Biology Students' Math and Computer Science Task Values Are Closely Linked

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ABSTRACT
Quantitative and computational skills are required of 21st-century biologists. While biology student abilities and attitudes toward math have been studied extensively, less is known about corresponding attitudes toward computer science (CS). It is important to understand how students perceive math and CS subjects and whether those perceptions are linked or operate contradictorily to determine instructional best practices. This study 1) determined biology students' perceptions of math and CS in biological contexts, 2) measured the linkage of those perceptions, and 3) examined additional factors affecting attitudes. Students (*N* = 272) were surveyed using the original and a CS-adapted version of the Math-Biology Values Instrument to determine interest, perceived utility, and perceived costs toward math and CS in biological contexts. Mixed-effects models were used to determine correlations between task values and investigate effects of exposure to topics and demographic factors. Math and CS values exhibited positive correlations, but utility and cost were more negative for CS, possibly due to less exposure to CS before college, and overall attitudes were influenced by CS background and gender. Given these findings, we make educational recommendations for CS and math exposure early, often, and embedded in the biology curriculum.

INTRODUCTION
Biological sciences are growing increasingly reliant on quantitative and computational skills (Luscombe *et al.*, 2001; Hood, 2003; National Research Council, 2003; Kelling *et al.*, 2009; Markowetz, 2017), particularly in modeling, analyzing, and managing large data sets (American Assocation for the Advancement of Science [AAAS], 2011). Developing the necessary data analysis skills builds upon math and computer science (CS) skills, linking these skill sets by their utility (Knuth, 1974). However, many undergraduate curricula still lack substantial and integrative quantitative and computational instruction (AAAS, 2011), which can lead to inadequate preparation for post-undergraduate plans (e.g., graduate school, industry positions), and more extremely, basic analytical errors among scientists (Thiese *et al.*, 2015). As student perceptions of a topic often dictate performance, understanding how students view these concepts is necessary to successfully incorporate them into curricula.

Expectancy-value theory can be a framework to help understand student attitudes and behavior. In short, students are more motivated to participate in tasks when they both value and are confident that they can complete said tasks (Wigfield and Cambria, 2010). In this theory, how students value a task is determined by interest (interest and enjoyment in task), utility (usefulness of task for future), and cost (negative aspects of the task; Wigfield and Eccles, 2000). These values are shaped by social influences and previous events to impact motivational beliefs toward future tasks, which ultimately manifest in observable behaviors, such as willingness to engage in tasks, effort, persistence, and performance. While one may simultaneously hold interest, utility, and cost values, they may be very different and can be independently shaped (Wigfield and Eccles, 2000). Thus, understanding these parameters and how they may differ relative to one another and task type helps to predict student behavior.

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Previous research has shown that students with higher interest and perceived utility and lower perceived costs are more likely to choose to study math and CS (Hembree, 1990; Lapan *et al.*, 1996; Gainor and Lent, 1998; Miller and Bichsel, 2004; Maltese and Tai, 2011; Andrews and Aikens, 2018). Studies have also shown that demographic factors (such as gender, ethnicity, and course background) can modulate these values in important ways, particularly with respect to decreased engagement predictors for marginalized groups (Eccles *et al.*, 1993; Harackiewicz *et al.*, 2016; Witherspoon *et al.*, 2016; Andrews and Aikens, 2018), which poses complex challenges when aiming to both modernize and diversify science.

Negative perceptions about math and CS, present at times even before instruction (Colon-Berlingeri and Burrowes, 2011; Thompson *et al.*, 2013), could hamper even the best attempts to incorporate math and CS instruction into undergraduate biology curricula. Worse yet, these perceptions can be compounded by the (lack of) required technical and pedagogical expertise of instructors and exacerbated in students with weak mathematical backgrounds in secondary school (Matthews *et al.*, 2009). Thus, even as we improve instructor and student preparation for such course work, understanding attitudes about math and CS and their interrelatedness is critical in determining to what degree historic perceptions may be shifting (or perhaps may be overestimated; Thompson *et al.* 2013) and finding best practices to approach teaching such material. Fully understanding how students perceive both math and CS and whether those perceptions are linked or operate contradictorily can shape pedagogical approaches to instruction, including how, what, and when to present information and skill-building practice to best prepare undergraduate biology students.

Several studies have investigated biology students' attitudes toward math. In recent years, Andrews and Aikens (2018) found that biology students somewhat agreed that using math in biology was interesting and agreed that math was useful for biology (utility), but also agreed that using math in biology had associated costs. Not surprisingly, they also determined that students who had higher interest and perceived utility and lower perceived costs were more likely to take biology courses that included math, specifically modeling and statistics (Andrews and Aikens, 2018). Other research has also indicated that students generally believe math is important in biology, but either had positive attitudes ("satisfying") or negative attitudes ("frustrating") about math (Wachsmuth *et al.*, 2017). Both studies' results are promising in showing that biology students are not as uniformly math averse as has been thought. Despite this knowledge with respect to math in biological contexts, comparable studies do not exist elucidating biology students' views on CS, despite its prevalence in modern biology. Several surveys for studying CS attitudes have been developed (Wiebe *et al.*, 2003; Hoegh and Moskal, 2009; Dorn and Elliott Tew, 2015; Bockmon *et al.*, 2020), but largely focus on attitude differences between genders and secondary school students, and none have been used specifically for undergraduate biology students. Research for incorporating computational thinking into general science, technology, engineering, and mathematics (STEM) has shown that including such concepts helps to build relationships between subjects and provide practical skills important for students' careers (Weintrop *et al.*, 2016).

Current curricular methods to teach math and CS in biology to undergraduates can generally be categorized into three groups: 1) teaching a math/CS course with biology examples incorporated (e.g., Aikens *et al.*, 2021), 2) incorporating math/CS into biology courses (e.g., Metz, 2008; Dodds *et al.*, 2010; Colon-Berlingeri and Burrowes, 2011; Schuchardt and Schunn, 2016; Dewey *et al.*, 2020; Williams *et al.*, 2021), or 3) more complex and extensive curricular changes (e.g., Depelteau *et al.*, 2010; Usher *et al.*, 2010). Incorporating biology examples into math courses, such as calculus, increases students perceived utility and feelings of competence in math (Aikens *et al.*, 2021; Williams *et al.*, 2021). However, as courses in other departments are not typically under biology faculty control, a common approach is to instead actively incorporate math/CS into biology courses (core lectures and labs), such as in the development of population disease models or programming statistics to test biological hypotheses. Incorporation of math/CS skills has previously been demonstrated to be effective in increasing knowledge and career relevance of mathematics (here, specifically statistics; Metz, 2008; Colon-Berlingeri and Burrowes, 2011) and knowledge retention in future classes (Metz, 2008). However, research has indicated that students still struggle with linking biological and mathematical, particularly statistical, concepts (Colon-Berlingeri and Burrowes, 2011), which may indicate broader curricular change is necessary. For CS specifically, evidence has shown that incorporation of CS does not hamper the learning of biological concepts (Dodds *et al.*, 2010), but it is unclear how students perceive such approaches and how attitudes around math and CS may interact in response to direct instruction, independent of the potential to increase biology students' skills in math and CS.

