Life Science Majors’ Math-Biology Task Values Relate to Student Characteristics and Predict the Likelihood of Taking Quantitative Biology Courses

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Expectancy-value theory of achievement motivation predicts that students’ task values, which include their interest in and enjoyment of a task, their perceptions of the usefulness of a task (utility value), and their perceptions of the costs of engaging in the task (e.g., extra effort, anxiety), influence their achievement and academic-related choices. Further, these task values are theorized to be informed by students’ sociocultural background. Although biology students are often considered to be math-averse, there is little empirical evidence of students’ values of mathematics in the context of biology (math-biology task values). To fill this gap in knowledge, we sought to determine 1) life science majors’ math-biology task values, 2) how math-biology task values differ according to students’ sociocultural background, and 3) whether math-biology task values predict students’ likelihood of taking quantitative biology courses. We surveyed life science majors about their likelihood of choosing to take quantitative biology courses and their interest in using mathematics to understand biology, the utility value of mathematics for their life science career, and the cost of doing mathematics in biology courses. Students on average reported some cost associated with doing mathematics in biology; however, they also reported high utility value and were more interested in using mathematics to understand biology than previously believed. Women and first-generation students reported more negative math-biology task values than men and continuing-generation students. Finally, students’ math-biology task values predicted their likelihood of taking biomodeling and biostatistics courses. Instructional strategies promoting positive math-biology task values could be particularly beneficial for women and first-generation students, increasing the likelihood that students would choose to take advanced quantitative biology courses.

INTRODUCTION

Efforts by undergraduate biology instructors and discipline-based education researchers to better integrate mathematics into undergraduate biology curricula have intensified in the last decade (1–8). Such efforts are motivated by the need to prepare life science majors for advanced coursework and careers in modern biology, which has become increasingly reliant on quantitative skills as technological advances and modern computing have led to the generation of large data sets and to more sophisticated modeling and predictive capabilities (9). Thus, to be successful researchers, students training in biology also need to have well-developed quantitative skills and become adept at using and applying quantitative reasoning to biological problems (9–11).

However, it is important to recognize the role motivation may play in mediating students’ success at completing quantitative biology tasks. According to expectancy-value theory of achievement motivation (12, 13), students are motivated to engage in a task when they place value on it. These values for accomplishing a task, called task values, include interest (e.g., enjoyment of the task), utility value (e.g., belief that the task is useful for their future goals), and cost (e.g., spending extra time on the task) (12–14). Theory and empirical evidence suggest task values predict both achievement and academic-related choices such as course enrollment intentions (12, 13, 15–17). Students’ perceptions of the utility value of mathematics (18) and their mathematics anxiety (18–20) have been linked to mathematics performance. Students with higher interest in mathematics (21–23) or lower mathematics anxiety (24, 25) are also more likely to choose a mathematics/science major and/or take more mathematics in college.

We currently lack sufficient evidence of students’ values of mathematics in a biology context (i.e., math-biology task values) to make inferences about the role such values play in student performance or academic-related choices. Despite a lack of empirical evidence, it is widely believed that biology students are math-averse. For example, Thompson...
and colleagues (5) found that instructors believed biology students had negative attitudes about mathematics in their biology courses; however, when students were polled, their attitudes were much more positive than predicted by instructors. Others found that students often believe mathematics is useful for their life science career (26–30). In contrast, recent empirical work found STEM majors reported mathematics to be slightly uncomfortable, frustrating, and unpleasant (31). Moreover, the data suggested life science majors may have more negative attitudes than physical science or mathematics majors (31). Thus, additional research is necessary before concluding biology students are math-averse.

Examining math-biology attitudes across a diverse group of students is especially important, as expectancy-value theory (12, 13) predicts that sociocultural background will inform students’ task values. Students who have internalized gender- or cultural-based stereotypes related to mathematics ability are predicted to have more negative attitudes toward mathematics than students who are not stereotyped. Women in particular are often stereotyped as having lower mathematics ability than men (32–35), and research has demonstrated that women report lower interest in mathematics (36, 37) and greater mathematics anxiety than men (18–20, 24, 25). Students who are the first in their family to attend college (first-generation students) may also be negatively affected by stereotypes, as they are often of low socioeconomic status (38), and such students are stereotyped as having lower academic ability (39). Therefore, first-generation students may have more negative task-values than continuing-generation students. In contrast to expectations, first-generation students in developmental mathematics at a community college reported better attitudes toward mathematics than continuing-generation students (40).

