What's the value? Motivations to pursue secondary computing CTE concentrations

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What’s the value? Motivations to pursue secondary computing CTE concentrations

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Introduction

Computing skills such as programming, graphic design, and networking are among the fastest growing in the modern workplace. Computing skills are increasingly critical in many roles including STEM (Malyn-Smith & Lee, 2012) and non-STEM occupations (Grinis, 2019). The American education system responded to this need by creating more educational opportunities for youth to prepare for these roles. For example, the number of California students attending schools offering a CS course has grown from 33.2% to 79.1% since 2010 (Bruno & Lewis, 2021). The growth is designed to support workforce readiness in computing-related occupations.

Federal policy frames Career and Technical Education (CTE) coursework as part of a college and career readiness strategy preparing youth for high-paying, in-demand occupations. Computing is one of many areas students can choose to concentrate in (defined as taking two or more credits in the field) during high school. Despite being the most popular secondary CTE concentration, computing coursework is being offered and taken in patterns unrelated to their utility value (Sublett & Griffith, 2019). Generally, there is little evidence to suggest why certain students choose or avoid certain CTE pathways (Leu & Arbeit, 2020). Where there is evidence, students draw from a multitude of factors including, but not limited to, future career interests (DeFeo, 2015; Fletcher & Cox, 2012). Given the broad labor market applicability of computing skills relative to other CTE concentrations, there is little evidence to guide policy-makers and researchers to design and investigate inclusive computing education pathways. We respond to this need by addressing the following research question:

- What are the school- and student-level factors associated with taking two or more computing courses during high school?

The present study investigates the factors associated with becoming a computing concentrator in high school. The prior literature suggests that computing coursework is framed as a workforce-readiness strategy though that does not play out in the data and little is known about what motivates students to pursue these courses. We apply Situated Expectancy Value Theory

(SEVT; Eccles & Wigfield, 2020) to model who takes two or more computing courses during high school using a two-level logistic regression model on data from the nationally representative High School Longitudinal Study of 2009 (HSLS:09).

Aims of Secondary Computing Education

Historically, computing courses in high school were framed as skill development. Courses like keyboarding, computer networking, and hardware repair were offered in business or CTE departments to prepare students with occupation-specific skills (Kesten & Lambrecht, 2010). Computing in secondary CTE now extends into manufacturing, construction, and engineering pathways (Montoya et al., 2018). Coding has also become more accessible and interdisciplinary, with block-based languages integrated with arts such as textiles (Peppler & Kafai, 2007) lacking an explicit workforce readiness aim. While there is a diverse group of stakeholders advocating for equitable access to computer science coursework (Jacob et al., 2022), literacy (Jacob & Warschauer, 2018), and increased access to high school, this is a wide tent with a varied rationale to expand access to computing coursework in ways that do not center workforce readiness (Vogel et al., 2017). Offering courses that center students' personal, rather than professional, interest is a promising approach to attracting more students into computing courses (National Academies of Sciences, Engineering, and Medicine, 2021).

Who Takes Computing Courses and Why?

Little is known about why students choose computing courses during high school. One qualitative study suggests that students see courses like AP Computer Science A as general career preparation rather than associated with STEM or computing interests (Jones & Hite, 2020). Many studies draw from sociocultural studies which suggest that disciplinary identity, expectancy for success, and personal values are key drivers of computing course-taking (Chow et al., 2012). These constructs are informed by an individual’s prior experience with the subject matter (Chen et al., 2019), influence from key role models such as parents employed in a similar field (Plasman et al., 2021), and future career aspirations. Programming is often used as the key skill associated with computing coursework and as a lens to study student interest in computing (e.g., Rachmatullah et al., 2020) though this approach fails to encompass a broader definition of computing.