Despite the intrinsic link between math and CS (Knuth, 1974) and their dual importance to modern science, students' views about math and CS have not been studied together in the context of undergraduate biology. When looking to K–12 literature, we know that elementary school students who are more proficient at math have an easier time learning CS concepts (Salac *et al.*, 2020) and that math ability is linked to performance in college-level CS classes (Fan and Li, 2002), but we know little about how abilities and attitudes about math relate to CS attitudes, and whether these links are applicable for both biology undergraduates and biology contexts. This is concerning, as often (and increasingly) biologically relevant mathematics, like statistics, is taught through coding (Weissgerber *et al.*, 2016). Research has shown that teaching elementary school students to code leads to increased mathematical thinking skills (Miller, 2019), and while this has not been tested on college students in biology, a similar effect on older students is likely.

In this study, students from a large southeastern R1 university were surveyed in a pre–post design about their attitudes surrounding math and CS in biological contexts. The survey contained both the original Math-Biology Values Instrument (MBVI; Andrews *et al.*, 2017) and a version adapted for CS. These versions are based on the "value" side of Eccles's Expectancy-value theory (Eccles *et al.*, 1983; Wigfield and Eccles, 1992, 2000). This study aims to explore three questions: 1) What are biology students' attitudes toward both math and CS (which has been comparatively understudied)? 2) How do factors related to student exposure to math and CS and demographics modulate attitudes? 3) Is there a link between students'

TABLE 1. Course descriptions and disclosed demographic information of study subjects[a]

Class	Biostats Lecture Fall 2019 (N = 64)	Biostats Lecture Spring 2020 (N = 89)	Ecology Lab Spring 2020 (N = 42)	Ecology Lab Fall 2020 (N = 77)
Mode	In person	In person to online midsemester	In person to online midsemester	Synchronous online
Gender				
Male %	18.18%	21.92%	35.48%	23.88%
Female %	80.00%	76.71%	64.52%	76.12%
Non-binary %	1.81%	1.37%	N/A	N/A
Racial/ethic demographics[b]				
White %	45.45%	38.73%	51.61%	44.12%
Asian and Asian American %	40.00%	41.10%	29.03%	35.29%
PEER %	14.55%	17.81%	19.35%	20.59%
Course description	Introductory lecture course on probability distributions and statistical testing, using techniques commonly applied in biology research. In-class activities are split between lectures, which introduce general concepts and outline formal steps for solving statistical problems, and independent and small-group exercises. All class activities are conducted using the statistical programming language R.		This laboratory skills–building course addresses populations, communities, and ecosystems. Students will practice the scientific method and its application to ecological principles and will hone skills in both statistical data analysis and communication with scientific and lay audiences. Weekly laboratory activities involve both a course-based undergraduate research project and weekly data analysis and visualization practice (individual and in groups) to build specific analytical skills as they relate to a given area of ecology. All class activities are conducted using the statistical programming language R.	
Contact hours	1.5 hours (3 hours total) twice weekly		3 hours (single meeting) once weekly	
Primary modes of assessment (scaled to percent for comparison)	In-class exercises (30%) Tests (50%) Homework assignments in R (20%)		In-class exercises (~23%) Lab report (subsections, full reports) (~42%) Lay summary video/presentation (~8%) Homework (R analyses and data collection) (~27%)	

[a]Percentages are based on number of students who answered the question.

[b]Racial and ethnic minorities include students identifying as Black, Pacific Islander, Native American, Indigenous Peoples, Hispanic or Latino, and two or more races.

attitudes about math and CS? We predict that answers to corresponding questions for math and CS will be positively correlated, leading to a better understanding of students' attitudes toward math and CS and new approaches for incorporating these skills into undergraduate curricula.

METHODS

Setting

Under an approved Institutional Review Board protocol (H17449), data were collected over the Fall 2019, Spring 2020, and Fall 2020 semesters in two different courses at a large southeastern R1 institution. The participants were undergraduate students enrolled in one of two biology courses that incorporated math and CS (Table 1). These students had successfully completed at least one semester of introductory biology before taking these courses.

Courses

Students were surveyed during one of two different courses: an introductory lecture course on basic statistical techniques and hypothesis testing in biology (hereafter "Biostats Lecture") and a lab that uses data analysis (statistics in R) to help students understand ecology (hereafter "Ecology Lab"; Table 1). Biostats Lecture was taught during Fall 2019 (in person) and during Spring 2020 (transitioned online midsemester). Ecology Lab was taught during Spring 2020 (transitioned online midsemester) and during Fall 2020 (synchronous online). Both courses have been historically surveyed in prior semesters using the MBVI and showed comparable MBVI responses in the current study. The courses are both one of several optional courses within the curriculum satisfying a quantitative requirement (Biostats Lecture) or core lab (Ecology Lab) requirement, and both may be taken by students of all years but are typically taken in the second year (Ecology Lab) or third year (Biostats Lecture) of the 4-year BS degree. The registration descriptions of both courses contain statistics as the math used in the course, and this is the primary form of explicit math, as it applies to biology that the students encounter in their degree. The CS skills most consistently reinforced in biology curriculum and directly addressed in these specific courses refer to Weintrop *et al.*'s. (2016) taxonomic term of "Data Practices" (e.g., collecting, analyzing, and visualizing data) and "Computational Problem Solving Practices" (e.g., programming, trouble-shooting, and debugging).

Data Collection and Study Design

Pre and Post Surveys. We conducted a pre/postsemester survey (Supplemental Files 1 and 2) to determine students' attitudes toward math and CS in biological contexts. We used this to determine baseline correlations of affect for math and computing and biological contexts and whether the correlation changed after experiencing a course that included math and computing in a biological context. The pre and post surveys were given at the beginning and end (respectively) of a 15-week semester. The survey had two parts: part 1 assessed their value for math in biological contexts from the MBVI (Andrews *et al.*, 2017) and part 2 modified the MBVI questions replacing "math" with "computer science" to assess value for computer science in biological contexts. Both surveys were assessed using confirmatory factor analysis (shown in Supplemental Methods and Results, Files 3–5) to confirm correct factor structure of our modified surveys.

To help assess the instrument for this population and understand how students view the substitution of CS, a group of 150 students ($N = 89$ enrolled in Ecology Lab, $N = 61$ enrolled in Biostats Lecture) were asked how they define "math" and "computer science." While these groups did not differ appreciably by course, consistent with the original MBVI, students viewed mathematics broadly, collectively defining mathematics with a mix of topics, primarily as statistics (39.3%), but also algebra (23.9%), calculus (23.5%), and arithmetic (13.3%). When consulted about how they would define computer science, students also had broad definitions, which fit into Weintrop *et al.*'s (2016) taxonomy of computational thinking as follows: modeling and simulation (finding and testing solutions; assessing computational models; 30.5%), data practices (collecting, analyzing, and visualizing data; 29.9%), computational problem-solving practices (programming, trouble-shooting, and debugging; 27.3%), and systems-thinking practices (understanding complex relationships; 12.2%). Thus, just as for math, students use a broad umbrella to conceptualize computer science, even beyond the activities privileged in the courses in which they are surveyed.

The Likert-style survey questions were all assessed on a scale of 1 (strongly disagree) to 7 (strongly agree). Survey questions represented three Task Value categories (interest, utility, and cost) from Andrews *et al.* (2017) and were asked twice: once for math and once for CS (see Table 2). An overall task value score was generated for each of the three value categories by averaging the response values for each question in that value category. Any duplicate students (e.g., students who took the survey in two classes) or students who did not complete both the pre and post surveys in either class were removed from the data set before all analyses (final $N = 272$). Additional information collected from students on the post survey included gender, race, grade point average, and previous experience with math and CS.

