Computer Science Education

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/ncse20

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To cite this article: Teresa M. Ober, Ying Cheng, Meghan R. Coggins, Paul Brenner, Janice Zdankus, Philip Gonsalves, Emmanuel Johnson, Tim Urdan & Curated Pathways to Innovation (Group) (2022): Charting a path for growth in middle school students' attitudes toward computer programming, Computer Science Education, DOI: 10.1080/08993408.2022.2134677

To link to this article: https://doi.org/10.1080/08993408.2022.2134677

Published online: 04 Nov 2022.

COMPUTER SCIENCE EDUCATION
https://doi.org/10.1080/08993408.2022.2134677

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Charting a path for growth in middle school students' attitudes toward computer programming

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ABSTRACT

Background and Context: Differences in children's and adolescents' initial attitudes about computing and other STEM fields may form during middle school and shape decisions leading to career entry. Early emerging differences in career interest may propagate a lack of diversity in computer science and programming fields.

Objective: Though middle school is recognized as a formative period in the development of career interest, there appears to be a gap in research considering growth disparities in students' attitudes towards computer programming. We examine outcomes related to students' use of an e-learning platform designed to promote exposure to computer science content. We consider growth in middle school students' attitudes towards computer programming during an academic year while controlling for variation in key baseline factors.

Method: We tracked growth in attitudes towards computer programming among middle school students (N = 610; M_{age} = 12.07) in schools serving underrepresented minority (URM) students (74.7% URM) during an academic year in which they used an online platform curating computer programming educational content.

Findings: We found baseline differences in students' interest and aspirations toward computer programming on the basis of gender and underrepresented status, after controlling for math attitudes. There was evidence of initial growth in all four domains of computer programming attitudes, irrespective of gender or underrepresented status.

Implications: These findings provide a framework for studying changes in students' computer programming attitudes, which may help in addressing workforce participation disparities. Future work is needed to promote early computer programming attitudes among all students.

ARTICLE HISTORY
Received 17 July 2021
Accepted 07 October 2022

KEYWORDS
Computer science education; middle school; STEM attitudes; STEM education; STEM workforce diversity; growth model

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Introduction

There is a growing demand in the United States for a workforce with expertise in computer science and programming. Between 2019–2029, careers in computer and information technology occupations are expected to grow approximately 11% in the U.S., which was higher than the national average of 4% across all job sectors (U.S. Bureau of Labor Statistics, 2021). The demand is growing so fast that there is a shortfall of qualified individuals with expertise in computer science and programming to meet this demand (U.S. Bureau of Labor Statistics, 2021). Meanwhile, the number of undergraduate computer science majors has also continued to increase rapidly. Studies indicate that computer science majors have tripled since 2006 and doubled since 2011, and an increasing number of non-computer science majors are enrolling in computer science classes (Camp et al., 2017). Despite a clear demand, and a growing number of computer science majors, participation in this workforce does not reflect the general population and there is still a need to diversify the participation in computer science and programming fields (Adrion et al., 2020; Code.org & Alliance, 2022). Though women comprise about half of the college-educated workforce (51.6%), women accounted for only 26.9% of computer and mathematical sciences occupations in 2017 (U.S. National Science Foundation [NSF] & National Center for Science and Engineering Statistics [NCSES], 2019). People from under-represented racial/ethnic minority groups, though also comprising a large percentage of the general U.S. population (27.7%) and college-educated workforce (17.1%), also reflect a small subset of individuals employed in computer and mathematical sciences occupations, accounting for only about 14.2% in the U.S. in 2017 (NSF, 2019). Individuals who identify as Hispanic/Latinx, Black/African American, or American Indian or Alaskan Native are currently considered members of an underrepresented minority group (URM) in science, technology, engineering, and math (STEM) disciplines (NSF & NCSES, 2019; see also Estrada et al., 2016).

Increasingly, computing is viewed as a critical dimension within STEM disciplines, leading some to opt for a more fully STEM and computing (STEM+C) integrated K-12 curriculum (Grover et al., 2020). Within the context of this discussion, computing broadly refers to the knowledge and skills required to use computers, while computer science refers to a discipline examining theory and applications of computing. Computer programming refers to a specific domain of knowledge or activities that require the application of that domain of knowledge within computing. Traditional K-12 STEM curriculum tends to lack specific preparation in computing, particularly the essential skills of computational thinking and problem-solving. Even so, participation in academic and extracurricular STEM activities in other subjects often serves as an initial introduction to learning computing concepts, especially in the formative years prior to secondary school (Vegas & Fowler, 2020). Considering this, combined with the fact that research on children's attitudes towards computing is presently emerging, it is important to consider the literature on attitudes towards STEM disciplines more generally, because it may provide information about the development of attitudes towards computing. Furthermore, while children and adolescents may not have a grasp of broad terms like "computer science" or "computer programming" (Vandenberg et al., 2020), they may still display an intuitive grasp of computational thinking and problem-solving skills if given programming tasks (Angeli & Giannakos, 2020). As such, students' orientations towards other STEM subject areas need to be considered when evaluating attitudes towards computer science and programming.

Middle school students' abilities in math have been shown to predict their progress in learning skills related to computer science and programming (Clements & Sarama, 2016; Grover et al., 2020). By some accounts, math attitudes consist of math identity, math self-efficacy, and math interest (Bohrnstedt et al., 2020). Unlike math identity, math self-efficacy may be more state-specific, meaning that it is more likely to depend on the student's immediate context or the task they are completing rather than the qualities of the student per se (Kim et al., 2018). The construct of interest may also be conceptualized as state-specific, though aspects of it may be considered trait-specific (Su, 2020). Ability in math aside, even students' attitudes towards math have been shown to predict their attitudes towards other STEM fields (Jiang et al., 2020; Leyva et al., 2022; Seo et al., 2019; You, 2013). As early as seventh grade, students who had more positive attitudes towards math were found to be over seven times more likely to have employment in STEM fields than students with consistently more negative orientations (Ahmed, 2018). However, to the best of our knowledge, there has been scant literature to date linking middle school students' math attitudes to their orientations towards computer science and programming. Examining the extent middle school students' initial attitudes toward math are associated with their attitudes towards computer science and programming therefore fills a gap of understanding of the connections between subject-specific STEM attitudes and their change during such formative years.

Understanding factors affecting diverse participation in computer science and programming

The lack of diverse participation in computer science and programming careers may reflect broader issues affecting the STEM workforce. By some accounts, and despite many initiatives to address this apparent disparity (Miller & Wai, 2015), overall STEM workforce participation among women and URM individuals has not substantially improved over the past decade (Varma, 2018). Disparities in early STEM attitudes and participation in school likely contribute to the lack of diversity in the computer science and programming workforce (Sadler et al., 2012). Differences in STEM experiences during late childhood and early adolescence appear to contribute to this gap, with some evidence suggesting its origins begin as early as middle school when children start to form identities around their academic interests that shape their career trajectories (Blotnicky et al., 2018; M. T. Wang & Degol, 2013, 2017) or sooner (Ball et al., 2017). For example, eighth-grade students who indicated they expected a career in STEM at age 30 were nearly twice as likely to obtain a college degree in STEM, a finding based on a nationally representative sample (Maltese & Tai, 2011). Though an understanding of middle school childrens attitudes towards computer science and programming is still emerging (Kong et al., 2018; Taub et al., 2012), research linking middle school STEM attitudes to career pathways may help in developing an understanding of how formative attitudes towards the subject can close workforce participation disparities.

Theoretical perspective linking attitudes and career development

Students generally feel competent and interested in domains in which they are more likely to achieve, and subsequently are interested in domains where they perceive their personal strengths (Denissen et al., 2007). Such interests appear to not only form early but they also appear to be somewhat stable. For example, findings from a large-scale longitudinal study indicate that there is a remarkable degree of stability in career interests from middle school into adulthood (Low et al., 2005).

Several theories of career development can be applied to understand how early emerging differences in middle school students' orientations towards STEM subjects, particularly those related to computer science and programming, drive such disparities. Viewed from one perspective, *social cognitive career theory* (SCCT) posits that individuals form an interest in an activity when they are good at it, and doing well at the activity is associated with desired outcomes (Lent et al., 2002). According to SCCT, early interests influence the choices and actions an individual makes. In addition, SCCT recognizes that these choices are influenced by external social and other contextual factors, which interact with an individuals aptitudes, values, and other person-specific factors. Within the framework of SCCT, the information one has about a particular career domain (i.e. *awareness*) influences ones *self-efficacy* in the domain. Self-efficacy is subsequently critical as it influences outcome expectations, which in turn both influence *interest*, intentions, and activity selection (i.e. *aspirations*), and finally, performance outcomes such as skill or career goal attainment (Lent et al., 1994). However, an individual may not develop interest in a career if they are not given opportunities to explore and develop a sense of self-efficacy, and certainly not if they have little awareness of the career, to begin with.

There is some empirical evidence for theoretical models, such as the SCCT, in explaining career choices (Su, 2020). For example, Rogers and Creed (2011) found that among high school students enrolled in grades 10–12, self-efficacy predicted career planning and exploration in a given area, regardless of grade level. However, the extent to which certain factors influence career interest development differs based on the students context and background. Environmental factors and the lived experience likely shape early attitudes towards math and STEM fields, and appear to contribute to the observed disparities in STEM participation between students based on gender and URM status (Blickenstaff, 2005; Gladstone et al., 2018; Griffith, 2010; Thomas & Strunk, 2017). Perceptions of personal strengths, particularly among female and URM students in STEM disciplines, may be susceptible to factors such as rejection sensitivity – the perception that one is not accepted within a discipline (Ahlqvist et al., 2013). As early as high school, students' attitudes towards math and computing appear to differ based on gender and URM status (Else-Quest et al., 2013), despite some estimates once indicating female and URM students take approximately the same number of high school courses in computing (Campbell & Willi, 1990). Social and cultural capital for learning STEM subject areas is thought to explain variation in career interest development among students of underserved or underrepresented backgrounds (Lichtenberger & George-Jackson, 2013; London et al., 2021; Moote et al., 2020; Wang, 2013).

Factors affecting participation among females

Self-efficacy and perceived peer expectations appear to play a role in female students' desire to pursue computer science (Du & Wimmer, 2019; Hur et al., 2017). Disparities in female students' aspirations for a career in STEM fields relative to male peers appear to increase between grades 9 to 12 (Saw et al., 2018), with gender differences in self-efficacy likely contributing to this widening gap (Downes & Looker, 2011). Yet, relatively simple pedagogical interventions may substantially shape female students' engagement in STEM learning. For example, when female middle school students are paired together to work on programming activities, research has found that they exhibit more behaviors conducive to learning than male-only pairs, including more time on task and fewer disruptive and more exploratory behaviors (Campe et al., 2020). Certain factors may buffer against widening differences in gender-based orientations toward computing among middle schoolers. Middle school girls who are open to a career in computing tend to have higher interest and confidence in computing, more social support for computing, and are more likely to view themselves as future computer scientists (Friend, 2015).

Factors affecting participation among underrepresented minority individuals

Like gender differences, racial and ethnic differences in STEM attitudes and career aspirations can be evident at a young age (Gottlieb, 2018). By adolescence, such differences are more apparent suggesting a widening disparity (Saw et al., 2018). Though math attitudes and achievement appear to positively predict STEM career path choices, certain factors may undermine this association for students from underrepresented backgrounds. For high school students enrolled in grade 10 from URM groups who have positive math attitudes and are high-achieving in math, the strength of the association between these positive math attitudes and later STEM career expectancy is not as strong as that among their non-URM classmates (Seo et al., 2019). Among female high school students, math attitudes may predict intent to pursue STEM careers based on the students' racial/ethnic minority status (Butler-Barnes et al., 2021). Examining differences based on URM status deserves additional sensitivity to the wide variety of cultures and lived experiences that contribute to variation in environmental and experiential factors affecting URM students' early attitudes towards resource-intensive computing subjects. Some of these factors may be closely intertwined with variation in socioeconomic status (SES) between students and the under-resourcing of schools (Riegle-Crumb & Grodsky, 2010; Ryoo et al., 2020; Saw et al., 2018). Furthermore, students who are both female and from an underrepresented minority group may be particularly disadvantaged (O'Brien et al., 2015).

Addressing participation disparities

To address the dire and ongoing need to close participation disparities in the computing workforce, relatively simple interventions can be highly effective. Aside from interventions that promote positive attitudes towards STEM learning (Casad et al., 2018), providing computer programming experiences, particularly to students from underrepresented groups in STEM, is thought to be one effective way to enhance career aspirations in computer science-related careers (Hur et al., 2017). Among students enrolled in middle school, developing awareness and self-efficacy appears to be critical for initiating positive career interests and aspirations in computer programming and computer science. Indeed, a lack of sufficient early experience in the subject may explain why certain individuals are underrepresented in the field of computer science (Cheryan et al., 2017). However, research examining career interest development in computer programming at this age is still generally sparse and needs to be further explored.

