The Relationship of Gender, Experiential, and Psychological Factors to Achievement in Computer Science

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ABSTRACT

Computer science (CS) is widely recognized as a field with a significant gender gap despite the growing prevalence of computing. Several factors including CS attitudes, exposure to CS, experience with computer programming, and confidence in using computers are understood to be correlated with the low participation of women in CS. These factors also play an important role in students' interest in CS careers and are particularly crucial during secondary school. However, there is a dearth of research that examines differences in how these factors are inter-correlated for younger students (ages 11-13). The purpose of this study was to generate and test a statistical model that demonstrates the inter-correlation amongst these factors with respect to gender. A total of 260 middle school students participated in this study. Four instruments measuring students' CS attitudes, confidence in using computers, CS conceptual understanding, and prior experience with CS-related activities were used. Structural equation modeling was utilized to test the hypothesized model. The findings showed that previous participation in CS-related activities had a significant direct effect on CS attitudes and confidence in using computers, but the effect on students' CS conceptual understanding was indirect. We also found that in a female specific model, previous participation had a significantly stronger direct effect on CS attitudes compared to its effect in a male specific model. The importance of providing more CS-related experience, especially to female students, as well as suggestions on activities that promote gender equity in the field are discussed.

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CCS CONCEPTS

• K-12 Education • Gender and diversity • Broadening participation

KEYWORDS

Middle grades, gender, self-efficacy, prior experience, CS knowledge

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1 Introduction

Compared to other STEM disciplines, computer science is severely lacking in terms of gender diversity despite the increased integration of computers and technology into our daily lives [21]. The notably small number of women obtaining computer science degrees has changed little in the last ten years, and while there have been small improvements in participation from female and other underrepresented minorities, the rates of attrition are higher for these groups [21]. As computing becomes an increasingly crucial component of the global economy, many of the leadership roles within global companies are awarded to those with degrees and experience in the field [28]. Therefore, increasing women's representation in computer science has both local and global implications on the leadership role women will play in society. This heightens the need to better understand gender-related factors to participation and success in computer science and allied areas [28]. Previous research identifies prior programming experience [1, 13, 18], confidence using computers [26], and computer science attitudes [6, 14] as crucial factors in determining CS conceptual understanding. Literature also suggests that middle school is an important timeframe within the K-12 academic trajectory for effective computer science interventions that target improved CS interest for female students [35].

Prior experience plays a central role in learning [5, 31]. For CS, this prior experience often takes place outside of the formal classroom setting. According to constructivism, learning is the process of building and extending knowledge, skills, and attitudes through transforming existing constructs [15, 31]. Among the many learning theories that fall under the umbrella of constructivism, experiential learning [16] places the greatest emphasis on the importance of previous learning experiences. Although Kolb's original experiential learning theory focused on students' cognition, Kolb and Kolb [15] extended the theory by acknowledging other facets of learning, including attitudes, motivation, and metacognition, as important components of previous learning experiences.

In this study, we analyzed data collected from middle school students (ages 11-13) who participated in a week-long computational modeling activity focused on science. The collected data was used to analyze a model that describes the relationship between factors that influence CS conceptual understanding. In order to determine if gender acts as a moderating factor within the model, male and female versions of the model were produced and their pathways compared. We build upon prior research regarding each of the factors included in the model in order to discuss the pathways holistically.

2 Related Work

Empirical studies that examine the impact of previous learning experience in CS and programming contexts on learning are rare in CS education [1, 5], and even fewer focus on the interaction of prior experience and gender. However, there are a few quantitative and qualitative studies that investigate the impact of programming experience on students' domain learning, while taking into account gender. Harrington et al. [13] used quantitative methods to examine the relationship between cognitive performance and prior programming experience and determined a positive relationship between the two factors for both males and females at the undergraduate level. Another study concluded that prior formal experience had a significant correlation to success for undergraduate females, but not males, while previous CS experience as a whole was significant for both genders [32]. Lewis [18] and Alexandron et al. [1] did not look specifically at gender, but concluded that prior programming experiences do not have a strong positive impact on students' attitudes, performances, and CS conceptual understanding. The magnitude of these impacts, the relationship amongst these factors, and how they interact with gender is still an open question, thus suggesting that more quantitative modeling is needed.