Findings related to race/ethnicity are also unclear, particularly as they are understudied compared with gender-related differences (41). While underrepresented minorities are also stereotyped as having lower mathematics or academic ability (42, 43), some studies have reported no differences in mathematics attitudes by race (25, 31), and even when race/ethnicity-related differences in mathematics attitudes have been shown (19, 25, 41, 44), findings are not always consistent. For example, one study found Black students had higher mathematics anxiety than White students (19), whereas another study found no difference (25). In summary, there are significant gaps in our understanding of the relationships among math-biology task values, academic-related achievement/choices, and student characteristics, and these gaps inhibit our ability to design effective quantitative instructional materials for biology courses that would meet the needs of diverse learners.

Here we describe our research addressing the following questions: 1) What are undergraduate life science majors’ math-biology task values (i.e., are biology students really math-averse)? 2) To what extent do students’ math-biology task values differ according to their sociocultural background? 3) Do students’ math-biology task values predict their likelihood of taking advanced quantitative biology courses? In particular, we hypothesized the following: 1) on average, undergraduate life science majors would report high math-biology utility value and cost, but low math-biology interest, 2) women, first-generation, and underrepresented minority students would report lower math-biology interest and utility value, but higher math-biology cost, than men, continuing-generation, and White students, respectively, and 3) students who report higher math-biology interest and utility value, and lower math-biology cost, would be more likely to take advanced quantitative biology courses.

**METHODS**

**Setting and participants**

Survey invitations were distributed to introductory and upper-level biology courses at 19 institutions between fall 2016 and fall 2017 (additional details in Appendix 1). In an effort to include students from traditionally underrepresented groups, we contacted colleagues at three minority-serving institutions and sent a request through the Society for the Advancement of Biology Education Research (SABER) listserve to invite instructors at institutions with high minority and/or first-generation student enrollment to participate in our study. While our study still includes relatively few African American/Black or Hispanic/Latinx students, one of the institutions was a Historically Black College/University (HBCU) and two were Hispanic Serving Institutions (HSI); two other institutions rank well above the national average in terms of racial/ethnic diversity. The anonymous survey was administered online through Qualtrics. Students self-identified as 18 years of age or older and as a life science major and consented to participate in order to enter the survey. Students who completed the survey were compensated with a $5 gift card. In total, 1,190 students responded, but 129 were dropped from analyses due to missing responses and an additional 35 were dropped for reasons described in Appendix 1, resulting in a final sample size of 1,026 (see Table 1 for student demographics). This study was approved by the IRB at the University of New Hampshire (#6562).

**Measures**

The online survey contained the Math-Biology Values Instrument (MBVI) (30), two items on students’ likelihood of choosing to take advanced quantitative biology courses, and a demographic/academic questionnaire. The MBVI was developed and validated as a measure of undergraduate life science majors’ math-biology task values (interest, utility value, and cost) and contained 11 Likert-type items on a 7-point response scale ranging from “strongly disagree” to “strongly agree” (30) (Appendix 1). Each subscale showed high internal consistency (interest: $\alpha = 0.96, n = 1,015$; utility value: $\alpha = 0.90, n = 994$; cost: $\alpha = 0.85, n = 991$). For each
student, we calculated a mean score for each math-biology task value.

Following the MBVI, two items asked students to rate how likely they were to take an elective Mathematical Models in Biology course and an elective biology course involving statistics. Both were on a 7-point response scale ranging from “Extremely unlikely” to “Extremely likely” (Appendix 1).