Research aims

The present study examines differences in middle school students' attitudes towards math and computer programming. Given the noted disparities in career participation within STEM and computing fields, we specifically examine differences among female and URM students. To address this broad aim, we investigate the outcomes of an intervention involving students' use of an e-learning platform designed to provide students exposure to computer science educational content. The study was conducted in two stages. First, we investigate differences in students' attitudes towards math and computer programming. Second, we examine growth in middle school students' attitudes towards computer programming over the course of an academic year, while controlling for variation due to baseline differences, including the influence of students' initial attitudes towards math.

Research questions and hypotheses

In pursuit of these aims, we addressed the following research questions:

- **RQ1**: What differences exist in students' initial (**a**) math (i.e. math self-efficacy, interest in math, math identity) and (**b**) computer programming (i.e. awareness, self-efficacy, interest, aspirations) attitudes at the beginning of the year on the basis of gender and URM status?
- **RQ2: (a)** Is there evidence of significant growth in each domain of students' computer programming attitudes? **(b)** If so, is growth consistent across time (i.e. linear) or does the rate of improvement change across time (i.e. non-linear)?
- **RQ3**: Assuming there is evidence of growth, to what extent is this growth influenced by: math attitudes (i.e. math self-efficacy, interest in math, math identity); grade level; gender; or URM status?

The literature reviewed previously on career interest development suggests that there is continuity and change in students' attitudes towards specific career pathways. For example, prior experiences involving computer programming are likely to shape students' orientations toward the subject. As such, we did not assume that students' attitudes towards computer programming would be linear over time (Ram & Grimm, 2007). In particular, given that the intervention itself was meant to provide experiences in computer programming to students that they may otherwise not have had, we expected to find non-linear growth in students' attitudes over time. We hypothesized that there would be an immediate increase in students' awareness and self-efficacy in computer programming, as these are more likely to be shaped by direct experience. We anticipated a more gradual and prolonged increase in students' interest and aspirations in computer programming during the academic year, as these are more likely to change due to multiple experiences as the student internalizes an orientation towards computer programming as a possible career pathway. We further hypothesized that there may be differences between students who were female or from a URM group in STEM relative to their counterparts, given past research. While the findings are correlational, they provide a framework for measuring growth in attitudes towards STEM disciplines, with a focus on underrepresented groups in computer science fields.

Methods

Participants

During the 2017–2018 and 2018–2019 academic years, middle school students (N = 610; $Mean_{age}$ = 12.07 years, SD_{age}= .77 years) enrolled in grades six (52.1%), seven (34.4%), and eight (13.5%) from a partnering middle school in Southern California were invited to take part in a longitudinal study. There were approximately the same number of males and females in the sample (44.3% female). Students identified as Hispanic/Latinx (68.3%), Asian/Asian American (16.3%), Hawaiian or Pacific Islander (4.9%), White/European American (4.7%), American Indian or Alaskan Native (3.5%), Black/African American (2.0%), or another racial/ethnic category (20.1%) with 24.7% identifying as a member of multiple racial/ethnic groups. A large proportion of the sample (74.7%) identified as a member of a URM group based on the criteria described above. These demographic characteristics of the sample roughly reflect the entire school population. More than half of the students reported their mother (53.7%) or father (62.3%) had received a high school degree or less as their highest education. Relatively few students had prior computer programming-related experiences outside of school at the beginning of the academic year, as indicated by the small proportion of students who had participated in a robotics camp or class (9.0%), or had participated in any online lessons about computer programming (11.9%), or had taken part in a camp where they worked with computers (12.7%).

Measures

Background questionnaire

A self-report questionnaire was administered in the late spring semester (February 2017) or the beginning of the academic year (September 2017 and 2018), which asked respondents to provide background information such as their current age, gender, race/ethnicity, and parents' highest educational attainment.

Math attitudes

Students' math attitudes were also measured at the beginning of the academic year (September 2018) with a 9-item Likert scale consisting of three distinct factors, with each factor measured by 3-items (Urdan, 2019). The three factors included math self-efficacy (McDonalds $\omega_{\text{Hierarchical}}$ = .84), math interest (McDonalds $\omega_{\text{Hierarchical}}$ = .90), and math identity (McDonalds $\omega_{\text{Hierarchical}}$ = .86). Like Cronbachs α, values of McDonalds $\omega_{\text{Hierarchical}}$ that are closer to 1 generally reflect better internal consistency, yet unlike

Table 1. Math attitudes scale and item-level descriptive statistics.

	Baseline		
	N	M	SD
Math Attitudes			
Self-efficacy in Math			
Scale Score (Average)	**610**	**3.49**	**0.98**
It is difficult for me to do well in math [R]	607	3.39	1.21
I think I am good at math	610	3.53	1.14
I feel like I am successful in my math class	609	3.55	1.19
Interest in Math			
Scale Score (Average)	**609**	**3.70**	**1.13**
My math class is interesting	608	3.71	1.21
I am enjoying my math class very much	605	3.67	1.30
I think my math class is boring [R]	609	3.71	1.32
Math Identity			
Scale Score (Average)	**610**	**2.87**	**1.09**
I am better at math than most of the other students in my math class	608	2.72	1.22
I see myself as a math person	608	2.94	1.29
I can imagine myself majoring in math in college	604	2.94	1.30

Note: Items ending in *[R]* were reverse-coded before the item- and scale-mean were calculated.

Cronbachs α, McDonalds $\omega_{\text{Hierarchical}}$ makes fewer assumptions that are often violated in practice (see McNeish, 2018). Table 1 contains the item wording and descriptives for the scale. All responses were provided using a 5-point scale (*1 = Strongly Disagree, 2 = Disagree, 3 = Neither Agree nor Disagree, 4 = Agree,* and *5 = Strongly Agree*).

Computer programming attitudes

A 10–12-item Likert scale measuring students' computer programming attitudes was administered on five separate occasions throughout the academic year (Urdan, 2019). The scale consisted of four distinct factors, each measured by 2–3 items: awareness (McDonalds $\omega_{\text{Hierarchical}}$ = .67-.79), self-efficacy (Baseline: McDonalds $\omega_{\text{Hierarchical}}$ = .32; Follow-up 1–4: McDonalds $\omega_{\text{Hierarchical}}$ = .51-.57), interest (McDonalds $\omega_{\text{Hierarchical}}$ = .80-.86), and aspirations for a future in computer programming (McDonalds $\omega_{\text{Hierarchical}}$ = .79-.83). All responses were provided using the same set of options used to measure math attitudes (*1 = Strongly Disagree, . . ., 5 = Strongly Agree*). Though some of the very short baseline self-efficacy subscales showed poor internal consistency, the scales internal consistency generally improved at the later time points. Furthermore, confirmatory factor analysis indicated a single factor fit the data collected from each of these four scales well, even when factor loadings were constrained between the two academic years of data collection (see Supplemental Materials).

While the scale measured at the baseline consisted of 12 items at all other time points, the baseline measure administered in the 2018–2019 academic year consisted of only 11 items. The item that did not appear on the baseline for the 2018–2019 academic year cohort was as follows: "*I know what you need to do to get a job as a computer programmer*" (awareness; 47.1% missing). In addition, one item was conditionally administered during the 2018–19 academic year only to students who indicated they had or were taking a computing class: "*I am confident I can get a good grade in my computer programming class*" (self-efficacy; 75.4% missing). As examples of the item content, the item wording shown in Tables 1 and 2 reflects the items used in the final follow-up survey administered

Table 2. Computer programming attitudes scale and item-level descriptive statistics.

	Baseline: Sept. 2017/18			Time 1: Dec. 2017/18			Time 2: Feb. 2018/19			Time 3: April 2018/19			Time 4: June 2018/19		
	N	*M*	*SD*	*N*	*M*	*SD*	*N*	*M*	*SD*	*N*	*M*	*SD*	*N*	*M*	*SD*
Awareness of CP															
Scale Score (Average)	**610**	**2.87**	**0.88**	**480**	**3.36**	**0.79**	**439**	**3.40**	**0.81**	**431**	**3.42**	**0.76**	**393**	**3.45**	**0.78**
I understand what computer programming means	607	3.36	1.13	473	3.53	0.95	438	3.57	1.04	430	3.64	0.95	391	3.62	0.99
I know what computer programmers do for work	607	3.00	1.24	472	3.50	0.90	428	3.52	0.93	422	3.54	0.90	387	3.61	0.89
I know what you need to do to get a job as a computer programmer †	610	2.26	1.18	472	3.05	1.09	428	3.09	1.03	423	3.07	1.00	387	3.11	1.04
Self-efficacy in CP															
Scale Score (Average)	**610**	**2.95**	**0.72**	**475**	**3.21**	**0.67**	**430**	**3.12**	**0.67**	**425**	**3.19**	**0.68**	**390**	**3.14**	**0.63**
I am good at working with computers	609	3.26	1.14	473	3.41	0.96	398	3.43	0.95	453	3.37	0.91	388	3.36	0.95
I believe I could get a good grade if I took a class in computer programming †	610	3.00	1.13	474	3.39	0.97	398	3.33	1.03	450	3.26	1.02	387	3.31	0.97
Computer programming is difficult [R]	608	2.59	1.10	474	2.85	0.98	397	2.73	0.98	455	2.79	0.90	388	2.78	0.96
Interest in CP															
Scale Score (Average)	**610**	**3.09**	**1.03**	**475**	**3.39**	**0.93**	**429**	**3.27**	**0.93**	**424**	**3.24**	**0.87**	**390**	**3.25**	**0.93**
I am interested in learning more about computer programming	608	2.89	1.31	473	3.27	1.16	427	3.12	1.16	424	3.12	1.08	388	3.10	1.15
I enjoy working on computers	608	3.49	1.25	475	3.74	1.01	426	3.62	1.07	422	3.64	0.98	386	3.62	1.02
I wish I had more chances to learn how to program computers	608	2.88	1.24	474	3.16	1.06	425	3.06	1.05	423	2.96	1.03	387	3.04	1.07
Aspirations for a Future in CP															
Scale Score (Average)	**610**	**2.87**	**1.00**	**475**	**3.04**	**0.91**	**429**	**2.92**	**0.92**	**425**	**2.95**	**0.89**	**389**	**3.01**	**0.91**
I can imagine myself having a job in computer programming	607	2.61	1.26	474	2.81	1.14	427	2.65	1.13	421	2.67	1.13	387	2.77	1.12
I hope to work in a computer related field one day	610	2.60	1.26	474	2.81	1.23	426	2.72	1.19	422	2.72	1.18	382	2.87	1.17
I think it is important to learn about computer programming	607	3.39	1.18	473	3.49	0.96	424	3.39	0.98	420	3.45	0.91	381	3.40	0.99

Note: Average scale scores are derived from an average of all completed items divided by the total number of items on the scale to which the participants provided answers. Items ending in *[R]* were reverse-coded before the item- and scale-mean were calculated.
†– Baseline means reflect imputed values.

in the 2018–2019 academic year. For a list of all items administered to measure computer programming attitudes, see Table A in Supplemental Materials.

Procedures

Throughout the academic year, students completed activities in the *Curated Pathways to Innovation* (CPI[1]) platform. The CPI is an online platform designed to curate developmentally appropriate and personalized educational content for middle and high school-aged students while also teaching computer programming and other STEM skills (Linnel et al., 2020). All students were expected to complete two initial sets of activities (i.e., *Digital Awareness, Cultivating Interest*, etc.). *Digital awareness* activities focus on exposing students to STEM+C and include, for example, videos of diverse role models speaking about their career choices, and infographics about opportunities in STEM+C. *Cultivating interest* activities help students engage in STEM+C learning through games where they gain confidence and learn basic programming. After completing these requirements, students have the option to pursue other activities such as learning block coding in basic typing skills, *Scratch*, and foundations of *Python* or *JavaScript*, among others. The platform was designed to recommend activities based on students' interests and ratings of past activities. In addition to completing activities in the CPI platform, students also completed a baseline survey and four follow-up surveys, each administered about two months apart.

Given that students were involved in a year-long pilot program and had access to the CPI platform, they received a basic orientation to computer programming around the time they completed the baseline survey. Thus, while the wording on the self-report measures needed to be carefully selected given students may not have had formal exposure to terms such as "programming", we note that at the baseline only 8.4% of students strongly disagreed with the statement, "*I understand what 'computer programming' means*". By the fourth/final time point, only 3.1% of students indicated as such. Thus, most students within the sample reported at least some basic familiarity with the term.