A student's belief that they are able to succeed or achieve a specific goal, or self-efficacy, has been regarded as an essential component of personal agency [17]. Self-efficacy acts as a product of the interaction between how a person perceives themselves and their surrounding environment [4]. Personal experiences also form outcome expectations, or how students believe particular behaviors or actions will affect their outcomes [17]. Self-efficacy and outcome expectancy are major components of the CS attitudes factor included in the current study's model. Female students have historically reported lower self-efficacy in computer science. Studies such as the one by Beyer & Haller [6] found that female undergraduate CS majors reported significantly lower self-efficacy and less previous programming experience than their male peers, suggesting increased participation may lead to higher self-efficacy. Experience positively impacting female self-efficacy was also reported by He & Freeman [14], who discovered that when controlling for computer anxiety, experience, and knowledge the gender difference in CS self-efficacy became non-significant.

While the majority of current CS studies regarding gender occur at the undergraduate level, attitudinal orientation to CS likely starts at earlier grades. Middle grades (ages 11-13) are an important time for students to be exposed to CS and programming in formal educational settings, helping to shape their affective response and build conceptual knowledge [12]. Qian & Lehman [23] conducted a study with middle school students and concluded that there was no gender difference for CS performance and stated that introducing programming experiences early on could be beneficial, as the girls showed no significant cognitive disadvantages before the age of 13. Despite showing similar cognitive ability, Dickhäuser & Pelster [8] found that female students ages 10 to 15 had lower CS outcome expectancy. Another study suggests attitudinal malleability with increased participation in computer programming activities, as interest and self-efficacy for elementary-aged students (ages 6-7) showed no gender difference when provided with robotic experiences [18, 19]. As an additional example of the criticality of the middle grades time period, Wiebe et al. [35] found that female interest in engineering begins to rapidly decrease around middle school, suggesting it to be a crucial time to study factors influencing CS attitudes.

More broadly, confidence in using computers is also related to computer science attitudes and ability. Román-González and colleagues [26] concluded that confidence in using a computer is positively associated with middle school students' computational thinking ability. In another study, they found that computational thinking ability is complementary to CS conceptual understanding [25]. Confidence in using computers was also explored by Shashanni [30] but in relation to prior experience and computer attitudes. Shashanni [30] discovered that previous experience and confidence using computers were positively correlated for boys but unrelated for girls at the high school level. Experience with computers may not be enough to overcome the confidence issue surrounding CS for girls, while it is able to significantly increase confidence for boys [30]. One can assume that since the time this study was conducted over two decades ago, students are generally more exposed to computers and beginning at an early age, meaning an overall higher confidence using computers for both genders, but not necessarily enough to overcome negative attitudes that surround CS for many girls.

3 Current Study

This paper contributes to the existing literature on gender and computer science education by further investigating the correlation between the following factors: (1) previous programming experience, (2) CS attitudes (self-efficacy and outcome expectancy),

(3) CS conceptual understanding, and (4) confidence in using a computer. The selection and interpretation of these factors was guided by Kolb's experiential learning theory [16]. A holistic structural equation model (SEM) is used to describe the interrelation of these factors at the middle grades level. We hypothesized that for female students there is a stronger correlation between prior experience and CS attitudes, and weaker correlation between confidence in using computers and CS attitudes. For this study, we were guided by the following research questions:

1. What is the inter-correlation of the above factors described by our structural equation model?
2. How does the relationship between the above factors differ for male and female students at the middle grades level?
3. What are the implications of these findings for educators and researchers who are introducing computer science prior to middle school?

4 Methods

4.1 Participants and Settings

The assenting participants in this study were drawn from 12 classes of students (ages 11-13) attending four middle schools in the Southeastern region of the United States, whose parents provided consent, and who completed all of the assessment instruments (*N*=260). The students were recruited through computer science and science teachers who agreed to participate in the study. The participants varied in terms of grade-level with 59% eighth grade, 14% seventh grade, 13% sixth grade, and the remaining 14% did not specify their grade level. Regarding gender, 49% of participants were identified as female, 35% were identified as male, and 16% preferred not to provide their gender information. The participants were ethnically and racially diverse with 35% White, 16% Hispanic/Latinx, 15% Black/African-American, 5% Asian, and 19% of students from other racial groups. Moreover, the samples consisted of a wide range of prior experience with computer science and/or programming activities (49% never/almost never, 28% occasionally, and 23% frequently).