Survey Analysis

Data Summary. Average, SD, and median were calculated for each overall task value score. Box plots were created in R (v. 4.1.0; R Core Team 2019) using the ggplot2 package (Wickham, 2016). To test for significant differences between students' scores for math and CS within the three task values (interest, utility, cost), a paired Wilcoxon signed-rank test was performed in R. Additionally, a Levene's test was performed using the car package (Fox and Weisberg, 2019) to determine whether significant differences existed in the variances of math and CS scores within each overall task value (interest, utility, cost). The r effect size statistic was calculated for each comparison using the rcompanion package (Mangiafico, 2022). Values less than 0.3 are considered small effects, values between 0.3 and 0.5 are moderate effects, and values exceeding 0.5 are large effects (Mangiafico, 2022).

Tests for Exposure and Demographic Effects. Additionally, Wilcoxon rank-sum tests or Kruskal-Wallis tests were used to determine whether significant differences existed between factors involving students' exposure to math or CS or demographic factors. Effect sizes were calculated for all comparisons using either r effect size statistic in the rcompanion package (Mangiafico, 2022) for Wilcoxon rank-sum tests or the *kruskal_effsize* function in the rstatix package (Kassambara, 2021) for Kruskal-Wallis tests. Values less than 0.06 are considered small effects, values between 0.06 and 0.14 are moderate effects, and values greater than 0.14 are large effects for Kruskal-Wallis effect sizes.

Except for the pre versus post survey comparisons, these tests were run on only student post scores. A Kruskal-Wallis test was used to determine whether CS background had a significant effect on students' attitude scores. CS background was placed into categories based on whether the students had no experience, intro-level experience (only one or two basic classes), or advanced knowledge (objected-oriented computing, algorithms, machine learning, three or more languages, etc.). Fifteen percent of students had advanced CS background, with the most common courses completed being object-oriented computing. The majority, 68% of students, had an intro level-background, having taken a basic procedural programming course to learn a language (e.g., Python). The last 17% of students had no CS background at all. A Wilcoxon rank-sum test was used to determine whether students' scores were significantly different depending on whether the student was completing the pre or post survey or the course (Biostats Lecture or Ecology Lab) in which the student was enrolled. A Wilcoxon rank-sum test was also performed on post survey scores to distinguish differences in gender (men or women; nonbinary and transgender identities were excluded due to small sample size). A Kruskal-Wallis test was also performed for race using three categories: White students, Asian and Asian-American students, and PEER (persons excluded because of ethnicity or race) students (Asai, 2020). Post hoc tests were performed when the global Kruskal-Wallis test was significant using a Dunn test for multiple comparisons from the FSA package (Ogle *et al.*, 2021). All tests were performed separately for math and CS on the averaged overall task value score and repeated individually for each course (Biostats Lecture and Ecology Lab; Supplemental File 6).

Robust Linear Mixed-Effects Models. Robust linear mixed-effects models (rlmer(); Koller 2016) were used in this study to determine the relationship between students' attitudes about math and CS. Robust linear mixed-effects models were chosen to deal with nonnormality and heteroskedasticity in residuals. These were chosen over traditional linear mixed-effects models with transformed data to make data interpretation easier, as robust linear mixed-effects models weight the residuals and have the same effect as a transformation. The full model tested for each overall task value score included the CS survey response for each task value (interest, utility, cost): $CS \sim Math + (1|StudentID) + (1|Class)$, where CS is the CS survey responses and math is the math survey responses. The random effects of

TABLE 2. Average of responses to survey questions[a]

	Question	Math average ± SD	CS average ± SD
Interest			
Int2	Using math/CS to understand biology intrigues/would intrigue me	5.22 ± 1.50	4.94 ± 1.90
Int6	It is/would be fun to use math/CS to understand biology.	5.05 ± 1.60	4.90 ± 2.06
Int7	Using math/CS to understand biology appeals/would appeal to me.	5.00 ± 1.66	4.76 ± 2.13
Int8	Using math/CS to understand biology is/would be interesting to me.	5.05 ± 1.64	4.87 ± 2.08
Utility			
Uty3	Math/CS is valuable for me for my life science career.	5.65 ± 1.35	4.71 ± 1.95
Uty4	It is important for me to be able to do math/CS for my career in the life sciences.	5.71 ± 1.35	4.61 ± 1.99
Uty5	An understanding of math/CS is essential for me for my life science career.	5.65 ± 1.41	4.47 ± 1.90
Uty6	Math/CS will be useful to me in my life science career.	5.74 ± 1.33	4.89 ± 1.84
Cost			
Cst6	I have/would have to work harder for a biology course that incorporates math/CS than for one that does not.	5.19 ± 1.71	5.49 ± 1.65
Cst7	I worry/would worry about getting worse grades in a biology course that incorporates math/CS than one that does not.	4.73 ± 1.90	5.04 ± 1.90
Cst8	Taking a biology course that incorporates math/CS intimidates/would intimidate me.	4.27 ± 1.90	4.91 ± 1.89

[a]Questions are numbered as in the original survey instrument from Andrews *et al.* (2017). Int, interest; Uty, utility; Cst, cost.

student ID (each individual student) and class (an individual instance of a single course taught in a single semester) are present to control for nonindependence of sampling across pre- and post-surveys and multiple classes and semesters. As Akaike information criterion cannot be used on robust linear mixed-effects models, the model was reduced by removing random slopes and intercepts that accounted for no variance in the model or random slopes that had a correlation of 1 or 0. The effects package (Fox, 2003; Fox and Weisberg, 2019) in R was used with ggplot2 (Wickham, 2016) to plot the regression lines for the subscore of each value (interest, utility, cost) and question for robust linear mixed-effects effects models and generalized linear mixed models.

Model Metrics. The p values are not calculated for robust linear mixed-effects models, as degrees of freedom cannot be calculated accurately; therefore, slopes were considered significant when $t > 1.96$ (Luke, 2017). Marginal and conditional R^2 values were calculated for robust linear mixed-effects models using the equations from Nakagawa and Schielzeth (2013). Marginal R^2 represents the variance explained by fixed effects only, while conditional R^2 represents the variance explained by both the fixed and random effects in the model (Nakagawa and Schielzeth, 2013; Nakagawa *et al.*, 2017; Johnson, 2014). Variance values required for the R^2 calculation were extracted from the model using the insight package (Lüdecke *et al.*, 2019).

RESULTS

What Are Biology Students' Attitudes toward Both Math and CS?

Interest. Students could respond on a scale from strongly disagree (1) to strongly agree (7) with the general statement, "It is interesting to use to understand Biology," where the blank represents math or CS (specific questions used for interest in Table 2). For both math and CS, scores were seen at every value in the range, with an average score of 5.08 ± 1.60 SD for math and an average score of 4.87 ± 2.04 SD for CS (Table 2). Students' math interest scores were higher than students' CS interest scores. A Wilcoxon signed-rank test indicated that this difference was significant ($T = 3202$, $p < 0.01$); however, the effect size was small ($r = 0.14$). CS scores were more variable than math scores, $F(1, 257) = 15.10$, $p < 0.001$ (Figure 1).