Data cleaning and preparation

Overall, 1,022 participants completed the baseline survey; however, 412 of these students did not complete another survey afterward. Thus, to avoid biasing the results, we removed from the analytic sample participants who completed the baseline but did not complete any later surveys. In an effort to ensure the integrity of the self-report data, careless responses were identified using a form of the longstring method (see Meade & Craig, 2012), and subsequently, 27 responses for which participants selected the same option throughout the survey questions for any of the four time-points were removed. This resulted in an analytic sample size of 610. To determine whether the sample size was still adequate, we conducted linear mixed model sample size calculations with the method proposed by Liu and Liang (1997) in the *longpower* package in *R* (Donohue et al., 2021). Though considerably smaller than the initial sample size, this power analysis suggested that the sample size was adequate for detecting a change of .082 between time points, which seemed reasonable considering the mean scale scores.

Given that one item was not administered to students who had not completed a computer programming class (see the previous section on "Measures"), we assumed a *missing-at-random* (MAR) mechanism and opted to impute those values using all data available from the responses to the baseline computer programming attitudes measure for both cohorts. Unlike complete case analysis, which involves deletion of incomplete cases, multiple imputation is valid for MAR situations and has the potential to use the information contained in the incomplete cases and auxiliary variables to reduce bias and/or improve precision (Hughes et al., 2019). Past studies involving simulation found that with sufficient information from auxiliary variables and a strong rationale for a MAR missing data mechanism, the use of multiple imputation reduced bias and did not appear to result in reduced efficiency (based on the mean squared error) and therefore may be appropriate in such contexts (Madley-Dowd et al., 2019). We used a dummy coded variable for cohort and dichotomously coded variable reflecting whether or not the student indicated having completed a computer programming class. Data were imputed simultaneously and exclusively for these two variables with the proportional odds model using the *MICE* package in *R* (van Buuren & Groothuis-Oudshoorn, 2011), which is appropriate for ordered variables with two or more levels. The remaining responses still did not result in a complete dataset (see Tables 1 and 2) and at worst, as much as 37.5% of data were missing for a particular variable at the final time point in the analytic sample, beyond the systematic missingness on two baseline questions as previously described. Though this is not an insubstantial amount of missing data, using the proportion of missing data is not recommended for making decisions on handling missing data (see Madley-Dowd et al., 2019). Furthermore, and as noted in further detail in the subsequent paragraphs, the analyses used to examine growth tend to be robust to missing data (see Brown, 2021).

Examining attrition

As a preliminary step, attrition analysis was conducted to determine whether participants who had completed the baseline only, and thus were removed from the original sample ($N = 1{,}022$) compared to the analytic sample ($N = 610$), differed on the basis of grade level, or being female or URM student. Chi-square tests with Yates continuity correction were conducted. Attrition was found to be non-independent of grade level ($\chi^2(\mathrm{df} = 2) = 136.57$, $p < .001$). Relative to the sample of participants who had completed the baseline ($N = 484$), in the sample used in the present analysis ($N = 610$), there appeared to be more grade eight students who were excluded (70.8%) compared to grade six (27.7%) and seven (33.0%). This likely reflects that among certain classes, completion of the survey was either not monitored or encouraged. The samples did not differ, however, on the basis of either being a female ($\chi^2(\mathrm{df} = 1) = 1.89$, $p = .169$) or a URM student ($\chi^2(\mathrm{df} = 1) = 2.08$, $p = .149$). Within the analytic sample ($N = 610$), there were also no differences between the two cohorts on the basis of either being a female ($\chi^2(\mathrm{df} = 1) = .02$, $p = .886$) or a URM student ($\chi^2(\mathrm{df} = 1) = 2.37$, $p = .123$). However, there did appear to be a greater proportion of students enrolled in grade eight in the 2018–2019 cohort (81.6%) compared with the previous year (18.4%).

Analysis

The main analyses were conducted in multiple phases. First, we examined baseline differences in math and computer programming attitudes measured by average scale scores on the basis of gender, URM status, and the interaction of the two while controlling for grade level using ANOVA models. Second, growth models for each of the four computer programming constructs were conducted. As a preliminary step, we sought evidence of good internal scale structure and measurement invariance both between cohorts (i.e. 2017–2018 v. 2018–2019) and measurement invariance over time (i.e. baseline, time 1, . . ., time 4) of the computer programming attitudes by evaluating the fit of latent factor measurement models.

After establishing evidence of the construct validity of the measure administered at the baseline and stability over time (see Supplemental Materials), piecewise growth model analyses were conducted to examine the association of multiple covariates and predictors to the growth models intercept and slopes. There are several advantages to this analytic technique over more conventional analyses involving repeated measures ANOVA or a pre-post design. First, we anticipated that the growth in students' attitudes may be non-linear and as such, the use of a pre-post design would not capture information about differences in rates of change over time. Given that we anticipated differences in the growth of students' computer programming attitudes between the baseline and the first follow-up and thereafter, two slope parameters were estimated in the model, thus allowing us to model growth in a so-called piecewise manner. Second, unlike repeated measures ANOVA, a mixed-effects model such as the piecewise model used in this analysis can handle missing data and unbalanced designs reasonably well. Though observations are removed when a value is missing in a mixed-effect model, each observation represents only one of many responses within an individual; therefore, the removal of a single observation has a considerably smaller effect in a mixed model than in ANOVA (Brown, 2021).

For the growth model, instead of using latent factor scores, average scale scores were derived for each of the four computer programming constructs at each time point. Scale scores were calculated based on an average of all the available responses provided by an individual. This allowed for a simpler and more interpretable model in which multiple covariates and predictors could be entered without the risk of model over-specification. As mentioned, we wanted to determine whether there were differences either at the baseline or in terms of growth in the four domains of computer programming attitudes on the basis of certain moderators (i.e., grade, gender, and underrepresented race/ethnicity status) while controlling for relevant covariates. Covariates included those related to math attitudes (i.e., math self-efficacy, interest, identity) and use of the learning platform (i.e., number of activities completed).

Piecewise growth model analyses were conducted in the *R* statistical environment using the *lme4* package (Bates et al., 2015). When assessing the fit of the piecewise growth analysis, models with smaller AIC, BIC, and deviance values, as well as those with log-likelihood values closer to 0 reflected better fitting models (Bates et al., 2015). In addition, a significant $\Delta\chi^2$ test indicates that the more complex, model results in improved fit above the simpler nested model.

Results

We sought first to establish some evidence of validity and measurement invariance of the latent factor models across time for the four domains of computer programming attitudes. Confirmatory factor analysis suggested that a single factor model fit the data well for each of the three math attitudes (i.e. math self-efficacy, math interest, math identity) and four computer programming attitudes (i.e. awareness, self-efficacy, interest, and aspirations) constructs (see Supplemental Materials). Item-level statistics for the math and computer programming attitudes scales are shown in Tables 1 and 2. An average scale score of about 3 indicates students were fairly neutral, while scale scores larger than 3 indicated that students tended to endorse statements indicative of more positive orientations within that domain of math or computer programming attitudes.

Baseline differences

Before considering longitudinal trends, we first examined potential sources of variation on the constructs at the baseline. In particular, we examined whether there were differences in the domains of math and computer programming attitudes between students on the basis of grade level, female (1 = female, 0 = non-female), or URM status (1 = URM, 0 = non-URM). An ANOVA predicting the scale score was conducted with a main effect for female status and URM status, as well as an interaction term. We then determined whether variation in students' initial computer programming attitudes could be explained by math attitudes, in addition to the demographic factors.

Math attitudes

First, we examined students' initial math attitudes (**RQ1a**; see Table 3). Each model accounted for 8% or less of the variation in the outcome (math self-efficacy: R^2 = .03, interest in math: R^2 = .08, math identity: R^2 = .04). Across all three domains of math attitudes, URM status appeared to explain significant variation (math self-efficacy: $F(1,603) = 5.45$, $p = .012$, $\eta_{partial}^2 = .009$; math interest: $F(1,602) = 3.99$, $p = .046$, $\eta_{partial}^2 = .007$, math identity: $F(1,603) = 12.39$, $p < .001$, $\eta_{partial}^2 = .020$). However, these effects were relatively small. Tukey post hoc comparison revealed that URM students tended to have more negative attitudes towards math (math self-efficacy: *Mean difference* = –0.21, *95% CI* = –0.38: –0.03; math interest: *Mean difference* = –0.20, *95% CI* = –0.39: –0.002; math identity: *Mean difference* = –0.34, *95% CI* = –0.54: –0.15). In addition, grade level appeared to significantly predict variation in students' initial interest in math ($F(2,602) = 21.12$, $p < .001$, $\eta_{partial}^2 = .063$) and math identity ($F(2,603) = 3.98$, $p = .019$, $\eta_{partial}^2 = .013$), but not self-efficacy in math ($p = .318$). The effect of grade level on math interest and identity appeared to have a small effect. Tukey post hoc contrast comparisons revealed that students in grade six had significantly greater interest in math (*Mean*

Table 3. ANOVA modeling scores for math attitudes on the baseline.

		Self-efficacy			Interest in Math			Math Identity		
Predictor	*df*	*F*	*p*	$\eta_{partial}^2$	*F*	*p*	$\eta_{partial}^2$	*F*	*p*	$\eta_{partial}^2$
Cohort (2018 = 1)	1	8.07	.005**	.013	6.24	.013*	.010	0.98	.322	.002
Grade (6, 7, 8)	2	1.15	.318	.004	20.12	.000***	.063	3.98	.019*	.013
Gender (Female = 1)	1	0.05	.827	.000	0.68	.410	.001	1.92	.166	.003
URM Status (URM = 1)	1	5.45	.020*	.009	3.99	.046*	.007	12.39	<.001***	.020
Gender * URM Status	1	0.85	.358	.001	1.40	.237	.002	2.73	.099	.005
Residuals	603†									

***$p < .001$, ** $p < .01$, * $p < .05$, • $p < .10$.
*Note: Residual DF for interest in math is 602.

difference = .61, *95% CI* = .38: .84) and more positive math identity (*Mean difference* = .25, *95% CI* = .03: .47) than students in grade seven, even when accounting for the other factors. Students in grade eight, in turn, had greater interest in math than students in grade seven (*Mean difference* = .25, *95% CI* = .01: .69). No other contrasts were significant.

Computer programming attitudes

We next examined students' computer programming attitudes (**RQ1b**; see Table 4). Differences in students' awareness ($F(1,603) = 5.37$, $p = .021$, $\eta_{partial}^2 = .009$), interest ($F(1,603) = 9.81$ $p = .002$, $\eta_{partial}^2 = .016$), and aspiration ($F(1,603) = 6.30$, $p = .012$, $\eta_{partial}^2 = .010$) towards computer programming could be partly explained by URM status, indicating that URM students tended to have less favorable attitudes toward computer programming across these three dimensions (awareness: *Mean difference* = –0.20, *95% CI* = –0.36: –0.03; interest: *Mean difference* = –0.24, *95% CI* = –0.50: –0.14; aspiration: *Mean difference* = –0.23, *95% CI* = –0.40: –0.05). Gender explained significant variation in students' interest ($F(1,603) = 8.69$, $p = .003$, $\eta_{partial}^2 = .014$) and aspirations towards a future ($F(1,603) = 15.11$, $p < .001$, $\eta_{partial}^2 = .024$) in computer programming. Female students tended to have lower interest (*Mean difference* = –0.24, *95% CI* = –0.40: –0.08) and aspirations (*Mean difference* = –0.31, *95% CI* = –0.46: –0.15). In addition, the interaction of gender and URM status explained significant variation in students' aspirations ($F(1,603) = 4.16$, $p = .042$, $\eta_{partial}^2 = .007$). Students who were URM and female had significantly lower aspirations than those who did not identify in both categories (*Mean difference* = –0.59, *95% CI* = –0.90: –0.28). Grade also appeared to explain a significant variation in students' interest ($F(2,603) = 5.06$, $p = .007$, $\eta_{partial}^2 = .017$) in computer programming. Students in grade six appeared to have greater interest in computer programming than students in grade seven (*Mean difference* = 0.28, *95% CI* = 0.07: 0.49). None of these variables explained significant variation in students' self-efficacy towards computer programming.

We subsequently considered whether variation in students' initial computer programming attitudes could be explained by math attitudes, on top of gender, URM status, and the interaction of the two (see also Table 4). Both math self-efficacy and math identity explained significant variation in all four domains of computer programming attitudes such that students with greater baseline math self-efficacy also tended to have greater initial attitudes towards computer programming. In addition, interest in math was significantly and positively associated with self-efficacy, but not awareness, interest, or aspirations towards computer programming. After controlling for variation attributable to math attitudes, we did not find the demographic variables explained variation in students' awareness or self-efficacy in computer programming. However, we did find that both gender ($F(1,581) = 8.45$, $p = .004$, $\eta_{partial}^2 = .014$) and URM status ($F(1,581) = 6.84$, $p = .004$, $\eta_{partial}^2 = .014$) explained significant variation in students' interest. Gender also explained variation in students' aspirations ($F(1,581) = 12.65$, $p < .001$, $\eta_{partial}^2 = .021$). Even when accounting for the other variables, both female (interest: *Mean difference* = –0.21, *95% CI* = –0.37: –0.06; aspirations: *Mean difference* = –0.27, *95% CI* = –0.42: –0.12) and URM (interest: *Mean difference* = –0.22, *95% CI* = –0.40: –0.01) students tended to have more negative orientations than their counterparts. Students' grade also appeared to explain significant differences in their interest in computer programming ($F(2,581) = 5.30$, $p = .005$, $\eta_{partial}^2 = .018$), but not their awareness, self-efficacy, or aspirations. We again

Table 4. ANOVA modeling scores for computer programming attitudes on the baseline.