Students in five different classrooms participated in a week-long computational modeling activity on either the topic of epidemic diseases, food webs, or force and motion. For example, during the epidemic disease activity, students created a computational model of the spread of diseases using a block-based programming environment. Each of the five teachers were trained to implement the activities by members of the research team during professional development sessions. The activity's curriculum was developed based on the K-12 CS Framework and a derived Focal Knowledge, Skills and Abilities (FKSA) Framework [11].

4.2 Research Instruments

Four different measures were included in the study: students' previous participation in activities that involve computer science or computer programming, CS attitudes, CS conceptual understanding, and confidence with using a computer. This data was collected the day before the weeklong classroom activities. CS conceptual understanding was again assessed the day after the classroom activities.

4.2.1 Previous participation scale. Students' previous experience was measured by one five-point scale Likert-type question in which they reported the extent of their previous programming experience.

4.2.2 Confidence in using a computer. To measure students' confidence with using a computer, they were asked to answer a ten-point, Likert-type question adopted from Román-González et al. [26]. The question was "How confident are you in your ability to use a computer?"

4.2.3 Computer science (CS) attitudes. CS attitudes were measured by using the self-reported questionnaire adopted from S-STEM Engineering scale [34], which consisted of nine, five-point scale Likert-type items on students' CS self-efficacy and outcome expectancy based on Eccles' expectancy-value theory [9]. In this study, the CS Attitudes questionnaire had a value of .93 for Cronbach's alpha, indicating satisfactory reliability [7].

4.2.4 Computer science conceptual understanding. The CS Concept Inventory (MG-CSCI) was administered to students to obtain a metric to indicate their level of conceptual understanding around the concepts of variables, conditionals, loops, and algorithms. The assessment was composed of 24 multiple choice questions developed and validated by Rachmatullah et al. [24] and based on Grover & Basu's [11] CS FKSAs Framework. In terms of reliability, the value of Cronbach's alpha for pretest was .81 and the posttest was .87. The test-retest reliability was also calculated, and the value was r = .80. According to DeVellis [7], these values are considered satisfactory.

4.3 Data Analysis

Prior to test our hypothesized model, data set was checked for normality. Skewness and Kurtosis values were used to evaluate normal distribution as suggested by George & Mallery [10]. Values ranging between -2 and 2 indicate normally distributed data. Descriptive statistics as well as correlation tests were run to the data set. Spearman correlation test was used to look at the correlation between previous participation with other variables, given the data for previous participation was in ordinal scale. Pearson bivariate correlation test was run to other variables except the previous participation. Moreover, we used paired-sample t-test to evaluate the score difference in CSCI before and after the intervention.

A pathway analysis through SEM was used the test our hypothesized model. Pathway analysis is based on a multivariate regression test and is used to build a structural model of the interrelated variables. We assessed the quality of our hypothesized model by following the cut-off values suggested by Schreiber et al. [29] (X^2/df < 3, CFI > .95, and RMSEA < .06).

Additionally, the robust maximum likelihood approach was used to test the hypothesized model. Then, a multiple-group analysis was performed to look at whether or not the model is different based upon gender. Last, a z-score was also computed to check for significant differences in each path based on gender. Model testing was done using IBM SPSS Amos version 25 [3].

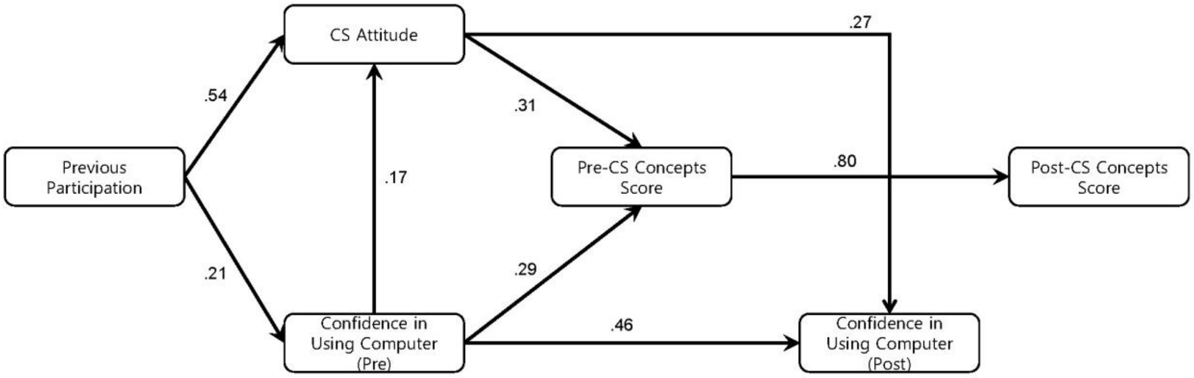

Figure 1: Pathway analysis results of the hypothetical model featured with the standardized regression coefficients (β) with full sample. Note: All paths are significant at α = .05