Utility. Students could respond on a scale from strongly disagree (1) to strongly agree (7) with the general statement, "It is useful to use in Biology," where the blank represents either math or CS (specific questions used for utility in Table 2). For both math and CS, scores were seen at every value in the range, with an average score of 5.67 ± 1.36 SD for math and an average score of 4.67 ± 1.92 SD for CS (Table 2). CS scores were significantly lower than the scores for math based on a Wilcoxon signed-rank test ($T = 5471.5$, $p < 0.001$) with a small effect size ($r = 0.11$). As for interest, CS scores were more variable than math scores, $F(1, 276) = 17.90$, $p < 0.001$ (Figure 1).

Cost. Students could respond on a scale from strongly disagree (1) to strongly agree (7) with the general statement, "It is costly to use in Biology," where the blank represents either math or CS (specific questions for cost in Table 2). For both math and CS, scores were seen at every value in the range, with an average score of 4.73 ± 1.84 SD for math and an average score of 5.14 ± 1.81 SD for CS (Table 2). A Wilcoxon signed-rank test indicated that students perceived significantly higher costs for CS than math ($T = 2008.5$, $p < 0.001$). The effect size for cost was large ($r = 0.70$). In contrast to results for interest and utility, variances of the math and CS cost scores were not significantly different between math and CS, $F(1, 280) = 0.006$, $p = 0.94$ (Figure 1).

How Do Factors Related to Student Exposure to Math and CS and Demographics Modulate Attitudes?

Interest. There were significant differences, as determined by a Kruskal-Wallis test, in students' interest scores based on degree of CS background for CS scores, $H(2) = 7.04$, $p < 0.05$, effect size = 0.04 (Figure 2B), but not for math scores, $H(2) = 4.77$,

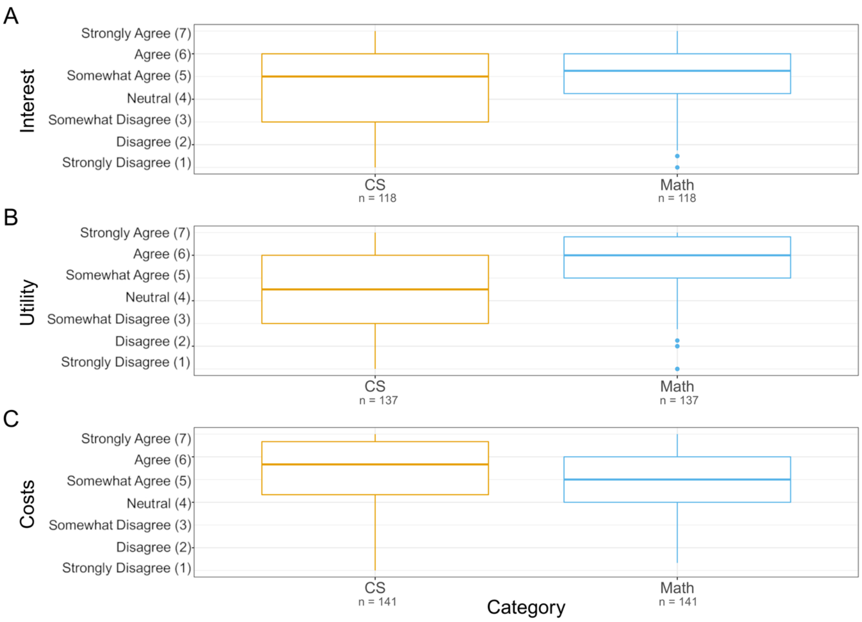

FIGURE 1. Students have more interest, see more utility in, and perceive lower costs for math in biological contexts over CS. Questions are scaled from 1 (strongly disagree) to 7 (strongly agree) based on a Likert scale. The dots signify outliers (± 1.5 * interquartile range).

$p = 0.09$, effect size = 0.02 (Figure 2A). Advanced students had taken at least two CS courses, including one on advanced topics (e.g., object-oriented programing or machine learning) or knew three or more CS languages as reported in the survey. A Dunn post hoc test showed that students with advanced CS knowledge reported significantly higher interest for both CS compared with students who had taken a single CS course on basics with intro knowledge ($z = 2.42$, adjusted $p < 0.05$) and students with no background in CS ($z = 2.44$, adjusted $p < 0.05$). However, Wilcoxon rank-sum tests indicated no significant differences in students' interest scores between the two courses (Biostats Lecture and Ecology Lab) in which they encountered both math and CS in biological contexts (math: $W(N_{\text{Ecology Lab}} = 76, N_{\text{Biostats Lecture}} = 76) = 2305$, $p = 0.49$, effect size = 0.06; CS: $W(N_{\text{Ecology Lab}} = 43, N_{\text{Biostats Lecture}} = 75) = 1690$, $p = 0.66$, effect size = 0.04; Supplemental File 7), nor did scores did differ after exposure to those topics within each course as shown by pre and post survey scores (math: $W(N_{\text{Pre}} = 141, N_{\text{Post}} = 141) = 10{,}238$, $p = 0.66$, effect size = 0.03; CS: $W(N_{\text{Pre}} = 118, N_{\text{Post}} = 118) = 7886$, $p = 0.075$, effect size = 0.12; Supplemental File 8). Additionally, there was a significant effect of gender on students' math scores ($W(N_{\text{Men}} = 31, N_{\text{Women}} = 107) = 2268$, $p < 0.01$, effect size = 0.24; Figure 2C) according to a Wilcoxon rank-sum test, but not on their CS scores ($W(N_{\text{Men}} = 26, N_{\text{Women}} = 90) = 1450.5$, $p = 0.06$, effect size = 0.17; Figure 2D). Race had no significant effect (math: H(2) = 0.53, $p = 0.77$, effect size = 0.01; Figure 2E; CS: (H(2) = 2.45, $p = 0.29$, effect size = 0.003; Figure 2F) on student interest scores.

Utility. A Kruskal-Wallis test showed a significant effect of student's CS background on students' CS utility scores (H(2) = 10.01, $p < 0.01$, effect size = 0.06; Figure 2B), but not their math utility scores (H(2) = 3.63, $p = 0.16$, effect size 0.01, Figure 3A). Advanced CS students saw significantly higher utility in using CS in biology than students with intro knowledge ($z = 3.16$, adjusted $p < 0.01$) and students with no CS experience ($z = 2.33$, adjusted $p < 0.05$) based on a Dunn post hoc test. A Wilcoxon rank-sum test showed that Ecology Lab students saw significant higher utility in using math in biology than students in Biostats Lecture ($W(N_{\text{Ecology Lab}} = 64, N_{\text{Biostats Lecture}} = 76) = 1817$, $p < 0.01$, effect size = 0.22; Supplemental File 7) but did not see significant difference in CS's utility ($W(N_{\text{Ecology Lab}} = 64, N_{\text{Biostats Lecture}} = 74) = 2192$, $p = 0.45$, effect size = 0.06; Supplemental File 7). As for interest, exposure over the duration of a course (pre vs. post survey) did not cause differences in the students' utility scores based on a Wilcoxon rank-sum test (math: $W(N_{\text{Pre}} = 140, N_{\text{Post}} = 140) = 10{,}622$, $p = 0.21$, effect size = 0.08; CS: $W(N_{\text{Pre}} = 138, N_{\text{Post}} = 138) = 10024$, $p = 0.45$, effect size = 0.05; Supplemental 8). A Wilcoxon rank-sum test showed a significant effect of gender on students' CS ($W(N_{\text{Men}} = 31, N_{\text{Women}} = 107) = 2220$, $p < 0.01$, effect size = 0.25; Figure 3D), but not their math scores ($W(N_{\text{Men}} = 32, N_{\text{Women}} = 104) = 1963.5$, $p = 0.12$, effect size = 0.13; Figure 3C), with men seeing higher utility in CS than women. Race had no significant effect on math (H(2) = 1.04, $p = 0.59$, effect size = 0.007; Figure 3E) or CS (H(2) = 1.48, $p = 0.48$, effect size = 0.004; Figure 3, E and F) interest scores.