		Awareness			*Self-efficacy*			*Interest*			*Aspirations*		
Predictor	*df*	*F*	*p*	$\eta_{partial}^2$	*F*	*p*	$\eta_{partial}^2$	*F*	*p*	$\eta_{partial}^2$	*F*	*p*	$\eta_{partial}^2$
Demographics Only													
Cohort (2018 = 1)	1	30.09	.001***	.048	0.50	.480	.001	5.00	.026*	.008	2.42	.121	.004
Grade (6, 7, 8)	2	1.75	.174	.006	2.17	.115	.007	5.06	.007**	.017	2.45	.087•	.008
Gender (Female = 1)	1	0.64	.425	.001	2.24	.135	.004	8.69	.003**	.014	15.11	.001***	.024
URM Status (URM = 1)	1	5.37	.021*	.009	0.37	.543	.001	9.81	.002**	.016	6.30	.012*	.010
Gender * URM Status	1	0.00	.978	.000	3.00	.084•	.005	3.20	.074•	.005	4.16	.042*	.007
Residuals	603												
Controlling for Math Attitudes													
Cohort (2018 = 1)	1	31.97	.001***	.052	0.47	.492	.001	4.55	.033*	.008	2.16	.142	.004
Grade (6, 7, 8)	2	2.08	.126	.007	2.91	.055•	.010	5.30	.005**	.018	2.91	.055•	.010
Self-efficacy in Math	1	22.48	.001***	.037	34.11	.001***	.055	9.19	.003**	.016	9.05	.003*	.015
Interest in Math	1	1.07	.300	.002	13.57	.001***	.023	3.38	.066•	.006	0.84	.358	.001
Math Identity	1	12.21	.001 **	.021	13.54	.001***	.023	16.96	.001***	.028	52.93	.001***	.083
Gender (Female = 1)	1	0.41	.522	.001	1.99	.159	.003	8.45	.004**	.014	12.65	.001***	.021
URM Status (URM = 1)	1	3.48	.063•	.006	0.04	.844	.000	6.84	.009**	.012	2.82	.094•	.005
Gender * URM Status	1	0.20	.654	.000	1.54	.214	.003	2.53	.112	.004	2.80	.095•	.005
Residuals	581												

***$p < .001$, ** $p < .01$, * $p < .05$, • $p < .10$

found that grade six students had greater interest than those in grade seven (*Mean difference* = 0.28, *95% CI* = 0.08: 0.49).

Non-linear growth in attitudes from the baseline to fourth follow-up

As is common among educational interventions, we suspected that improvement in the outcome could potentially be non-linear. When change is presumed to be non-linear, using a pre-post or simple linear model analysis is not appropriate as it obscures the complexity of growth. Figure 1 provides some graphical evidence of a drastic initial increase in attitudes across all four dimensions of computer programming attitudes. We thus opted to consider the rate of change from the baseline to the first follow-up in each domain as distinct from the rate of change from the first follow-up thereafter.

Growth in computer programming attitudes across multiple time points

After establishing some evidence of longitudinal measurement invariance of the computer programming attitudes (see Supplemental Materials), we then sought to examine change in the constructs over time (**RQ2**). Separate linear growth models were tested, one each for the four dimensions of the computer programming attitudes. As noted previously, a graphical analysis indicated that there was evidence of a non-linear trend across all five time points (see Figure 1) as we observed a steep increase in attitudes between the baseline and the first follow-up with less sharp growth thereafter. A piecewise growth curve approach was therefore used to model the four constructs from baseline to the first follow-up and from the first to the final follow-up separately. From the first to the final follow-up, there appeared to be a linear change for awareness and a quadratic change for the other three domains. We subsequently tested four successive models: intercept only plus random effects for slope 1 (baseline to first follow-up) and slope 2 (first to final follow-up) in model 1, intercept and fixed effects, and random effects for slope 1 and 2 in model

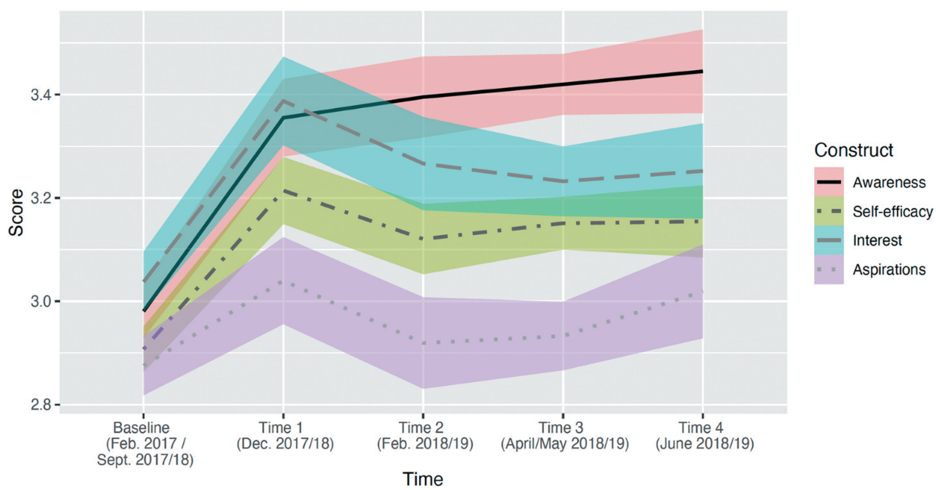

Figure 1. Average scale score measured across time in each dimension of computer programming attitudes (N = 610). The shaded bar reflects the 95% confidence interval around the mean.

2, the same parameters in model 2 plus a quadratic effect of slope 2 in model 3. Between models 2 and 3, we selected a model based on the results of a chi-square difference test and comparison of model fit parameters (i.e. AIC, BIC, Log-likelihood, deviance, $\Delta\chi^2$ test). Whichever model fit better (with or without quadratic term) was then used as the basis for model 4. In addition to the predictors, we also included interaction terms of each predictor with slope 1 and/or 2, depending on whether the parameter was significant in the base model. If it was not significant, we opted not to include interaction terms as it was presumed there was no association that could be moderated. Table 5 shows the fit for each successive model tested.

After establishing some evidence of linear growth between the baseline and the first follow-up, we subsequently examined if certain background characteristics moderated the change between the baseline and the first follow-up by including the aforementioned predictors in model 4 (**RQ3**). The background characteristics included students' math attitudes (i.e. math self-efficacy, interest in math, math identity), grade level, gender, and URM status, in addition to a control variable for the number of activities completed.

Table 5. *Model fit comparison (N = 610).*

	Goodness-of-fit Indices					*$\Delta\chi^2$ Test*				
Construct Model	*df*	*AIC*	*BIC*	*Log Likelihood*	*Deviance*	*Model Comparison*	$\Delta\chi^2$	Δdf	*p*	
Awareness										
M1: Intercept Only	7	5144.56	5190.65	−2564.28	5128.56	-	-	-	-	-
M2: Intercept + Slope 1 and Slope 2	9	4967.83	5025.44	−2473.91	4947.83	M1 v. M2	180.73	2	<.001	***
M3: Intercept + Slope 1 and Slope 2 and (Slope 2)^2	10	4969.33	5032.71	−2473.67	4947.33	M2 v. M3	0.50	1	0.481	
M4: Inclusion of Main and Interaction Effects	30	4940.90	5125.26	−2438.45	4876.90	M3 v. M4	70.43	20	<.001	***
Self-efficacy										
M1: Intercept Only	7	4194.58	4240.59	−2089.29	4178.58	-	-	-	-	
M2: Intercept + Slope 1 and Slope 2	9	4154.21	4211.73	−2067.11	4134.21	M1 v. M2	44.36	2	<.001	***
M3: Intercept + Slope 1 and Slope 2 and (Slope 2)^2	10	4155.64	4218.91	−2066.82	4133.64	M2 v. M3	0.57	1	0.450	
M4: Inclusion of Main and Interaction Effects	23	4101.59	4245.38	−2025.80	4051.59	M3 v. M4	82.05	13	<.001	***
Interest										
M1: Intercept Only	7	5402.69	5448.69	−2693.34	5386.69	-	-	-	-	
M2: Intercept + Slope 1 and Slope 2	9	5376.46	5433.96	−2678.23	5356.46	M1 v. M2	30.23	2	<.001	***
M3: Intercept + Slope 1 and Slope 2 and (Slope 2)^2	10	5373.78	5437.03	−2675.89	5351.78	M2 v. M3	4.68	1	0.031	*
M4: Inclusion of Main and Interaction Effects	31	5343.33	5533.10	−2638.66	5277.33	M3 v. M4	74.45	21	<.001	***
Aspirations										
M1: Intercept Only	7	5267.01	5313.01	−2625.50	5251.01	-	-	-	-	
M2: Intercept + Slope 1 and Slope 2	9	5263.38	5320.88	−2621.69	5243.38	M1 v. M2	7.63	2	0.022	*
M3: Intercept + Slope 1 and Slope 2 and (Slope 2)^2	10	5254.74	5318.00	−2616.37	5232.74	M2 v. M3	10.64	1	0.001	**
M4: Inclusion of Main and Interaction Effects	31	5202.90	5392.67	−2568.45	5136.90	M3 v. M4	95.84	21	<.001	***

***$p < .001$, ** $p < .01$, * $p < .05$, • $p < .10$

Note: Slope 1 refers to the slope between the baseline and the first follow-up. Slope 2 refers to the slope between the first and final follow-up. All models contain a random effect for Slope1 and Slope 2.

Table 6 shows the corresponding standardized parameter estimates for each successive model tested.

Awareness

Based on the results of the $\Delta\chi^2$ test and fit indices, model 2 (i.e. linear model) appeared to fit significantly better than the intercept-only model 1. Including the quadratic term did not result in an improved model (see Table 5). Therefore, we opted to use model 2 as the basis for model 4, which included the predictors. Examining the estimates for model 2 suggested that the slope of the trendline between the baseline and the first follow-up (slope 1; $\beta = .24$, $t = 12.15$, $p < .001$) and between first and final follow-up (slope 2; $\beta = .05$, $t = 2.73$, $p = .007$) were both significant (see Table 6). Thus, we included an interaction of each predictor with the two slopes in model 4 to test for moderation. The results suggested a main effect of math self-efficacy ($\beta = .07$, $t = 2.39$, $p = .017$), indicating that students with greater initial math self-efficacy also tended to have greater awareness of computer programming. There also appeared to be a significant interaction of math identity ($\beta = -.07$, $t = -2.41$, $p = .016$) with slope 1. Relative to students with greater initial math identity, students with lower initial math identity tended to grow more quickly in their awareness of computer programming between the baseline and the first follow-up. Growth in students' awareness did not appear to differ between either the baseline and first follow-up or thereafter based on whether or not the student was female or from a URM group.

Self-efficacy

As we had found with the models predicting growth in awareness, model 2 (intercept and slopes) had significantly better fit than model 1 (intercept only). We also found that the inclusion of the quadratic effect for slope 2 in model 3 did not result in improved fit above model 2 (see Table 5). Therefore, as we had with the awareness growth model, we used model 2 as the basis for including predictors in model 4. Examining the estimates for model 2 suggested that the slope of the trendline between the baseline and the first follow-up (slope 1) was significant while the slope of the trendline between the first and final follow-up (slope 2) was not. Though there was significant improvement in students' self-efficacy between the baseline and the first follow-up ($\beta = .14$, $t = 6.43$ $p < .001$), there was little change thereafter and students' self-efficacy remained stable ($\beta = -.01$, $t = -.66$, $p = .511$; see Table 6). Since the slope 2 parameter was not significant, we did not include interaction terms between it and the predictors entered into model 4.