5 Findings

5.1 Descriptive Statistics and Correlation Results

Table 1 presents the descriptive statistics and correlation coefficients (r) for all the variables. The analyses were run on the 260 samples. It can be seen that all the skewness and kurtosis values are in between -2 and 2 indicating that all the variables were normally distributed. Significant and positive correlation coefficients were also obtained from the correlational tests with the magnitude ranged from weak (r = .20 previous participation and pre computer confidence) to strong (r = .80 pretest and posttest CSCI scores). A paired-sample t-test was run to check the significant gain in pretest and posttest scores. We found that the average posttest score (M = 55.13, SD = 24.08) was higher than the average pretest score (M = 50.02, SD = 21.53) and the difference was statistically significant with a small effect size, $t(259) = -7.04$, $p < .01$, $d = 0.22$.

5.2 Path Analysis

SEM was used to fit the data to the hypothesized model. Two cycles of fitting were used: one was testing the overall hypothesized model, and the second time testing the same model, but the non-significant paths were removed. We compared the two models to see whether the final model would be better with or without the non-significant paths. SEM analysis revealed that the fit indices for the model with non-significant paths removed reached the acceptable criteria, $X^2/df = 2.04$, $p = .047$, CFI = .986, RMSEA = .063, RMSEA 90% CI = .007, .110. Figure 1 shows the final full model with standardized regression weights (β).

Based on Figure 1, Previous Participation in computer science related activities was significantly predictive of greater CS Attitude (β = .54, $p < .001$) with a .54 standard deviation increase in the average of CS Attitude for every 1.0 standard deviation increase in Previous Participation. Previous Participation was also significantly predictive of greater Confidence in Using Computer (β = .21, $p < .05$) with a .21 standard deviation increase in the average of Confidence in Using Computer for every 1.0 standard deviation increase in Previous Participation. However, we found that Previous Participation was not significantly predictive of CS Conceptual Understanding (β = -.16, $p > .05$). Even so, the impact of Previous Participation on CS Conceptual Understanding was indirect through CS Attitude (β = .31, $p < .01$) and Confidence in Using Computer (β = .29, $p < .01$). The total of indirect effect from Previous Participation to CS Conceptual Understanding was found significant (β = .24, $p < .01$) with a .24 standard deviation increase in pre-CS Conceptual Understanding scores for every 1.0 standard deviation increase in Previous Participation.

Table 1. Descriptive statistics and correlation coefficients (r). *Notes*: [a]Spearman correlation, [b]Median for previous participation, CC = confidence in using computer

Variable		(1)	(2)	(3)	(4)	(5)	(6)
Previous Participation	(1)	1					
CS Attitudes	(2)	.55**	1				
Pretest Score	(3)	.22**	.40**	1			
Posttest Score	(4)	.21**	.40**	.80**	1		
Pre CC	(5)	.20**	.29**	.37**	.34**	1	
Post CC	(6)	.28**	.45**	.34**	.38**	.54**	1
Mean/Median[b]		3.00	3.04	50.02	55.13	7.85	7.87
SD		0.93	0.97	21.53	24.08	2.91	2.86
Skewness		0.11	-0.13	0.36	0.05	-0.63	-0.69
Kurtosis		0.16	-0.71	-0.70	-1.22	-0.53	-0.21

We also found that pre-CS Conceptual Understanding score was significantly predictive of post-CS Conceptual Understanding score (β = .80, $p < .01$). Similarly, Confidence is Using Computer before the intervention (pre) was also significantly predictive of greater Confidence in Using Computer after the intervention (β = .46, $p < .01$). Interestingly, CS Attitude was found predictive of greater Confidence in Using Computer after intervention, but not for post-CS Conceptual Understanding score.

Multi-group analysis was then run to look at whether the model for males differs from the model for females. The results indicated that the overall model was not different based on gender, $X2/df = 0.85$, $p = .620$. Figure 2 shows the model with β values for both genders.