Cost. CS background had a significant effect on both math and CS cost scores based on a Kruskal-Wallis test (math: H(2) = 7.29, $p < 0.05$, effect size = 0.04; CS: H(2) = 16.17, $p < 0.001$, effect size = 0.10; Figure 4, A and B). Advanced students perceived lower cost than students with no CS experience (math: $z = 2.47$, adjusted $p < 0.05$; CS: $z = 3.88$, adjusted $p < 0.001$). Based on a Dunn post hoc test, students with intro CS experience also perceived lower costs than students with no CS experience (math: $z = 2.33$, adjusted $p < 0.05$; CS: $z = 3.14$, adjusted $p < 0.01$). Additionally, intro students perceived lower costs than students with no experience (math: $z = 2.47$, $p < 0.05$; CS: $z = 3.14$, $p < 0.01$). A Wilcoxon rank-sum test showed that Ecology Lab students perceived higher costs for including math ($W(N_{\text{Ecology Lab}} = 65, N_{\text{Biostats Lecture}} = 76) = 1927$, $p < 0.05$, effect size = 0.19) and CS ($W(N_{\text{Ecology Lab}} = 65, N_{\text{Biostats Lecture}} = 76) = 1862$, $p < 0.05$, effect size = 0.21) components in their biology courses than students in the Biostats Lecture (Supplemental File 7). Again, there was no difference (math: $W(N_{\text{Pre}} = 141, N_{\text{Post}} = 141) = 10{,}017$, $p = 0.91$, effect size = 0.007; CS: $W(N_{\text{Pre}} = 141, N_{\text{Post}} = 141) = 9485$, $p = 0\ 0.50$, effect size = 0.04; Supplemental File 8) based on a Wilcoxon rank-sum test in students' cost scores before versus after taking either class (pre vs. post survey). Gender also had a significant effect on cost scores based on a Wilcoxon rank-sum test, but only for CS ($W(N_{\text{Men}} = 32, N_{\text{Women}} = 107) = 1286.5$, $p < 0.05$, effect size = 0.18; Figure 4D), with men perceiving fewer costs than women, and not math

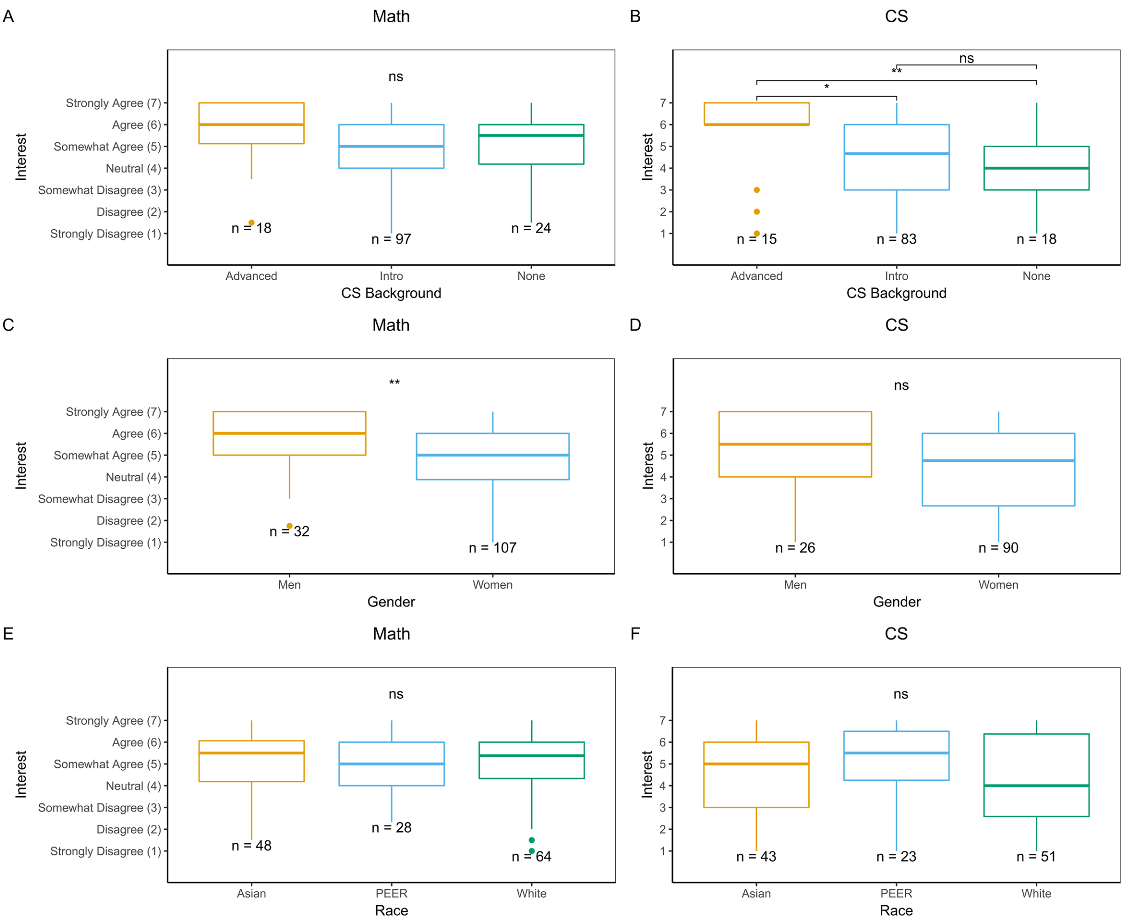

FIGURE 2. Effects of student exposure and demographics on students interest scores. (A, B) Students with advanced CS experience show significantly higher interest in using CS in biology than students with intro or no CS experience. CS experience has no significant effect on math scores. (C, D) There is no significant effect of gender on interest for either math or CS. (E, F) There is no significant effect of race on interest for either math or CS. Questions are scaled from 1 (strongly disagree) to 7 (strongly agree) based on a Likert scale. The dots on the plot signify outliers (± 1.5 * interquartile range). Within a subplot, asterisk indicate significant differences. Significance levels are * < 0.05, ** < 0.01, * < 0.001.**

($W(N_{\text{Men}} = 32, N_{\text{Women}} = 107) = 1697$, $p = 0$ 0.94, effect size = 0.006; Figure 4C). Race, however, had no significant effect on students' math cost scores (H(2) = 1.31, $p = 0.52$, effect size = 0.005; Figure 3E) or CS (H(2) = 2.23, $p = 0.33$, effect size = 0.002; Figure 4, E and F).

Is There a Link between Students' Attitudes about Math and CS?

We examined how student values (interest, utility, and cost) in math and CS were correlated using robust linear mixed-effects models. Each model contained the fixed effects of a single value (either interest, utility, or cost) in math and the corresponding value in CS, and the random effects of student ID, class (one instance of a course in a single semester). Overall task value scores were calculated by averaging the answers from the individual questions (Table 2).