The inclusion of the predictors revealed several significant effects in model 4. We found that students' initial math self-efficacy ($\beta = .15$, $t = 2.80$, $p = .005$) and math identity ($\beta = .13$, $t = 2.00$, $p = .046$) were both positively associated with self-efficacy in computer programming. As had been found in the model predicting awareness, students in grade eight appeared to improve in their self-efficacy toward computer programming more slowly than students in grade six between the baseline and first follow-up, as evidenced by a significant interaction term ($\beta = -.14$, $t = -2.27$, $p = .023$). Also between the baseline and the first follow-up, students with greater initial math interest tended to have more rapid growth in their self-efficacy toward computer programming ($\beta = .06$, $t = 2.43$, $p = .015$), further implicating the association between attitudes toward math and computer programming. As had been found in the model predicting awareness, growth in

Table 6. *Standardized coefficients (β) corresponding to parameters shown in the path model (N = 610).*

	Awareness						Self-efficacy						Interest						Aspirations					
			95% CI						95% CI						95% CI						95% CI			
	β	SE	Lower	Upper	t	p	β	SE	Lower	Upper	t	p	β	SE	Lower	Upper	t	p	β	SE	Lower	Upper	t	p
M1: Intercept Only																								
Intercept	-0.05	0.03	-0.11	0.01	124.04	<.001***	-0.04	0.03	-0.10	0.02	144.21	<.001***	-0.04	0.03	-0.10	0.03	100.81	<.001***	-0.02	0.03	-0.08	0.05	94.16	<.001***
M2: Intercept Only + Slope 1 and Slope 2																								
Intercept	-0.01	0.03	-0.08	0.05	100.90	<.001***	-0.01	0.03	-0.07	0.06	113.66	<.001***	-0.02	0.03	-0.09	0.04	85.98	<.001***	-0.01	0.03	-0.08	0.06	78.09	<.001***
Slope 1	0.24	0.02	0.20	0.28	12.15	<.001***	0.14	0.02	0.10	0.18	6.43	<.001***	0.10	0.02	0.07	0.14	5.48	<.001***	0.05	0.02	0.01	0.09	2.52	0.012*
Slope 2	0.05	0.02	0.01	0.08	2.73	0.007*	-0.01	0.02	-0.04	0.02	-0.66	0.511	-0.05	0.02	-0.08	-0.02	-3.05	.002**	0.00	0.02	-0.03	0.03	0.09	0.929
M3: Intercept Only + Slope 1 and Slope 2 and (Slope 2)^2																								
Intercept	0.00	0.04	-0.07	0.07	95.70	<.001***	-0.02	0.04	-0.09	0.05	107.94	<.001***	-0.06	0.04	-0.14	0.01	83.07	<.001***	-0.06	0.04	-0.14	0.01	76.12	<.001***
Slope 1	0.24	0.02	0.20	0.28	11.50	<.001***	0.15	0.02	0.10	0.19	6.40	<.001***	0.12	0.02	0.08	0.16	5.86	<.001***	0.06	0.02	0.03	0.10	3.29	0.001**
Slope 2	0.05	0.02	0.01	0.10	1.58	0.114	-0.02	0.02	-0.06	0.02	-0.92	0.359	-0.07	0.02	-0.11	-0.04	-3.05	.002**	-0.04	0.02	-0.08	0.00	-3.02	0.003**
(Slope 2)^2	-0.01	0.02	-0.05	0.02	-0.71	0.481	0.02	0.02	-0.02	0.05	0.75	0.451	0.04	0.02	0.00	0.07	2.17	.030*	0.06	0.02	0.02	0.09	3.27	0.001**
M4: Inclusion of Main and Interaction Effects																								
Intercept and Slope																								
Intercept	0.03	0.07	-0.11	0.17	17.70	<.001***	0.11	0.07	-0.03	0.24	24.81	<.001***	0.20	0.08	0.05	0.36	16.58	<.001***	0.19	0.08	0.04	0.34	15.81	<.001***
Slope 1	0.22	0.05	0.12	0.31	2.28	0.023*	0.16	0.05	0.07	0.26	0.94	0.349	0.06	0.05	-0.02	0.15	0.74	0.457	0.04	0.04	-0.04	0.13	1.02	0.310
Slope 2	0.05	0.04	-0.03	0.13	0.10	0.918	-0.01	0.02	-0.04	0.02	-0.80	0.424	-0.10	0.04	-0.18	-0.02	-1.84	0.067	-0.01	0.04	-0.09	0.07	-1.77	0.077
(Slope 2)^2	-	-	-	-	-	-	-	-	-	-	-	-	0.04	0.02	0.00	0.07	2.20	0.028*	0.06	0.02	0.02	0.09	3.31	<.001***
Main Effects of Predictors																								
Cohort (2018 = 1)	-0.03	0.03	-0.09	0.03	-0.94	0.348	0.03	0.03	-0.03	0.09	0.87	0.385	-0.07	0.03	-0.14	0.00	-2.09	0.037*	-0.08	0.03	-0.15	-0.01	-2.39	0.017*
Grade (7)	0.07	0.07	-0.06	0.20	0.56	0.577	-0.14	0.07	-0.28	-0.01	-1.89	0.059	-0.10	0.07	-0.24	0.04	-0.26	0.796	-0.02	0.07	-0.16	0.12	0.21	0.835
Grade (8)	0.10	0.10	-0.09	0.29	1.03	0.304	-0.11	0.10	-0.30	0.09	-1.73	0.084	-0.01	0.11	-0.22	0.20	-0.42	0.678	0.08	0.11	-0.13	0.29	0.86	0.391
Math Self-efficacy	0.07	0.04	-0.01	0.16	2.39	0.017*	0.15	0.04	0.06	0.23	2.80	0.005**	0.00	0.05	-0.09	0.09	0.54	0.587	-0.03	0.05	-0.12	0.06	0.32	0.747
Math Interest	-0.04	0.04	-0.12	0.03	-1.12	0.263	-0.09	0.04	-0.17	-0.02	-1.29	0.196	0.03	0.04	-0.05	0.11	0.21	0.830	-0.02	0.04	-0.10	0.05	-0.88	0.381
Math Identity	0.17	0.04	0.08	0.25	1.36	0.175	0.13	0.04	0.04	0.22	2.00	0.046*	0.15	0.05	0.06	0.24	2.22	0.027*	0.21	0.05	0.12	0.30	2.43	0.015*
Gender (Female=1)	-0.09	0.06	-0.21	0.03	-1.55	0.121	-0.09	0.06	-0.21	0.03	-1.61	0.108	-0.23	0.06	-0.35	-0.10	-3.06	0.002**	-0.24	0.06	-0.36	-0.11	-2.58	0.010
URM Status (URM=1)	-0.05	0.07	-0.18	0.08	-0.01	0.989	0.01	0.07	-0.12	0.15	-0.32	0.746	-0.17	0.07	-0.32	-0.02	-2.01	0.045*	-0.21	0.07	-0.35	-0.06	-2.24	0.025*
Moderation of Predictors with Slope 1																								
Grade (7)	-0.02	0.04	-0.11	0.07	-0.41	0.679	-0.01	0.04	-0.10	0.08	-0.18	0.858	0.10	0.04	0.01	0.18	2.21	0.028*	0.05	0.04	-0.03	0.13	1.22	0.222
Grade (8)	-0.04	0.06	-0.16	0.09	-0.61	0.542	-0.14	0.06	-0.27	-0.02	-2.27	0.023*	0.01	0.06	-0.11	0.13	0.22	0.826	0.00	0.06	-0.12	0.12	0.03	0.974
Math Self-efficacy	0.04	0.03	-0.02	0.09	1.27	0.205	-0.01	0.03	-0.07	0.04	-0.52	0.606	0.04	0.03	-0.02	0.09	1.38	0.168	0.07	0.03	0.01	0.12	2.45	0.015*
Math Interest	0.01	0.03	-0.04	0.06	0.50	0.617	0.06	0.02	0.01	0.11	2.43	0.015*	-0.01	0.02	-0.06	0.03	-0.54	0.592	0.00	0.02	-0.05	0.05	-0.04	0.969
Math Identity	-0.07	0.03	-0.13	-0.01	-2.41	0.016*	-0.05	0.03	-0.11	0.00	-1.81	0.071	-0.04	0.03	-0.09	0.02	-1.40	0.162	-0.11	0.03	-0.16	-0.06	-4.02	<.001
Gender (Female=1)	-0.03	0.04	-0.11	0.04	-0.85	0.396	-0.03	0.04	-0.11	0.04	-0.84	0.400	-0.01	0.04	-0.09	0.07	-0.26	0.797	0.04	0.04	-0.04	0.11	0.98	0.329
URM Status (URM=1)	0.07	0.05	-0.02	0.16	1.49	0.137	-0.06	0.05	-0.15	0.03	-1.38	0.168	0.03	0.04	-0.06	0.11	0.65	0.519	-0.02	0.04	-0.10	0.06	-0.47	0.640
Moderation of Predictors with Slope 2																								
Grade (7)	0.01	0.04	-0.06	0.08	0.27	0.790	-	-	-	-	-	-	-0.02	0.04	-0.09	0.05	-0.65	0.519	-0.01	0.04	-0.09	0.06	-0.30	0.763
Grade (8)	-0.06	0.05	-0.16	0.05	-1.07	0.285	-	-	-	-	-	-	0.06	0.05	-0.04	0.15	1.14	0.257	-0.03	0.05	-0.14	0.07	-0.65	0.515
Math Self-efficacy	-0.04	0.02	-0.09	0.00	-1.79	0.074	-	-	-	-	-	-	-0.01	0.02	-0.05	0.04	-0.29	0.775	-0.01	0.02	-0.06	0.04	-0.41	0.681

(*Continued*)

Table 6. (Continued).

	Awareness						Self-efficacy						Interest						Aspirations					
			95% CI						95% CI						95% CI						95% CI			
	β	SE	Lower	Upper	t	p	β	SE	Lower	Upper	t	p	β	SE	Lower	Upper	t	p	β	SE	Lower	Upper	t	p
Math Interest	0.02	0.02	-0.02	0.06	0.95	0.342	-	-	-	-	-	-	0.01	0.02	-0.03	0.05	0.45	0.653	0.02	0.02	-0.02	0.06	1.05	0.295
Math Identity	0.05	0.02	0.00	0.10	2.13	0.034*	-	-	-	-	-	-	0.00	0.02	-0.05	0.04	-0.14	0.890	0.01	0.02	-0.04	0.05	0.27	0.787
Gender (Female=1)	0.01	0.03	-0.05	0.08	0.42	0.673	-	-	-	-	-	-	0.01	0.03	-0.05	0.07	0.37	0.713	-0.01	0.03	-0.07	0.06	-0.21	0.836
URM Status (URM=1)	-0.01	0.04	-0.08	0.07	-0.24	0.809	-	-	-	-	-	-	0.03	0.04	-0.04	0.10	0.89	0.376	-0.01	0.04	-0.09	0.06	-0.37	0.709

***$p < .001$, ** $p < .01$, * $p < .05$, • $p < .10$

students' self-efficacy toward computer programming did not appear to differ based on whether or not the student was female or from a URM group.

Interest

We again found that model 2 (intercept plus slope 1 and 2) demonstrated a significantly better fit than model 1 (intercept only). Unlike the analyses for awareness and self-efficacy, we also found that model 3 (intercept, slope 1 and 2, plus quadratic of slope 2) appeared to fit significantly better than model 2 (without the quadratic term; see Table 5). Therefore, we used model 3 as the basis model for including predictors. Inspecting the standardized estimates for model 3 suggested that there was significant positive growth in students' interest in computer programming between the baseline and the first follow-up (β = .12, t = 5.86, p < .001; see Table 6). However, between the first and final follow-up, interest waned slightly at first as suggested by a negative slope 2 coefficient (β = −.07, t = −3.05, p = .002) though increased soon after, as suggested by a significant quadratic term (β = .04, t = 2.17, p = .030).

Including the predictors in model 4 revealed several significant effects. Students with greater initial math identity tended to have greater interest in computer programming (β = .15, t = 2.22, p = .027). Female (β = −.23, t = −3.06, p = .002) and URM (β = −.17, t = −2.01, p = .045) students appeared to have less interest in computer programming than their male and non-URM counterparts. The lack of an interaction effect between either of these demographic variables and the slope term suggests that change in interest did not differ based on these characteristics. In other words, interest in computer programming among both female and URM students and their respective counterparts grew at approximately the same rate. We also found that students in grade seven appeared to have greater growth in their interest in computer programming compared with students in grade six (β = .10, t = 2.21, p = .028).

Aspirations

Finally, we considered piecewise growth in students' aspirations for a future in computer programming. As we had found with interest construct, the results of the measurement invariance provided evidence of scalar invariance for the aspirations construct, both in terms of maintaining good model fit and the χ^2 test (see Table 5). We thus proceeded with the piecewise growth curve analysis in a similar fashion as with the other dimensions of computer programming attitudes. Model 2 (intercept plus slope 1 and 2) demonstrated a significantly better fit than model 1 (intercept only). Much like the results of model selection for interest in computer programming, we found that model 3 (intercept, slope 1 and 2, plus quadratic of slope 2) appeared to fit significantly better than model 2 (without the quadratic term). As such, we used model 3 as the basis model for including predictors in model 4. The standardized coefficients for model 3 suggested significant positive growth in students' aspirations toward computer programming between the baseline and the first follow-up (β = .07, t = 3.29, p = .001; see Table 6). Between the first and final follow-up, aspirations decreased slightly at first as suggested by a negative slope 2 coefficient (β = −.04, t = −3.02, p = .003) though increased soon afterwards, as indicated by a significant quadratic term (β = .06, t = 3.27, p = .001). This suggested some non-linear U-shaped change between the first and final follow-up.