Recent attention in secondary computing education research has been focused on the failure to broaden computing participation. Despite nearly doubling CS degree attainment for Latinx students from 5.2% in 1996 to 10.1% in 2016 (National Center for Science and Engineering Statistics, 2019). CS degree attainment for women has dropped from 27.2% in 1997 to 18.7% in 2016 (Snyder et al., 2016). Furthermore, school-level access (Margolis, 2008) and within-school sorting (Rafalow & Puckett, 2022) have become increasingly problematic ways to exclude some students from computing coursework. Such statistics necessitate interrogation. What drives enrollment or aversion to computing coursework is an essential question.

Despite computing being one of the most popular secondary CTE pathways, prior researchers suggest that "it is probably a mistake to think of most [computing] course-taking as a form of industry-specific CTE" (Sublett & Griffith, 2019, p. 20). CTE is meant to prepare students for high-paying, in-demand occupations in their local labor market. If students are not using these courses to prepare for college and career pathways in computing, what value do they ascribe to these courses? An alternative explanation is that students view secondary computing course taking associated with general preparation for STEM college and career pathways. Computing is often lumped into a "STEM-CTE" or "Applied Science-CTE" pathway signaling this connection (Gottfried et al., 2014). If this is the case, we would expect students who select computing courses in high school also to value their math and science courses. The wide-ranging nature of computing skills and CTE coursework necessitates further research to explore the motivations of youth who choose these pathways.

Theoretical Framework

Completing two or more credits of CIS coursework is an achievement-related choice. Situated Expectancy-Value Theory suggests two constructs are associated with achievement-related choices: expectancy of success and subjective task value (Eccles & Wigfield, 2020). Subjective task value is further reduced to subcomponents: attainment value (subject-matter identity), intrinsic value (course interest), utility value (future-oriented goals), and cost (negative value). Prior experiences with the subject inform these constructs, the youth's sociocultural context, and how those individual youth interpret those contexts. HSLS:09 contains survey items that measure these constructs directly in the context of the student's math and science coursework (Ingels et al., 2011) and have been previously used to investigate STEM-related college and career pathways (Andersen & Ward, 2014; Gottlieb, 2018; Perry, 2022).

Methods

The data come from the restricted-use HSLS:09. This nationally representative sample followed over 20,000 ninth graders in 2009 and links student surveys, school-level data, and postsecondary outcomes. This study utilizes student- and school-level data from the initial survey and student transcript data collected in 2013-14 after the typical student had completed four years of high school. Only students with access to CTE courses (n = 21,930) are included in this study. Data reported in this study are rounded to the nearest ten (consistent with NCES requirements), so percentages may not add to 100%. Descriptive statistics of the variables included in this study (as informed by prior research) are included in Table 1.

The research question is addressed through a multi-level modeling approach. Given the evidence suggesting that opportunities to participate in computing education vary drastically between schools (e.g., Bruno & Lewis, 2021; Margolis, 2008), a two-level model allows for the identification of the proportion of variance clustered at the individual and school levels. Multiple imputations in Stata 16 were used to preserve some of the statistical power in the model (Allison, 2002).

The dependent variable, whether a student was a computing concentrator, was created from the NCES taxonomy of course titles (Hudson, 2019). Students with two or more Carnegie credits in computing coursework on their transcript in 2013 were defined as concentrators. These data were collected during Perkins IV, which has no standard definition of a concentrator, but this choice aligns with many state policies and prior research with the HSLS:09 dataset. The independent variables were measured on the student and counselor surveys during the student's ninth-grade year: the same time when youth plan their high school course taking.

Results/Findings

The ICC for computing concentrators is 0.38, meaning between-school effects account for 38% of the variance. The school-level factors associated with increased odds of CIS concentration include percent of students qualifying for free and reduced-price meals (OR = 1.01, $p<.001$), being in the South compared to the Northeast (OR = 2.10, $p<.001$), and the school offering career programs of study (OR = 1.28, $p<.01$). The student-level factors include math aptitude (OR = 1.02, $p<.001$) and being female compared to male (OR =.52, $p<.001$). None of the SEVT measures in math and science were associated with the likelihood of CIS concentration with a p-value threshold of .05.

