting and Computing with Electronic Textiles (pp. 9–16). ACM Press. https://doi.org/10.1145/2807565.2807707

Shapiro, M., Grossman, D., Carter, S., Martin, K., Deyton, P., & Hammer, D. (2015). Middle school girls and the "leaky pipeline" to leadership. *Middle School Journal; Columbus*, *46*(5), 3–13.

Sheridan, K. M., Halverson, E. R., Litts, B. K., Brahms, L., Jacobs-Priebe, L., & Owens, T. (2014). Learning in the making: A comparative case study of three makerspaces. *Harvard Educational Review*, *84*(4), 505–531.

Shumow, L., & Schmidt, J. A. (2013). Academic grades and motivation in high school science classrooms among male and female students: Associations with teachers' characteristics, beliefs, and practices. In R. Haumann & G. Zimmer (Eds.), *Handbook of academic performance: predictors, learning strategies and influences of gender* (pp. 53–72). Hauppauge, New York: Nova Science Publisher's.

Smith, J. L., Brown, E. R., Thoman, D. B., & Deemer, E. D. (2015). Losing its expected communal value: how stereotype threat undermines women's identity as research scientists. *Social Psychology of Education : An International Journal; Dordrecht*, *18*(3), 443–466. https://doi.org/http://dx.doi.org.proxy1.cl.msu.edu.proxy2.cl.msu.edu/10.1007/s11218-015-9296-8

Smith, J. L., Lewis, K. L., Hawthorne, L., & Hodges, S. D. (2013). When Trying Hard Isn't Natural: Women's Belonging With and Motivation for Male-Dominated STEM Fields As a Function of Effort Expenditure Concerns. *Personality and Social Psychology Bulletin*, *39*(2), 131–143. https://doi.org/10.1177/0146167212468332

Steele, C. M. (1997). A threat in the air: How stereotypes shape intellectual identity and performance. *American Psychologist*, *52*(6), 613.

Steele, C. M., & Aronson, J. (1995). Stereotype threat and the intellectual test performance of African Americans. *Journal of Personality and Social Psychology*, *69*(5), 797.

Tellhed, U., Bäckström, M., & Björklund, F. (2017). Will I Fit in and Do Well? The Importance of Social Belongingness and Self-Efficacy for Explaining Gender Differences in Interest in STEM and HEED Majors. *Sex Roles*, *77*(1–2), 86–96. https://doi.org/10.1007/s11199-

016-0694-y

The College Board. (2014). AP Computer Science A Course Description. The College Board. Retrieved from https://secure-media.collegeboard.org/digitalServices/pdf/ap/ap-computer-science-a-course-description.pdf

The College Board. (2016a). AP Computer Science Principles Curriculum Framework. Retrieved from https://advancesinap.collegeboard.org/stem/computer-science-principles/course-details

The College Board. (2016b). AP Program Participation and Performance Data 2016 - National Report. The College Board. Retrieved from https://research.collegeboard.org/programs/ap/data/participation/ap-2016

Trump, D. J. (2017, September 25). Presidential Memorandum for the Secretary of Education. Retrieved October 16, 2017, from https://www.whitehouse.gov/the-press-office/2017/09/25/memorandum-secretary-education

Turkle, S. (1997). *Life on the Screen: Identity in the Age of the Internet*. New York: Simon & Schuster.

Turkle, S., & Papert, S. (1990). Epistemological Pluralism: Styles and Voices within the Computer Culture. *Signs*, *16*(1), 128–157.

Turkle, S., & Papert, S. (1992). Epistemological pluralism and the revaluation of the concrete. *Journal of Mathematical Behavior*, *11*(1), 3–33.

U.S. Department of Education. (2017). *WebCASPAR*. Institute of Education Sciences, National Center for Science and Engineering Statistics. Retrieved from https://ncsesdata.nsf.gov/webcaspar/

Vitores, A., & Gil-Juárez, A. (2015). The trouble with "women in computing": a critical examination of the deployment of research on the gender gap in computer science. *Journal of Gender Studies*, 1–15. https://doi.org/10.1080/09589236.2015.1087309

Voogt, J., Fisser, P., Good, J., Mishra, P., & Yadav, A. (2015). Computational thinking in compulsory education: Towards an agenda for research and practice. *Education and Information Technologies*, *20*(4), 715–728. https://doi.org/10.1007/s10639-015-9412-6

Wagh, A., Gravel, B., & Tucker-Raymond, E. (2017). The Role of Computational Thinking Practices in Making: How Beginning Youth Makers Encounter & Appropriate CT Practices in Making. In *Proceedings of the 7th Annual Conference on Creativity and Fabrication in Education* (p. 9:1–9:8). New York, NY, USA: ACM. https://doi.org/10.1145/3141798.3141808

Walton, G. M., Logel, C., Peach, J. M., Spencer, S. J., & Zanna, M. P. (2015). Two brief interventions to mitigate a “chilly climate” transform women’s experience, relationships, and achievement in engineering. *Journal of Educational Psychology*, *107*(2), 468–485. https://doi.org/10.1037/a0037461

Yadav, A., Gretter, S., & Good, J. (2017). Computer science for all: Role of gender in middle school students’ perceptions about programming. Presented at the Annual Meeting of American Educational Research Association, San Antonio, TX.

Yadav, A., Hong, H., & Stephenson, C. (2016). Computational Thinking for All: Pedagogical Approaches to Embedding 21st Century Problem Solving in K-12 Classrooms. *TechTrends*, 1–4. https://doi.org/10.1007/s11528-016-0087-7

Yadav, A., Mayfield, C., Zhou, N., Hambrusch, S., & Korb, J. T. (2014). Computational Thinking in Elementary and Secondary Teacher Education. *ACM Transactions on Computing Education*, *14*(1), 1–16. https://doi.org/10.1145/2576872

Zinth, J. (2016). Computer Science in High School Graduation Requirements. *Education Commission of the States, Education Trends*. Retrieved from http://eric.ed.gov/?id=ED568885

Zweben, S. (2013). *Computing Degree and Enrollment Trends. Computing Research*.

Zweben, S., & Bizot, B. (2016). 2015 Taulbee Survey. *Computing*, *18*(5). Retrieved from http://craorg.c.presscdn.com/wp-content/uploads/2015/01/Taulbee-2012-13.pdf