Including the predictors in model 4 revealed several important trends that mirrored those of the findings related to the interest construct. Students with greater initial math identity tended to have greater aspirations towards computer programming (β = .21, t = 2.43, p = .015). In addition, female (β = −.24, t = −2.58, p = .010) and URM (β = −.21, t = −2.24, p = .025) students appeared to have lower aspirations for a future in computer programming than their counterparts. Furthermore, the lack of an interaction effect between either of these demographic variables in the two slope terms suggests that change in aspirations towards computer programming among both female and URM students and their respective counterparts grew at approximately the same rate. Students with greater math self-efficacy appeared to have greater growth in their aspirations towards computer programming (β = .07, t = 2.45, p = .015).

Discussion

In the present study, we first examined baseline differences in middle school students' attitudes towards computer programming, controlling for differences in math attitudes. We then investigated changes in computer programming attitudes and the extent to which gender and URM status influenced growth after accounting for baseline differences in students' math attitudes, grade level, and engagement with an online platform that was designed to improve students' orientations towards computer programming. One novelty of this approach is that we examined growth in dimensions of computer programming attitudes using a non-linear model that appeared to closely reflect its actual change. To capture improvement with greater specificity, we included math attitudes as predictors, reflecting students' math self-efficacy, interest in math, and math identity. Similarly, we considered computer programming attitudes with respect to awareness, self-efficacy, interest, and aspirations for a future. These four domains of computer programming attitudes were selected based on SCCT (Lent et al., 2002), which describes a framework for the development of long-term career interests.

Initial differences in math and computer programming based on gender and URM Status

Several important findings were revealed with respect to baseline differences. For math attitudes, there were no significant differences between male and female students. However, we did find differences between URM and non-URM students, with URM students tending to have more negative orientations towards math. This finding may reflect the negative impact of stereotypes that URM students hold about their abilities (OBrien et al., 2015). Grade level also explained differences in students' math interest and math identity as measured against the baseline. Students in grade six appeared to have significantly more positive attitudes in both domains than students in grade seven. It is possible that as students encounter more difficult math content in grade seven compared with the previous year; the greater challenge could disrupt and lower their attitudes towards the subject area (Pajares & Graham, 1999), with female and URM students being particularly negatively affected (Catsambis, 1994; Huang et al., 2019). Through formal and informal learning experiences, students may develop more positive and stable orientations towards math (Degenhart et al., 2007; Plant et al., 2009). Further research using the platform described in the present study could help determine the association between these types of learning experiences and positive orientations towards computer science and programming, in addition to what factors promote such positive orientations and whether the association differs between certain students.

We found no significant differences in students' awareness and self-efficacy toward computer programming based on gender or URM status after controlling for math attitudes. However, apart from the variation explained by math attitudes, there were differences in students' computer programming interest on the basis of gender and URM status, as well as differences in computer programming aspirations on the basis of gender. Both females and URM students expressed having lower initial interest and aspirations toward computer programming than their respective counterparts. Past research indicates that interest and intention to achieve in the subject area are critical for academic pursuits in the short-term (Geary et al., 2019; Niepel et al., 2018; M. T. Wang et al., 2021) and future scholarly and professional ambitions later on (Lent et al., 2019; Su, 2020). These findings may point towards early emerging attitudinal differences that likely contribute to a widening gap in participation in computing careers among female and URM students. By the time students enroll in middle school, disparities in female and URM students' interest and aspirations toward computer programming may be shaped by multiple factors, including lower self-efficacy in STEM fields (Ball et al., 2017; Seo et al., 2019) and possibly formed through the influence of societal expectations and stereotypes (O'Brien et al., 2015; Pantic et al., 2018), which effectively serve as barriers to early participation in these fields (Butler-Barnes et al., 2021).

Growth in computer programming attitudes

We also sought to establish some evidence of longitudinal measurement invariance before proceeding with the growth model analysis. This would help to ensure that the construct was measured consistently at each time point and thus conclusions could be validly drawn from a model examining change in the construct over time. Consistent with past research examining construct stability of STEM attitudes (Unfried et al., 2015), we were able to establish evidence of scalar measurement invariance for interest and aspirations, but not awareness and self-efficacy. During the academic year, students' understanding of computer programming is likely to have changed, and thus their interpretation of questions about their knowledge and ability in computer programming is also potentially susceptible to change. Many middle school students may be unfamiliar with computer science and programming (Doerschuk et al., 2007; Pantic et al., 2018), and thus may not know how to answer such a question as this. As their knowledge of the subject grows, so too does students' awareness and self-efficacy within the subject, as well as their ability to self-monitor their understanding of it (Z. Z. Wang et al., 2020). Although this limited the interpretability of the subsequent growth models, this issue may reflect the complicated nature of the constructs of awareness and self-efficacy towards computer programming, as well as the difficulty of validly and reliably measuring such constructs over the long run.

The growth model analyses for all four domains of computer programming suggested significant positive growth between the baseline and the first follow-up when not accounting for the predictors. Consistent with SCCT, past research and theory suggest that the development of awareness, self-efficacy, interest, and finally, aspirations is somewhat sequential (Gainor & Lent, 1998; Su, 2020). While awareness and self-efficacy of computer science can be improved through shorter-term positive experiences (Pollock et al., 2004), interest and aspirations may require repeated exposure to positive experiences to remain stable over time (Low et al., 2005). This may explain why we found some evidence of non-linear growth in interest and aspirations after the first follow-up, but not in awareness and self-efficacy, which remained stable after the initial period of growth between the baseline and the first follow-up. The change in lower-level computer programming attitudes between time points suggests that improvement in the four domains may occur according to different timespans.

The extent to which attitudes towards subjects like math are related to the trajectory of interest development is less well understood within a framework such as SCCT. Our findings from the growth model analyses suggest that students who hold more favorable math attitudes tend to have a greater improvement in computer programming attitudes. These findings hint at the possibility that positive math attitudes may precipitate more favorable attitudes towards other STEM subjects (Ching et al., 2019; Lin et al., 2018; Seo et al., 2019; Wiebe et al., 2018), such as computer programming. Other factors related to prior experiences, such as grade level may also influence growth in attitudes toward computer programming. In line with SCCT, we would expect growth in a students interest in computer programming to occur after the student has developed a foundation of awareness and self-efficacy in the subject. This assumption is at least partially supported by the findings that grade seven students grew more rapidly in their interest in computer programming. Students often complete a class which teaches computer skills as they begin middle school in grade six. As such, grade seven students may have just enough experience in computer programming to support a deeper level of interest development than less experienced students in grade six and more experienced students in grade eight.

After accounting for other factors in the models, we found several important differences in the growth of computer programming attitudes among certain groups of students. We found that female and URM students tended to begin with significantly lower interest and aspirations toward computer programming, even when accounting for all of the other predictors in the growth model. These findings are largely consistent with the results of the ANOVA models, which found some baseline differences between male and female or URM and non-URM students. We did not find that changes in growth in computer programming either between the baseline and the first follow-up or thereafter were associated with gender or URM status. These findings may speak towards some initial efficacy of the intervention in at least preventing widening disparities in attitudes towards STEM subject areas. From an educational perspective, the personalization offered by the online platform is critical for connecting students with content, particularly in a subject such as computer programming, in which students are likely to have had limited previous exposure (Štuikys & Burbaitė, 2018). However, this creates an obvious research challenge as students' experiences using the online platform may vary widely and thus should be further examined in future research.

Implications

The present study findings contribute to a growing understanding of changes that occur among middle school students in their attitudes towards computer programming.

Furthermore, our findings are drawn from attitudinal data collected from a diverse sample of middle school students, a relatively understudied population within STEM disciplines. Middle school is a critical yet underappreciated time for future career discovery in STEM disciplines (Blotnicky et al., 2018). The present findings provide a roadmap for researchers and educators to understand how middle schoolers' computer programming attitudes may change over the course of an academic year. Recognizing that certain attitudes towards computer programming develop over a different time span is an important first step for (1) studying the associations between orientations towards computer programming and later scholarly and professional pathways; and (2) promoting early change in students' orientations towards computer programming. There was some general support for a theoretical model positing that students' orientation towards computer programming develops sequentially (Gainor & Lent, 1998; Su, 2020). It may therefore be unrealistic to expect immediate changes in students' interest and aspirations in computer programming yet seeing evidence of improvement in awareness and self-efficacy is a good indication of growth in a positive orientation towards computer programming.

We were able to confirm longitudinal stability in students' interest and aspirations for a future in computer programming. However, we also found that the constructs of awareness and self-efficacy were not sufficiently stable. These findings shed light on the difficulty of measuring such constructs because their essence itself may be susceptible to change. As students gain exposure to computer programming, the information against which they evaluate their understanding also changes. In some contexts, it is not entirely surprising that students' perceived awareness and self-efficacy diminished initially after gaining some experience with computer programming. As students gain more information about a subject, they may soon realize the depth of knowledge required to understand it. This may lead to more conservative estimates of awareness of a subject, despite an increase in knowledge of it. While research on perceived awareness is limited, much like self-efficacy it is likely highly susceptible to fluctuations during learning (Bernacki et al., 2015). The present study also found that there are stubborn gaps in students' initial orientations towards computer programming based on gender and URM status among middle school students. We found this surprising, given that all students within the sample were likely to have had minimal exposure to computer programming at the start of the year. Providing curated content using AI-enabled recommender systems is one means to achieve personalization and promote effective learning (Tsybulsky, 2020).

Limitations

Despite the significance of these findings, there are several limitations of the present study. Some of these limitations arise from issues that often occur in applied educational settings. First, there are methodological issues that affect the validity of the measures. While we attempted to be thorough in ensuring valid and reliable measures by conducting measurement invariance, we did not establish definitive evidence of invariance across time with respect to the awareness and self-efficacy measures. Furthermore, the self-efficacy measure at the baseline appeared to have low internal consistency. The reasons for this are presently unclear though may reflect fundamental changes in the construct itself, particularly after some initial experience with the target skill of computer programming (for a discussion of this issue, see Meade et al., 2005). Students may have had the most difficulty in grasping the meaning of items on the scale. As noted by Vandenberg et al. (2020), the terms used by instructional designers to refer to computing curriculum may not be commonly understood by youth. Aside from age, other cultural and language background factors may affect ones ability to interpret and appropriately respond to items on the scale. Despite these limitations, we note that internal consistency appeared to improve at later time points for the self-efficacy measure, potentially reflecting a developing vocabulary and knowledge base in the subject.

Aside from limited sample size, which is further diminished by attrition that so often occurs in longitudinal research, several additional limitations may affect the generalizability of the study. First, students were also part of an intervention designed to expose them to computer science educational content, with the intent to trigger interest in a career in computing or a related field. As such, it is unclear how well these findings generalize to students who have not been using a platform such as the one in the present study. The findings are also correlational and therefore we cannot distinguish the possibility that other factors may have contributed to improvement in students' orientations towards computer programming such as other school curricula or natural growth due to maturation. Further experimental or quasi-experimental research is needed to draw conclusions about the efficacy of the platform itself in promoting such change. Second, we also note that these findings are not drawn from a multi-year longitudinal study and thus any claims about long-term change between grade levels are tenuous. Third, other factors beyond grade level not controlled for in the growth models could have explained the variation in the long-term growth of computer programming attitudes, such as extracurricular experiences. Future work should consider how such experiences may positively shape the development of students' orientations towards computing careers, particularly for underserved and underrepresented students in the field. Finally, given that the study involves middle school students, it would be difficult to make claims about how the findings generalize to younger and older students. Conducting a longitudinal study following multiple cohorts across ages or grade levels could help to increase knowledge of this important topic.

Conclusions

In this study, we examined growth in middle school students' attitudes towards computer programming, as well as factors that may contribute to such growth, during an academic year in which they used an online platform designed to provide curated content for learning computer programming. Middle school may be an ideal time to prevent negative orientations from forming among individuals from groups that have historically been underrepresented in computing fields. We found baseline differences in certain computer programming attitudes on the basis of gender and URM status; however, we did not find such differences in baseline math attitudes. We also found that between the baseline and the first follow-up, there was evidence of improvement in all four domains of students' computer programming attitudes. These findings provide a framework for studying changes in students' computer programming attitudes. We hope that these findings may be applied increasing parity in the field of computing.

Note

1. https://www.curatedpathways.org/

Acknowledgments

We would like to thank the National Science Foundation for providing support for the Research Experience for Undergraduates (REU) program at the Center for Research Computing at the University of Notre Dame (PI: Paul Brenner, Ph.D.; #1852457). We would also like to thank Audrey Filonczuk, Maya Mosley, Eliana Sanchez, and Allison Wang, who served as research assistants in the early stages of the analysis described in this manuscript, in addition to Emily Kane who provided insightful comments in the manuscript revision process. Finally, we would like to thank the teachers and students who participated in this project. A portion of this work was presented at the Society for Research in Child Development 2021 Biennial Meeting.