Interest. For interest in the subject, math and CS overall task value scores were strongly positively correlated (conditional $R^2 = 0.75$; Figure 5A), with a significant positive slope of 0.66 ($t = 5.41 > 1.96$; Table 3).

Utility. Utility scores for math and CS were strongly positively correlated (conditional $R^2 = 0.83$) for the utility overall task value score (Figure 5B), with a significant positive slope of 0.69 ($t = 3.09 > 1.96$; Table 3).

Cost. The perceived costs overall task value scores for math and CS were strongly positively correlated (conditional $R^2 = 0.74$; Figure 5C), with a significant positive slope of 0.44 ($t = 15.49 > 1.96$; Table 3).

DISCUSSION

Quantitative and computational skills are increasingly useful in the life sciences, but expectancy-value theory predicts that students' value toward these topics will determine whether and how they engage (Wigfield and Cambria, 2010). In particular, higher interest and utility but lower costs predict higher likelihoods that a student would choose to study math and CS (Hembree, 1990; Lapan *et al.*, 1996; Gainor and Lent, 1998; Miller and Bichsel, 2004; Maltese and Tai, 2011; Andrews and Aikens, 2018). Biology students at an R1 research university who were surveyed about their opinions on math and CS in biological

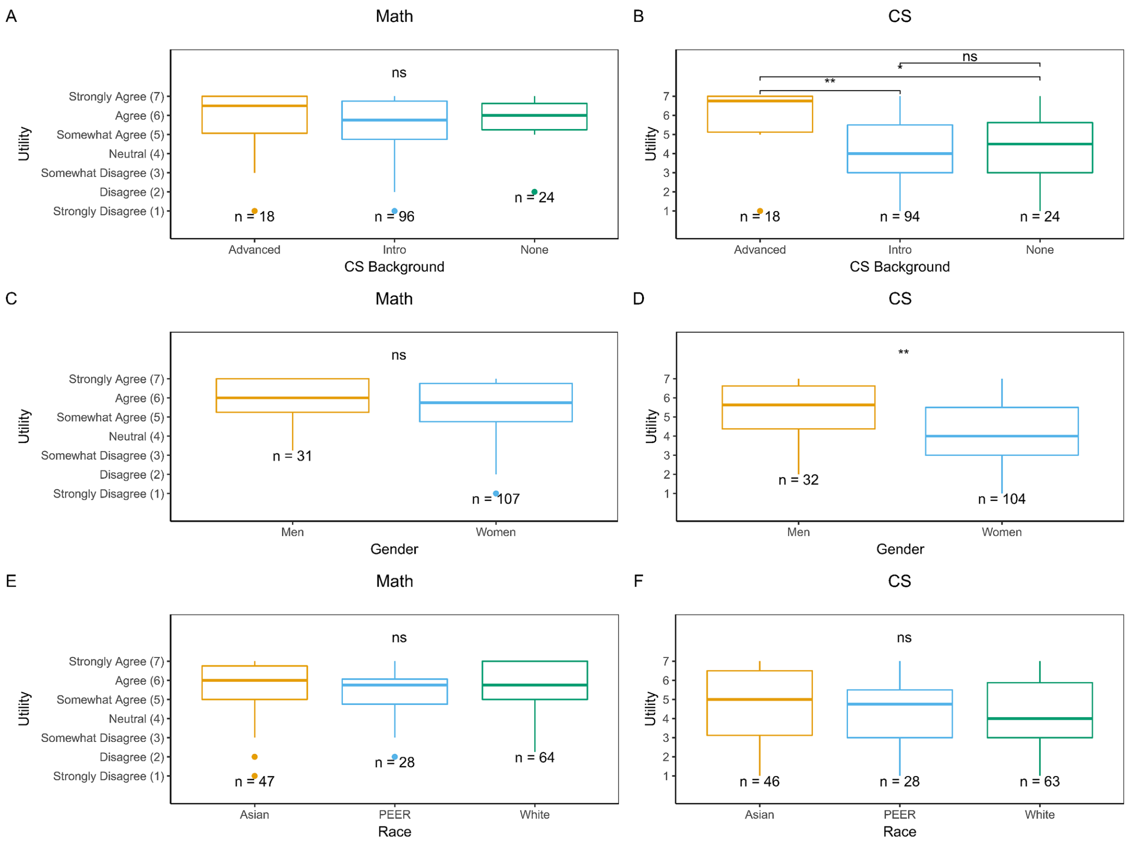

FIGURE 3. Effects of student exposure and demographics on student utility scores. (A, B) Students with advanced CS experience perceive significantly higher utility in using CS in biology than students with intro or no CS experience. CS experience has no significant effect on math scores. (C, D) Men perceive significantly higher utility in using CS in biology than women, but there is no significant effect for math. (E, F) There is no significant effect of race on utility for either math or CS. Questions are scaled from 1 (strongly disagree) to 7 (strongly agree) based on a Likert scale. The dots on the plot signify outliers (± 1.5 * interquartile range). Within a subplot, asterisk indicate significant differences. Significance levels are * < 0.05, ** < 0.01, * < 0.001.**

contexts showed variable but generally positive attitudes in terms of interest (somewhat agreed) and utility (agreed to somewhat agreed); however, they also perceived costs (somewhat agreed). These results are consistent with prior studies on math using the same survey (Andrews and Aikens, 2018) and other instruments (Wachsmuth *et al.*, 2017). This study establishes the first documentation of undergraduate values of CS in biological contexts. Specifically, we show that students show less interest in using CS in biology and perceive CS as having higher costs and lower utility than math, although values between math and CS are positively correlated across all three categories (interest, utility, and cost). Differences in utility might be the most meaningful to consider, as they had the largest effect size. These scores may represent a best-case scenario, as they arise from a sample of students at a STEM-oriented technology university, but nonetheless, the data still indicate that biology students may not be as averse to math and CS as commonly assumed.

Students Show More Variable Interest and Utility Values for CS

Students' scores for interest and utility of using CS in biological contexts were significantly more variable than for math, which likely points to more variability in knowledge and experience with computer science. CS has not been widely integrated into secondary school curricula (Computer Science Teachers Association, 2019) or college course work. However, students regularly take classes devoted only to math throughout their schooling, and those courses typically share common/consistent standards and instructional practices with explicit teacher credentialing in the subject. While states are increasingly introducing CS standards (Computer Science Teachers Association, 2019), course work, resources, and teacher supports (Blum and Cortina, 2007; Ericson *et al.*, 2007; Hart *et al.*, 2008; Ni *et al.*, 2011; Schulte *et al.*, 2012; Dengel, 2017; Reding and Dorn, 2017), there remains a lack of teachers qualified to teach CS, especially at the Advanced Placement level (Ericson *et al.*, 2007). Thus, large variability exists in the CS knowledge, skills, and experiences students bring with them to college. As college educators "inherit" these students, an important practice would be to intentionally assess student backgrounds at the beginning of courses requiring CS and consider 1) supplemental material for students who are not performing at the desired level and 2) intentionally grouping students by comfort and skill with CS.