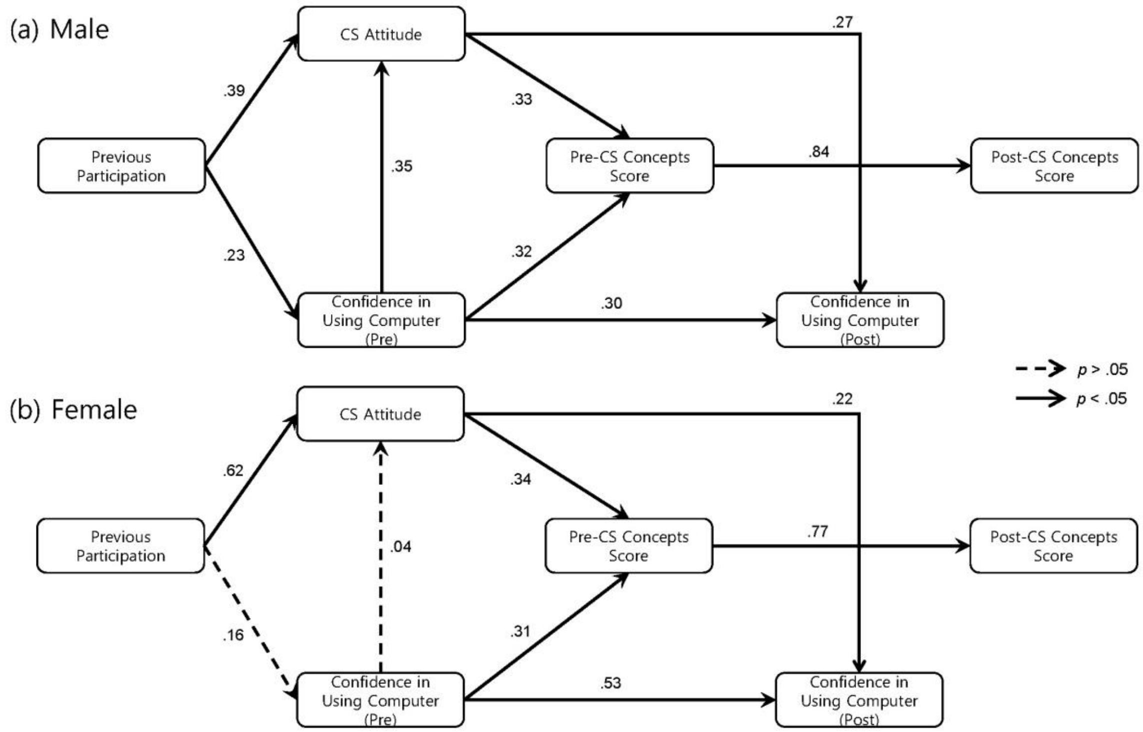

Figure 2: The comparison between Male and Female's path analyses

Table 2. Model paths' standardized β values and associated p value for the path for both genders. Comparison of the β values is given as a z-score. *Notes*: ** $p < .01$, * $p < .05$, no asterisk = not significant, Pre/Post CC = Pre/Post Confidence in Using Computer

Path	Male	Female	z-score
	β	β	
Pre CC ⟵ Previous Participation	.23*	.16	-0.33
CS Attitude ⟵ Previous Participation	.39**	.62**	2.94**
CS Attitude ⟵ Pre CC	.35**	.04	-2.57*
Pre-CS Concepts Score ⟵ CS Attitude	.33**	.34**	-0.39
Pre-CS Concept Score ⟵ Pre CC	.32**	.31**	-0.37
Post-CS Concept Score ⟵ Pre-CS Concept Score	.84**	.77**	-1.34
Post Confidence ⟵ Pre CC	.30**	.53**	1.99*
CS Attitude ⟵ Post CC	.36**	.22**	-1.19

Next, we looked at differences based on gender for each path, and the results are presented in Table 2. Based on Table 2, three paths were found significantly different in the male and female models. The first one was the path from Previous Participation to CS Attitude. In this path, Previous Participation for female students had almost twice the impact on CS Attitude (β = .62) compared to the impact for male students (β = .39). Similarly, pre-Confidence in Using Computer for females was found twice the level of impact on post-Confidence (β = .53) compared to the impact for male students (β = .30). Last, a significant difference in β values was found in the path from pre-Confidence in Using Computer to CS Attitude, where in male model the effect of pre-Confidence in Using Computer on CS Attitude (β = .35) was seven times higher than its impact for females (β = .04). Not only did we find that the impact was higher for male, but also we found that the path was not significant in the female model (p = .550).