Disclosure statement

The authors have no competing interests to declare.

Funding

Preliminary work on this project was supported by the Research Experience for Undergraduates (REU) program at the Center for Research Computing at the University of Notre Dame (PI: Paul Brenner, Ph.D.; # 1852457; National Science Foundation, United States.

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Data availability statement

The data that support the findings of this study are available upon request from the corresponding author.

Geolocation information

Data reported in the present study was collected from participants located in the United States of America.

References

Adrion, W. R., Dunton, S. T., Ericson, B., Fall, R., Fletcher, C., & Guzdial, M. (2020, Dec). U.S. States must broaden participation while expanding access to computer science education. *Communications of the ACM*, *63*(12), 22–25. https://cacm.acm.org/magazines/2020/12/248789-u-s-states-must-broaden-participation-while-expanding-access-to-computer-science-education/fulltext

Ahlqvist, S., London, B., & Rosenthal, L. (2013). Unstable identity compatibility: How gender rejection sensitivity undermines the success of women in science, technology, engineering, and mathematics fields. *Psychological Science*, *24*(9), 1644–1652. https://doi.org/10.1177/0956797613476048

Ahmed, W. (2018). Developmental trajectories of math anxiety during adolescence: Associations with stem career choice. *Journal of Adolescence (London, England.)*, *67*, 158–166. https://doi.org/10.1016/j.adolescence.2018.06.010

Angeli, C., & Giannakos, M. (2020). Computational thinking education: Issues and challenges. *Computers in Human Behavior*, *105*, 106185. https://doi.org/10.1016/j.chb.2019.106185

Ball, C., Huang, K. T., Cotten, S. R., & Rikard, R. V. (2017). Pressurizing the STEM pipeline: An expectancy-value theory analysis of youths' STEM attitudes. *Journal of Science Education and Technology*, *26*(4), 372–382. https://doi.org/10.1007/s10956-017-9685-1

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, *67*(1). https://doi.org/10.18637/jss.v067.i01

Bernacki, M. L., Nokes-Malach, T. J., & Aleven, V. (2015). Examining self-efficacy during learning: Variability and relations to behavior, performance, and learning. *Metacognition and Learning*, *10*(1), 99–117. https://doi.org/10.1007/s11409-014-9127-x

Blickenstaff, J. C. (2005). Women and science careers: Leaky pipeline or gender filter? *Gender and Education*, *17*(4), 369–386. https://doi.org/10.1080/09540250500145072

Blotnicky, K. A., Franz-Odendaal, T., French, F., & Joy, P. (2018). A study of the correlation between STEM career knowledge, mathematics self-efficacy, career interests, and career activities on the likelihood of pursuing a STEM career among middle school students. *International Journal of STEM Education*, *5*(1), 22. https://doi.org/10.1186/s40594-018-0118-3

Bohrnstedt, G. W., Zhang, J., Park, B. J., Ikoma, S., Broer, M., & Ogut, B. (2020). Mathematics identity, self-efficacy, and interest and their relationships to mathematics achievement: A longitudinal analysis. In R. T. Serpe R. Stryker & B. Powell (Eds.), *Identity and Symbolic Interaction* (pp. 169–210). Springer. https://doi.org/10.1007/978-3-030-41231-9_7

Brown, V. A. (2021). An introduction to linear mixed-effects modeling in R. *Advances in Methods and Practices in Psychological Science*, *4*(1), 2515245920960351. https://doi.org/10.1177/2515245920960351

Butler-Barnes, S. T., Cheeks, B., Barnes, D. L., & Ibrahim, H. (2021). STEM pipeline: Mathematics beliefs, attitudes, and opportunities of racial/ethnic minority girls. *Journal for STEM Education Research*, 1–28. https://doi.org/10.1007/s41979-021-00059-x

Camp, T., Adrion, W., Bizot, B., Davidson, S., Hall, M., Hambrusch, S., Walker, E., & Zweben, S. (2017). Generation CS: The growth of computer science. *ACM Inroads*, *8*(2), 44–50. https://doi.org/10.1145/3084362

Campe, S., Denner, J., Green, E., & Torres, D. (2020). Pair programming in middle school: Variations in interactions and behaviors. *Computer Science Education*, *30*(1), 22–46. https://doi.org/10.1080/08993408.2019.1648119

Casad, B. J., Oyler, D. L., Sullivan, E. T., McClellan, E. M., Tierney, D. N., Anderson, D. A., Greeley, P. A., Fague, M. A., & Flammang, B. J. (2018). Wise psychological interventions to improve gender and racial equality in STEM. *Group Processes & Intergroup Relations*, *21*(5), 767–787. https://doi.org/10.1177/1368430218767034

Catsambis, S. (1994). The path to math: gender and racial-ethnic differences in mathematics participation from middle school to high school. *Sociology of Education*, *67*(3), 199–215. https://doi.org/10.2307/2112791

Cheryan, S., Ziegler, S. A., Montoya, A. K., & Jiang, L. (2017). Why are some STEM fields more gender balanced than others? *Psychological Bulletin*, *143*(1), 1–35. https://doi.org/10.1037/bul0000052

Ching, Y. H., Yang, D., Wang, S., Baek, Y., Swanson, S., & Chittoori, B. (2019). Elementary school student development of STEM attitudes and perceived learning in a STEM integrated robotics curriculum. *TechTrends*, *63*(5), 590–601. https://doi.org/10.1007/s11528-019-00388-0

Clements, D. H., & Sarama, J. (2016). Math, science, and technology in the early grades. *The Future of Children*, *26*(2), 75–94. doi:https://doi.org/10.1353/foc.2016.0013

Code.org, C. S. T. A., & Alliance, E. C. E. P. (2022). *2022 State of Computer Science Education: Illuminating Disparities*. https://advocacy.code.org/stateofcs

Degenhart, S. H., Wingenbach, G. J., Dooley, K. E., Lindner, J. R., Mowen, D. L., & Johnson, L. (2007). Middle school students' attitudes toward pursuing careers in science, technology, engineering, and math. *NACTA Journal*, 52–59. https://www.jstor.org/stable/43766229

Denissen, J. J., Zarrett, N. R., & Eccles, J. S. (2007). I like to do it, I'm able, and I know I am: Longitudinal couplings between domain-specific achievement, self-concept, and interest. *Child Development*, *78*(2), 430–447. https://doi.org/10.1111/j.1467-8624.2007.01007.x

Doerschuk, P., Liu, J., & Mann, J. (2007). Pilot summer camps in computing for middle school girls: From organization through assessment. In *Proceedings of the 12th annual SIGCSE conference on Innovation and technology in computer science education*, Dundee, Scotland (pp. 4–8). https://doi.org/10.1145/1268784.1268789

Donohue, M. C., Gamst, A. C., & Edland, S. D. (2021). Package 'longpower'. *CRAN*. https://cran.r-project.org/web/packages/longpower/longpower.pdf

Downes, T., & Looker, D. (2011). Factors that influence students' plans to take computing and information technology subjects in senior secondary school. *Computer Science Education*, *21*(2), 175–199. https://doi.org/10.1080/08993408.2011.579811

Du, J., & Wimmer, H. (2019). Hour of code: A study of gender differences in computing. *Information Systems Education Journal*, *17*(4), 91–100. http://isedj.org/2019-17/n4/ISEDJv17n4p91.html

Else-Quest, N., Mineo, C. C., & Higgins, A. (2013). Math and science attitudes and achievement at the intersection of gender and ethnicity. *Psychology of Women Quarterly*, *37*(3), 293–309. https://doi.org/10.1177/0361684313480694

Estrada, M., Burnett, M., Campbell, A. G., Campbell, P. B., Denetclaw, W. F., Gutiérrez, C. G., Okpodu, C. M., John, G. H., Matsui, J., McGee, R., Okpodu, C. M., Robinson, T. J., Summers, M. F., Werner-Washburne, M., & Zavala, M. (2016). Improving underrepresented minority student persistence in STEM. *CBE—Life Sciences Education*, *15*(3), es5. https://doi.org/10.1187/cbe.16-01-0038

Friend, M. (2015). Middle school girls' envisioned future in computing. *Computer Science Education*, *25*(2), 152–173. https://doi.org/10.1080/08993408.2015.1033128

Gainor, K. A., & Lent, R. W. (1998). Social cognitive expectations and racial identity attitudes in predicting the math choice intentions of black college students. *Journal of Counseling Psychology*, *45*(4), 403–413. https://doi.org/10.1037/0022-0167.45.4.403

Geary, D. C., Hoard, M. K., Nugent, L., Chu, F., Scofield, J. E., & Ferguson Hibbard, D. (2019). Sex differences in mathematics anxiety and attitudes: concurrent and longitudinal relations to mathematical competence. *Journal of Educational Psychology*, *111*(8), 1447–1461. https://doi.org/10.1037/edu0000355

Gladstone, J. R., Häfner, I., Turci, L., Kneißler, H., & Muenks, K. (2018). Associations between parents and students' motivational beliefs in mathematics and mathematical performance: The role of gender. *Contemporary Educational Psychology*, *54*, 221–234. https://doi.org/10.1016/j.cedpsych.2018.06.009

Gottlieb, J. J. (2018). STEM career aspirations in Black, Hispanic, and White ninth-grade students. *Journal of Research in Science Teaching*, *55*(10), 1365–1392. https://doi.org/10.1002/tea.21456

Griffith, A. L. (2010). Persistence of women and minorities in STEM field majors: Is it the school that matters? *Economics of Education Review*, *29*(6), 911–922. https://doi.org/10.1016/j.econedurev.2010.06.010

Grover, S., Fisler, K., Lee, I., & Yadav, A. (2020, February). Integrating computing and computational thinking into K-12 STEM learning. In *Proceedings of the 51st ACM Technical Symposium on Computer Science Education*, Portland, OR, USA (pp. 481–482). https://doi.org/10.1145/3328778.3366970

Huang, X., Zhang, J., & Hudson, L. (2019). Impact of math self-efficacy, math anxiety, and growth mindset on math and science career interest for middle school students: The gender moderating effect. *European Journal of Psychology of Education*, *34*(3), 621–640. https://doi.org/10.1007/s10212-018-0403-z

Huber, P. J. (1967, June). The behavior of maximum likelihood estimates under nonstandard conditions. In *Proceedings of the fifth Berkeley symposium on mathematical statistics and probability*, Berkeley, CA, USA (Vol. 1, No. 1, pp. 221–233).

Hughes, R. A., Heron, J., Sterne, J. A., & Tilling, K. (2019). Accounting for missing data in statistical analyses: Multiple imputation is not always the answer. *International Journal of Epidemiology*, *48*(4), 1294–1304. https://doi.org/10.1093/ije/dyz032

Hur, J. W., Andrzejewski, C. E., & Marghitu, D. (2017). Girls and computer science: Experiences, perceptions, and career aspirations. *Computer Science Education*, *27*(2), 100–120. https://doi.org/10.1080/08993408.2017.1376385

Jiang, S., Simpkins, S. D., & Eccles, J. S. (2020). Individuals' math and science motivation and their subsequent STEM choices and achievement in high school and college: A longitudinal study of gender and college generation status differences. *Developmental Psychology*, *56*(11), 2137–2151. https://doi.org/10.1037/dev0001110

Jo Campbell, N., & Williams, J. E. (1990). Relation of Computer Attitudes and Computer Attributions to Enrollment in High School Computer Courses and Self-Perceived Computer Proficiency. *Journal of Research on Computing in Education*, *22*(3), 276–289. https://doi.org/10.1080/08886504.1990.10781921

Kim, A. Y., Sinatra, G. M., & Seyranian, V. (2018). Developing a STEM identity among young women: A social identity perspective. *Review of Educational Research*, *88*(4), 589–625. https://doi.org/10.3102/0034654318779957

Kong, S. C., Chiu, M. M., & Lai, M. (2018). A study of primary school students' interest, collaboration attitude, and programming empowerment in computational thinking education. *Computers & Education*, *127*, 178–189. https://doi.org/10.1016/j.compedu.2018.08.026

Lent, R. W., Brown, S. D., & Hackett, G. (1994). Toward a unifying social cognitive theory of career and academic interest, choice, and performance [Monograph]. *Journal of Vocational Behavior*, *45*, 79–122. https://doi.org/10.1006/jvbe.1994.1027

Lent, R. W., Brown, S. D., & Hackett, G. (2002). Social cognitive career theory. D. Brown Ed. In *Career Choice and Development* (4th ed., pp. 255–311). Jossey-Bass.