Instructors Should Prioritize Engaging Students Directly in Math and CS in Biological Contexts

Positive correlations between students' attitudes about math and CS indicate that individual students tend to view both

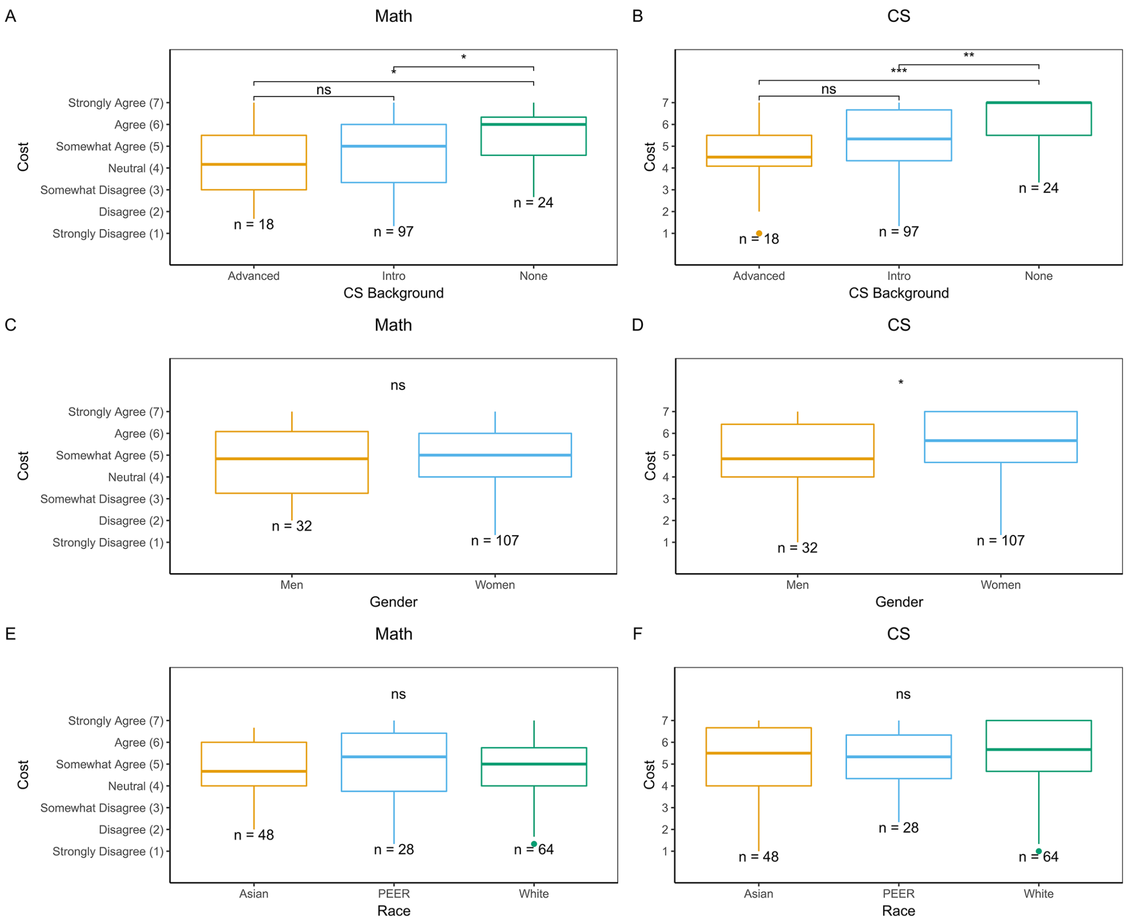

FIGURE 4. Effects of student exposure and demographics on student cost scores. (A, B) Students with no CS experience perceive significantly higher costs for using both math and CS in biology than students with introductory and advanced CS experience. (C, D) Men perceive significantly lower costs for using CS in biology than women, but there is no significant effect for math. (E, F) There is no significant effect of race on costs for either math or CS. Questions are scaled from 1 (strongly disagree) to 7 (strongly agree) based on a Likert scale. The dots on the plot signify outliers (± 1.5 * interquartile range). Within a subplot, asterisk indicate significant differences. Significance levels are * < 0.05, ** < 0.01, * < 0.001.**

subjects similarly. This correlation is strongest for utility, followed by interest, then cost. These positive correlations were expected, given the intrinsic link between math and CS (Knuth, 1974), but point to the usefulness of teaching these subjects together. Guzman *et al.*, (2019) studied how incorporating homework assignments in R (vs. JMP, a plug-and-chug statistical software) into a biostatistics class increased positive emotions toward the class. Students using R were more motivated in the class and were excited to learn a valuable skill (Guzman *et al.*, 2019). This suggests that teaching math and CS concurrently can help increase biology students' enjoyment and understanding of both subjects and highlight their applicability to real-world problems.

Biology Departments and Curriculum Designers Should Consider Combining Math and CS Instruction versus Separate Course Work

Departments shape undergraduate education by helping to determine which content, courses, and sequence classes should be taken by students for their degrees. Biology departments may help students to take and see relevance in math and CS by offering at least one combined math-CS–based biology course, rather than relying on student skill development through course work offered separately through math and CS departments. This can be achieved in several ways by 1) changing current courses to include math and CS; 2) creating new courses combining math, CS, and biological topics more meaningfully; or 3) thoroughly incorporating math and CS throughout the curriculum. When possible, the biology courses created to combine these skills should be informed by math and CS educational frameworks (e.g., Portnoff, 2020) and/or codeveloped with extradepartmental faculty. This approach need not require students take *additional* course work (often a barrier for students; Dodds *et al.*, 2010), but could merely modify *existing* requirements to better suit the computational skill development needs of biology students.

If values are predictive of performance, then teaching these subjects together may increase student understanding of both subjects (as seen in McMaster *et al.*, 2007; Wiedemann *et al.*, 2020). Previous approaches to develop courses that combine biology with math (Aikens *et al.*, 2021) and CS (Dodds *et al.*, 2010) have had success; specifically, these