Discussion

This study investigated the factors associated with increased odds of concentrating in a computing pathway during high school. The logistic regression model yielded nearly null results–especially with the expectancy-value constructs measured in the context of math and science coursework. The results suggest limitations to our approach which assumed high school computing course taking as a STEM-related college and career choice and provides further evidence that computing concentrations are a "curious case" among all CTE concentrations (Sublett & Griffith, 2019).

Situated Expectancy Value Theory is applicable only when 1) the outcome variable is an achievement-related choice and 2) the constructs are measured in the same domain as the outcome variable. The null results suggest that one or both criteria were not met in this model. Secondary computing course taking may not be an achievement-related choice. Students take CTE courses for a variety of reasons including having friends in the class, being interested in the subject matter, or being the only elective fitting into an available time slot (DeFeo, 2015). *De facto* or *de jure* tracking is persistent (Rafalow & Puckett, 2022) which creates artificial barriers to access for many students–especially students from low-income backgrounds or students minoritized in computing by gender, race, ethnicities, and intersections thereof (Rawhiya Jacob et al., 2022).

The lack of association between math/science expectancy-value constructs and increased odds of concentrating in computing indicates that the survey items failed to capture the factors that motivate students to take computing courses. Recent studies have developed programming-centric survey instruments to measure the SEVT constructs for computing (Rachmatullah et al., 2020) yet the domain encompasses other skills such as web design, computer networking, and cyber security. Future research should continue to investigate how to adequately capture the expectancies of success and values youth ascribe to secondary computing course taking.

This study's results should be interpreted cautiously. However, in the context of the prior literature, these results suggest that youth are not choosing computing concentrations because they aspire to STEM-related college and career pathways. As CTE researchers, we need to consider how technical skill development can support the alternate aims of computing education discussed in the literature review. CTE curriculum can support student agency to express their creativity and address personally meaningful issues that may not intersect with utility-value-oriented course designs (Jocson, 2018). In other contexts, researchers have suggested that utility value is over-emphasized and course selection interventions should aim to increase attainment value and intrinsic value while reducing costs (Rosenzweig et al., 2022). Future research should embrace this perspective and continue with more exploratory research to positively identify the student- and school-level factors associated with completing two or more computing courses during high school. We recommend adequate systems to ensure access to computing outside of standalone computing CTE pathways. Student's motivations to engage with these courses could be satisfied through embedded computing principles in other disciplines such as STEM (Wang et al., 2022) or literacy (Jacob et al., 2021) coursework. Similarly, computing can be a theme in other CTE career clusters such as family and consumer sciences (Callahan, 2017) or construction (Montoya et al., 2018). These approaches support schools in designing adequate systems where all students develop in-demand skills aligned with their career interests.

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Table 1.

Descriptive Statistics for study sample (n = 21,930)

Variable	Mean (Percent for categorical variable)	SD	Missing Fraction
Computing Concentrator	4.23%		.127
Student-level Factors			
Female	49.08%		.002
Scaled Math Aptitude in 9th grade	50.7	10.1	.152
Family Socioeconomic status	-.02	.76	.128
Parent in STEM			.102
0	57.68%		
1	39.85%		
2	2.48%		
Math Attainment Value	.025	1.01	.163
Math Intrinsic Value	.022	1.00	.275
Math Expectancy of Success	.019	1.00	.262
Math Utility Value	-.014	1.00	.260
Science Attainment Value	.023	1.01	.166
Science Intrinsic Value	.017	.99	.336
Science Expectancy of Success	.023	1.00	.324
Science Utility Value	.00	.99	.323
Math and Science Cost	0	1.00	.185
School-Level Factors			
Locale			.000
City	25.31%		
Suburb	37.29%		

Town	11.87%		
Rural	25.53%		
Census Region			.000
Northeast	15.46%		
Midwest	27.03%		
South	39.84%		
West	17.66%		
Offering CTE Career Pathways			
Yes	66.40%		.124
Percent of students qualifying for free or reduced-price meals	35.8%	23.9	.090