6 Discussion

Prior research has indicated that previous experience in a particular academic subject could trigger students to have more positive attitudes towards and better performance in that subject [22, 34]. Similarly, in the field of CS education, studies correlating these factors found that there is an impact of previous participation in CS-related activities on students' attitudes towards CS and cognitive performance [13, 27]. However, the cause and effect correlation amongst these variables are not well-explored. The current study extended the understanding of pairwise correlations between the three mentioned variables by generating a more holistic statistical model. Based on our findings visualized in Figure 1, we found that the impact of previous participation in CS-related activities on CS conceptual understanding is not direct; instead, it is indirect through attitudinal beliefs, which is CS attitudes and confidence in using a computer. This finding suggests that a core mechanism of middle grades students' CS conceptual learning may be through their attitudinal orientation towards CS. This, in turn, is influenced by the intensity of previous participation in CS-related activities. These findings suggest a need to both understand students' prior programming experiences, and monitor and support a positive attitudinal orientation before and during CS learning activities.

While the model did not show direct correlation between previous participation in CS activities and CS conceptual understanding, the female model showed a significantly stronger correlation between previous participation and CS attitudes, which acts as a mediating variable between experience and cognitive performance. Other studies have also found that females typically have low-self efficacy and negative attitudes towards CS when they report low amounts of experience [6, 14]. While most studies regarding gender and CS are situated at the undergraduate level, Master et al. [19] note the malleability of elementary-aged female students' CS attitudes through programming experiences. The current study suggests that at the middle school level, participation in computer programming activities acts as a strong predictor for CS attitudes, implying that providing experiences for girls in middle grades could positively impact their attitudes towards, and ultimately their performance in, computer science going forward. This study also concluded that for middle school girls, confidence in using a computer is not a strong predictor for CS attitudes. As computers and technology become increasingly prevalent in all aspects of students' lives, it is important to note that while girls may seem comfortable and confident using a computer this may not be enough to overcome previously established negative attitudes or low self-efficacy regarding CS and programming [30].

Although we believe that the findings of this study have extended the understanding of inter-correlation between three essential factors in relation to middle grades level CS learning, we acknowledge several limitations that can serve as suggestions for future study. The first one is related to the question we used to harvest students' data about their previous participation. Given that we only asked students to rate the extent of their previous participation in CS-related activities, we could not differentiate types of activities that promote better CS learning. This wording might impact the non-significant finding on the path from previous experience to the cognitive assessment factor we found in this study. For future studies, gathering more specific information about the type of CS-related activities is suggested to provide a more robust explanation of the role of previous participation in influencing other factors of CS learning. Qualitative approaches may also be a more appropriate methodology to address this limitation. The second limitation is regarding the item measuring confidence in using a computer. Given that we only used one question to measure this variable, biases in results might exist due to the tendency of a single question in producing low-reliability results [7]. Therefore, future studies should address this issue by having more items measuring students' confidence in using computers.

7 Implications

The findings in this study suggest that providing early computer science experiences to girls at or before the middle school level could be advantageous for improving CS attitudes in female students, which ultimately impacts CS learning outcomes. While previous experience is correlated to CS attitudes for both genders, the significantly stronger correlation for female students implies that creating positive CS experiences for primary and early secondary female students could have a significant payoff with regards to female CS attitudes. Educators should also consider that while integrating technology more generally into classroom instruction may increase female students' confidence in using computers, without experiences that are explicitly utilizing computational thinking, computer science or computer programming, female students' attitudes towards computer science may not change as readily as it would for male students.

8 Conclusion

This study utilized SEM to generate gender-specific models to investigate the inter-correlations between prior experience, CS attitudes, confidence in using computers, and CS conceptual understanding for middle school students. Students' attitudinal orientation towards CS was found to be an important contributor to CS cognitive performance for all students. Previous participation in CS activities was found to have a more significant influence on CS attitudes for female students than male students. This study indicates that exposing female students to CS experiences at an early age could positively impact on their attitudes towards CS which is directly correlated to CS learning outcomes. The findings also suggest that while confidence in using computers is significantly correlated to CS attitudes for male students, expressing high levels of confidence with computers does not predict positive CS attitudes for female students. It is essential that researchers continue to explore the factors that contribute to CS learning in relation to gender at different age-levels and within a variety of contexts in order to help address the field's substantial gender gap.

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