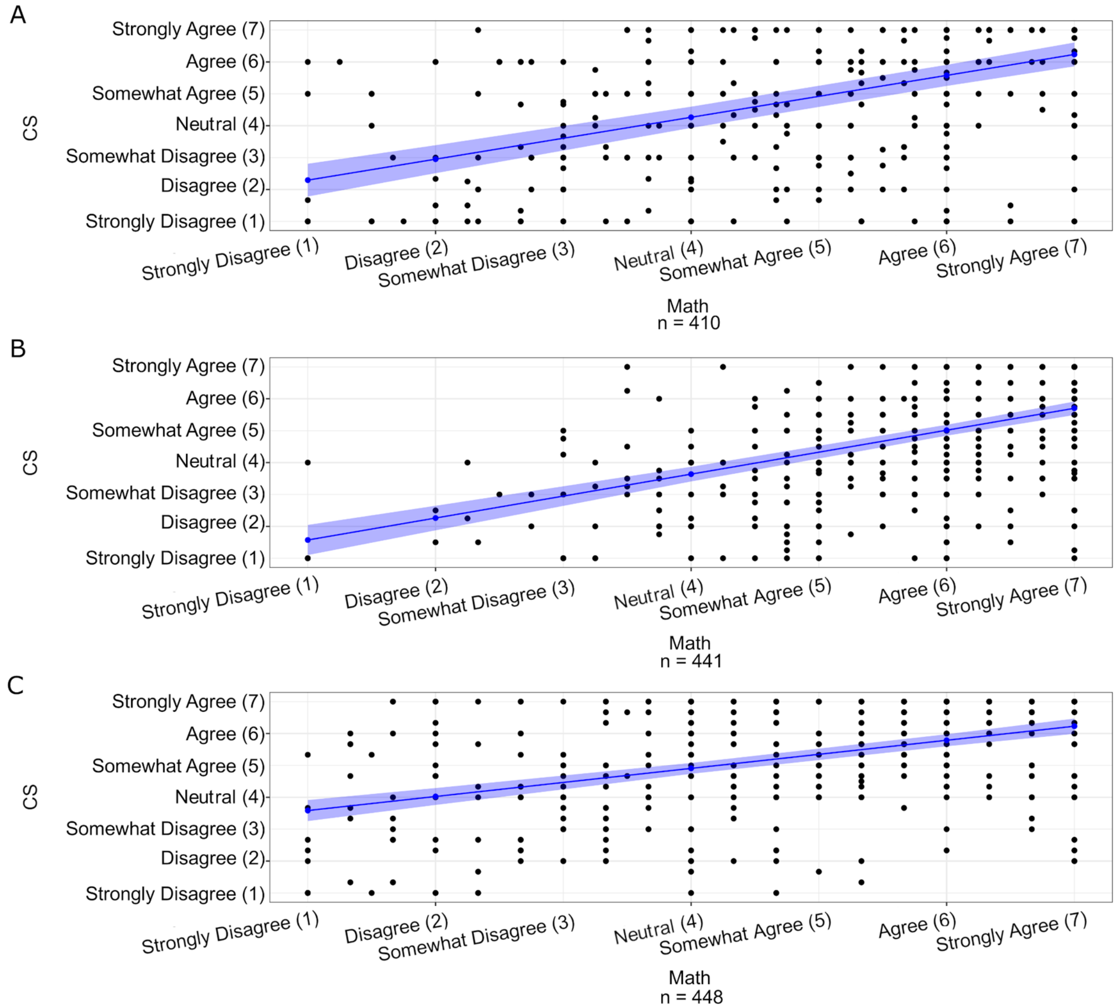

FIGURE 5. Scatterplot of overall value scores for (A) interest, (B) utility, and (C) cost with linear regression line based on linear mixed-effects model. The *x*-axis represents the sum of student responses for each question within a value for math. The *y*-axis represents the sum of student responses for each question within a value for CS. Shaded area represents 95% confidence intervals. Overall task value scores are calculated by averaging the values within a category (interest, utility, and cost).

studies demonstrated the ability to increase perceived utility for students, which is predictive of taking further course work (Andrews and Aikens, 2018). Thus, if combined course work is pursued, to increase student engagement in future courses and develop meaningful skills, it should occur early in the curriculum and any elective or prerequisite structures should be carefully considered, especially if they serve more as a barrier to students than to ensure their preparation for the course.

Prior and Repeated Exposure Matters for Increasing the Value of Math and CS in Biological Contexts

While it is likely easier to add a single course than alter an entire curriculum, we wish to stress that experience gained in one course is not likely to have immediate, positive effect on students' values. We found no significant change across the semester in values for the courses we examined, which suggests that integrated, repeated practice across courses, rather than a single course approach, may be necessary to impact task values more demonstrably. Students may simply need to spend a specific amount of time on a subject before they learn it adequately (Fredrick and Walberg, 1980) and change values (see Downing and Finlay, 2021). This can easily and meaningfully be accomplished with several courses over the length of a degree rather than as a stand-alone course.

Because students in this study differed widely in their CS background (advanced: 15%; intro: 68%; no experience: 17%), we were able to correlate increases in experience with increases in utility and decreases in perceived cost, particularly for students who were in the advanced category. Similar correlations have been found with increasing number of math courses (Simpkins *et al.*, 2006; Andrews and Aikens 2018). While it is harder to disentangle whether the students with CS backgrounds had inherently higher baseline values or whether experience in those courses increased scores, gaining CS experience likely influences task values within at least a subset of students. These findings suggest that potentially requiring math and CS courses earlier in biology curricula (particularly for CS, which may be more unfamiliar to students) could lead to a reduction in perceived costs and potentially an increase in

TABLE 3. Results from robust linear mixed-effects models predicting the relationship between interest, utility, and cost values of CS in relation to values of mathematics The second column gives the exact model. The next three columns detail the sample size, *t* value, and slope estimate. Robust linear mixed-effects models do not include degrees of freedom, as these are not able to be calculated accurately, so there are no *p* values; *t* values > 1.96 are considered significant (Luke, 2017). The next three columns give the variance of the random effect student ID, Class, and the residual variance. The final two columns give the R^2 value based on Nakagawa and Schielzeth (2013).

Question	Model	*N*	*t* value	Slope estimate	Student ID variance	Class variance	Residual variance	Marginal R^2	Conditional R^2
Interest	CS ~ Math + (1|StudentID) + (1|Class)	410	5.41*	0.66	1.49	0.06	0.86	0.31	0.75
Utility	CS ~ Math + (1|StudentID)	441	3.09*	0.69	1.53	N/A	0.49	0.28	0.83
Cost	CS ~ Math + (1|StudentID)	448	15.49	0.44	1.31	N/A	0.68	0.22	0.74

interest and the ability to take further biology courses that use math and CS.

Biologically Based Math and CS Instruction Must Be Aware of Diverse Learners and How to Support Them

In addition to exposure, we found demographic characteristics influence students' scores, consistent with prior studies (Harackiewicz *et al.*, 2016; Witherspoon *et al.*, 2016; Aikens and Andrews, 2018). Gender was the most impactful demographic factor on value scores: men exhibited more positive scores (more interest in math, more perceived utility in CS, and fewer perceived costs in CS) than women students. Our results here are consistent with those reported in Andrews and Aikens (2018) for the original MBVI study, as well as other studies outside biology for both math (Hyde *et al.*, 1990) and CS (Baser, 2013). While women do not differ in ability compared with men (Hyde and Linn, 2006; Williams and Ceci, 2007; Halpern *et al.*, 2007), confidence in their abilities and anxiety levels differ between men and women and seem to drive student achievement and attitudes toward math (Else-Quest and Mineo, 2013; Baser, 2013).

Our study showed no significant differences in value scores based on race, which mirrors results from similar studies (Andrews and Aikens 2018). This may be due to underlying population demographic differences or unexamined interactions between race, ethnicity, and social class, which have previously been shown to affect student achievement in introductory science courses (Harackiewicz *et al.*, 2016). Additionally, broad categories, like PEER students, which included Black students, Hispanic students, and students of multiple ethnicities in this study, are not nuanced enough and may mask differences between individual ethnicities. While categorically similar, the specifics of ethnic and racial categories are often functionally different between studies (Hunt and Megyesi 2008) and are complicated by cultural identity of individuals, making comparisons between studies difficult. Future studies should examine more about student identity, not only race or ethnicity, but other potential factors, such as career aspirations, and their impact on such scores.

Limitations and Future Directions

While we were able to examine course work in multiple classes over a few semesters and modalities, these data are still derived from a single R1 institute with a strong STEM culture, which may limit the overall applicability of the findings to other institutions. Additionally, our sample sizes are small, especially within the CS background, gender, and ethnicity comparisons. Small effect sizes were seen in many of the analyses preformed but are likely highly variable due to our small sample size. Future work should directly examine the impact of the suggested curricular and course interventions on student task values and performance in other institutional settings and particularly on groups underserved by current practices.

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