Lent, R. W., Morris, T. R., Penn, L. T., & Ireland, G. W. (2019). Social–cognitive predictors of career exploration and decision-making: Longitudinal test of the career self-management model. *Journal of Counseling Psychology*, *66*(2), 184–194. https://doi.org/10.1037/cou0000307

Leyva, E., Walkington, C., Perera, H., & Bernacki, M. (2022). Making mathematics relevant: An examination of student interest in mathematics, interest in STEM careers, and perceived relevance. *International Journal of Research in Undergraduate Mathematics Education*, 1–30. https://doi.org/10.1007/s40753-021-00159-4

Lichtenberger, E., & George-Jackson, C. (2013). Predicting high school students' interest in majoring in a STEM field: insight into high school students' postsecondary plans. *Journal of Career and Technical Education*, *28*(1), 19–38. https://eric.ed.gov/?id=EJ1043177

Lin, L., Lee, T., & Snyder, L. A. (2018). Math self-efficacy and STEM intentions: A person-centered approach. *Frontiers in Psychology*, *9*, 2033. https://doi.org/10.3389/fpsyg.2018.02033

Linnel, N., Dayal, A., Gonsalves, P., Kakodkar, M., Ribiero, B., Starr, A., & Zdankus, J. (2020). Curated pathways to innovation: Personalized CS education to promote diversity. *Journal of Computing Sciences in Colleges*, *35*(10), 39–45. https://www.ccsc.org/publications/journals/SW2020.pdf#page=39

Liu, G., & Liang, K. Y. (1997). Sample size calculations for studies with correlated observations. *Biometrics*, *53*(3), 937–947. https://doi.org/10.2307/2533554

London, J. S., Lee, W. C., & Hawkins Ash, C. D. (2021). Potential engineers: A systematic literature review exploring black children's access to and experiences withSTEM. *Journal of Engineering Education*, *110*(4), 1003–1026. https://doi.org/10.1002/jee.20426

Low, K. S. D., Yoon, M., Roberts, B. W., & Rounds, J. (2005). The stability of vocational interests from early adolescence to middle adulthood: A quantitative review of longitudinal studies. *Psychological Bulletin*, *131*(5), 713–737. https://doi.org/10.1037/0033-2909.131.5.713

Madley-Dowd, P., Hughes, R., Tilling, K., & Heron, J. (2019). The proportion of missing data should not be used to guide decisions on multiple imputation. *Journal of Clinical Epidemiology*, *110*, 63–73. https://doi.org/10.1016/j.jclinepi.2019.02.016

Maltese, A. V., & Tai, R. H. (2011). Pipeline persistence: Examining the association of educational experiences with earned degrees in STEM among U.S. students. *Science Education*, *95*(5), 877–907. https://doi.org/10.1002/sce.20441

McNeish, D. (2018). Thanks coefficient alpha, we'll take it from here. *Psychological Methods*, *23*(3), 412–433. https://doi.org/10.1037/met0000144

Meade, A. W., & Craig, S. B. (2012). Identifying careless responses in survey data. *Psychological Methods*, *17*(3), 437–455. https://doi.org/10.1037/a0028085

Meade, A. W., Lautenschlager, G. J., & Hecht, J. E. (2005). Establishing measurement equivalence and invariance in longitudinal data with item response theory. *International Journal of Testing*, *5*(3), 279–300. https://doi.org/10.1207/s15327574ijt0503_6

Miller, D. I., & Wai, J. (2015). The bachelor's to Ph.D. STEM pipeline no longer leaks more women than men: A 30-year analysis. *Frontiers in Psychology*, *6*, 37. https://doi.org/10.3389/fpsyg.2015.00037

Moote, J., Archer, L., DeWitt, J., & MacLeod, E. (2020). Science capital or STEM capital? Exploring relationships between science capital and technology, engineering, and maths aspirations and attitudes among young people aged 17/18. *Journal of Research in Science Teaching*, *57*(8), 1228–1249. https://doi.org/10.1002/tea.21628

Niepel, C., Burrus, J., Greiff, S., Lipnevich, A. A., Brenneman, M. W., & Roberts, R. D. (2018). Students' beliefs and attitudes toward mathematics across time: A longitudinal examination of the theory of planned behavior. *Learning and Individual Differences*, *63*, 24–33. https://doi.org/10.1016/j.lindif.2018.02.010

O'Brien, L. T., Blodorn, A., Adams, G., Garcia, D. M., & Hammer, E. (2015). Ethnic variation in gender-STEM stereotypes and STEM participation: An intersectional approach. *Cultural Diversity and Ethnic Minority Psychology*, *21*(2), 169–180. https://doi.org/10.1037/a0037944

Olivera-Aguilar, M. (2013). *Impact of violations of longitudinal measurement invariance in latent growth models and autoregressive quasi-simplex models*. [Dissertation].Arizona State University. https://core.ac.uk/download/pdf/79567262.pdf

Pajares, F., & Graham, L. (1999). Self-efficacy, motivation constructs, and mathematics performance of entering middle school students. *Contemporary Educational Psychology*, *24*(2), 124–139. https://doi.org/10.1006/ceps.1998.0991

Pantic, K., Clarke-Midura, J., Poole, F., Roller, J., & Allan, V. (2018). Drawing a computer scientist: Stereotypical representations or lack of awareness? *Computer Science Education*, *28*(3), 232–254. https://doi.org/10.1080/08993408.2018.1533780

Plant, E. A., Baylor, A. L., Doerr, C. E., & Rosenberg-Kima, R. B. (2009). Changing middle-school students' attitudes and performance regarding engineering with computer-based social models. *Computers & Education*, *53*(2), 209–215. https://doi.org/10.1016/j.compedu.2009.01.013

Pollock, L., McCoy, K., Carberry, S., Hundigopal, N., & You, X. (2004). Increasing high school girls' self-confidence and awareness of CS through a positive summer experience. *ACM SIGCSE Bulletin*, *36*(1), 185–189. https://doi.org/10.1145/1028174.971369

Ram, N., & Grimm, K. (2007). Using simple and complex growth models to articulate developmental change: Matching theory to method. *International Journal of Behavioral Development*, *31*(4), 303–316. https://doi.org/10.1177/0165025407077751

Riegle-Crumb, C., & Grodsky, E. (2010). Racial-ethnic differences at the intersection of math course-taking and achievement. *Sociology of Education*, *83*(3), 248–270. https://doi.org/10.1177/0038040710375689

Rogers, M. E., & Creed, P. A. (2011). A longitudinal examination of adolescent career planning and exploration using a social cognitive career theory framework. *Journal of Adolescence*, *34*(1), 163–172. https://doi.org/10.1016/j.adolescence.2009.12.010

Ryoo, J. J., Tanksley, T., Estrada, C., & Margolis, J. (2020). Take space, make space: How students use computer science to disrupt and resist marginalization in schools. *Computer Science Education*, *30*(3), 337–361. https://doi.org/10.1080/08993408.2020.1805284

Sadler, P. M., Sonnert, G., Hazari, Z., & Tai, R. (2012). Stability and volatility of STEM career interest in high school: A gender study. *Science Education*, *96*(3), 411–427. https://doi.org/10.1002/sce.21007

Saw, G., Chang, C., & Chan, H. (2018). Cross-sectional and longitudinal disparities in STEM career aspirations at the intersection of gender, race/ethnicity, and socioeconomic status. *Educational Researcher*, *47*(8), 525–531. https://doi.org/10.3102/0013189X18787818

Seo, E., Shen, Y., & Alfaro, E. C. (2019). Adolescents' beliefs about math ability and their relations to STEM career attainment: Joint consideration of race/ethnicity and gender. *Journal of Youth and Adolescence*, *48*(2), 306–325. https://doi.org/10.1007/s10964-018-0911-9

Štuikys, V., & Burbaitė, R. (2018). *Smart STEM-driven computer science education: Theory, methodology and robot-based practices*. Springer. https://doi.org/10.1007/978-3-319-78485-4

Su, R. (2020). The three faces of interests: An integrative review of interest research in vocational, organizational, and educational psychology. *Journal of Vocational Behavior*, *116*, 103240. https://doi.org/10.1016/j.jvb.2018.10.016

Taub, R., Armoni, M., & Ben-Ari, M. (2012). CS unplugged and middle-school students' views, attitudes, and intentions regarding CS. *ACM Transactions on Computing Education (TOCE)*, *12*(2), 1–29. https://doi.org/10.1145/2160547.2160551

Thomas, J. A., & Strunk, K. K. (2017). Expectancy-value and children's science achievement: Parents matter. *Journal of Research in Science Teaching*, *54*(6), 693–712. https://doi.org/10.1002/tea.21382

Tsybulsky, D. (2020). Digital curation for promoting personalized learning: A study of secondary-school science students' learning experiences. *Journal of Research on Technology in Education*, *52*(3), 429–440. https://doi.org/10.1080/15391523.2020.1728447

Unfried, A., Faber, M., Stanhope, D. S., & Wiebe, E. (2015). The development and validation of a measure of student attitudes toward science, technology, engineering, and math (S-STEM).

Journal of Psychoeducational Assessment, *33*(7), 622–639. https://doi.org/10.1177/0734282915571160

Urdan, T. (2019). *Curated Pathways to Innovation Survey*. Unpublished survey instrument.

U.S. Bureau of Labor Statistics [BLS]. (2021). *Occupational Outlook Handbook: Computer and Information Research Scientists*. Retrieved 11 Feb 2021. From https://www.bls.gov/ooh/computer-and-information-technology/computer-and-information-research-scientists.htm#tab-6

U.S. National Science Foundation [NSF]. (2019, Sept). *Science and Engineering Labor Force: Demographic Trends of the S&E Workforce*. https://ncses.nsf.gov/pubs/nsb20198/demographic-trends-of-the-s-e-workforce

U.S. National Science Foundation [NSF] & National Center for Science and Engineering Statistics [NCSES]. (2019, March). *Women, minorities, and persons with disabilities in science and engineering: glossary and key to acronyms*. Report created with surveys by the Surveys conducted by the National Center for Science and Engineering Statistics (NCSES). Retrieved 12 Feb 2021 from https://ncses.nsf.gov/pubs/nsf19304/digest/glossary-and-key-to-acronyms

van Buuren, S., & Groothuis-Oudshoorn, K. (2011). mice: Multivariate imputation by chained equations in R. *Journal of Statistical Software*, *45*(3), 1–68. https://doi.org/10.18637/jss.v045.i03

Vandenberg, J., Tsan, J., Boulden, D., Zakaria, Z., Lynch, C., Boyer, K. E., & Wiebe, E. (2020). Elementary students' understanding of CS terms. *ACM Transactions on Computing Education (TOCE)*, *20*(3), 1–19. https://doi.org/10.1145/3386364

Varma, R. (2018). US science and engineering workforce: Underrepresentation of women and minorities. *American Behavioral Scientist*, *62*(5), 692–697. https://doi.org/10.1177/0002764218768844

Vegas, E., & Fowler, B. (2020). What do we know about the expansion of K-12 computer science education. *Brookings Institute. Retrieved February*, *2*. 2021https://www.brookings.edu/research/what-do-we-know-about-the-expansion-of-k-12-computer-science-education/ .

Wang, X. (2013). Why students choose STEM majors: Motivation, high school learning, and postsecondary context of support. *American Educational Research Journal*, *50*(5), 1081–1121. https://doi.org/10.3102/0002831213488622

Wang, M. T., Binning, K. R., Del Toro, J., Qin, X., & Zepeda, C. D. (2021). Skill, thrill, and will: The role of metacognition, interest, and self-control in predicting student engagement in mathematics learning over time. *Child Development*, *92*(4), 1369–1387. https://doi.org/10.1111/cdev.13531

Wang, M. T., & Degol, J. (2013). Motivational pathways to STEM career choices: Using expectancy–value perspective to understand individual and gender differences in STEM fields. *Developmental Review*, *33*(4), 304–340. https://doi.org/10.1016/j.dr.2013.08.001

Wang, M. T., & Degol, J. L. (2017). Gender gap in science, technology, engineering, and mathematics (STEM): Current knowledge, implications for practice, policy, and future directions. *Educational Psychology Review*, *29*(1), 119–140. https://doi.org/10.1007/s10648-015-9355-x

Wang, Z., Rimfeld, K., Shakeshaft, N., Schofield, K., & Malanchini, M. (2020). The longitudinal role of mathematics anxiety in mathematics development: Issues of gender differences and domain-specificity. *Journal of Adolescence*, *80*, 220–232. https://doi.org/10.1016/j.adolescence.2020.03.003

Wiebe, E., Unfried, A., & Faber, M. (2018). The relationship of STEM attitudes and career interest. *EURASIA Journal of Mathematics, Science and Technology Education*, *14*(10). https://doi.org/10.29333/ejmste/92286

You, S. (2013). Gender and ethnic differences in precollege mathematics coursework related to science, technology, engineering, and mathematics (STEM) pathways. *School Effectiveness and School Improvement*, *24*(1), 64–86. https://doi.org/10.1080/09243453.2012.681384