The final portion of the survey contained items on students’ demographic and academic characteristics. Although we were primarily interested in students’ gender, parents’ education (to create a first-generation variable), race, and ethnicity, we also asked students to report their highest high school mathematics course (math-preparedness), year in college, and any science pre-professional program in which they were participating. To control for achievement and math-biology related experiences, we asked students to report their SAT or ACT Math score, whether they were in an honors program, and the number of college math-biology courses taken (biology courses where mathematics was used regularly or mathematics courses where biology was used regularly). Finally, we asked students to report their institution, to be used as a random effect (see Appendix 1 for all survey item options and complete explanations for coding variables).

**Data analyses**

All analyses were conducted in R (R Foundation for Statistical Computing, Vienna, Austria [https://www.R-project.org/]). To test for differences in students’ math-biology task values due to student characteristics, we used separate linear mixed-effects models (lme4 (45) and lmerTest (46) packages) with students’ mean scores for each math-biology task value (interest, utility value, and cost) as the dependent variable. In each model, gender, first-generation status, race/ethnicity, highest high school mathematics course, year in college, and pre-professional status were included as fixed effects, honors status and number of college math-biology courses were included as controls, and institution was specified as a random effect (random intercept only). We were unable to include students’ self-reported SAT/ACT Math scores as a control for achievement because many students did not report these scores. Models originally included a gender*first-generation status interaction term, but it was not significant in any model and was removed (data not shown). Models also originally included a gender*race/ethnicity interaction term. However, due to small sample size within some levels of race/ethnicity (Table 1), we did not have enough power to examine an interaction with this effect, so the interaction term was removed.

To determine whether students’ math-biology values predicted their likelihood of choosing to take advanced math-biology courses, we performed separate linear mixed-effects models as above, using students’ biomodeling and biostatistics likelihood scores, based on students’ responses to a 7-point Likert-type question, as dependent variables. Students’ mean scores for interest, utility value, and cost were treated as fixed effects, and all fixed effects and control variables described in the preceding models were included as control variables here.

All models were fitted using restricted maximum likelihood (REML) and only complete cases (n = 1,015 for interest, n = 994 for utility value, n = 991 for cost, n = 954 for biomodeling, and n = 955 for biostatistics). We used
ANOVA to test for the overall significance of categorical fixed effects (type III with Satterthwaite approximation for degrees of freedom). When a categorical fixed effect with more than two levels was found to be significant, we conducted all post-hoc pairwise comparisons using Tukey’s method for $p$ value correction (lsmeans package, weights = proportional (47)). Marginal $R^2$ (proportion explained only by fixed effects) and conditional $R^2$ (proportion explained by fixed and random effects) were obtained using the MuMIn package (Version 1.15.6; Bartoń K, [https://cran.r-project.org/package=MuMIn]). We checked assumptions of linear regression (multicollinearity, normality, homoscedasticity, autocorrelation) and found no issues (variance inflation factors were calculated using code found here: https://github.com/aufrank/R-hacks/blob/master/mer-utils.R).

RESULTS

Mean scores for students’ math-biology interest, utility value, and cost were 4.5, 5.6, and 4.8, respectively (SD = +/- 1.7, 1.2, and 1.6, respectively; Fig. 1). In other words, life science majors on average were somewhat interested in using mathematics to understand biology and saw mathematics as useful for their life science career but perceived some cost associated with doing mathematics in their biology courses. Correlations among all variables used in this study can be found in Appendix 2.

Effects of student characteristics on students’ math-biology task values

Women reported almost a half-point lower math-biology interest score ($\beta = -0.41$, $p < 0.001$) and higher cost ($\beta = 0.27$, $p = 0.01$) than men (Fig. 2A, Appendix 3). First-generation students reported lower interest and utility value ($\beta = -0.40$ and $-0.28$, $p = 0.01$ for both) than continuing-generation students (Fig. 2B, Appendix 3). Race/ethnicity was a significant predictor of cost ($p = 0.04$), with Asian ($\beta = 0.28$, $p = 0.03$), Hispanic/Latinx ($\beta = 0.33$, $p = 0.04$), and multiracial students ($\beta = 0.50$, $p = 0.01$) reporting higher cost than White students (Fig. 3, Appendix 3). However, when all pairwise comparisons were conducted using Tukey’s method for $p$ value correction, no comparisons within race/ethnicity were significant (Appendix 3).

Highest high school mathematics course, a measure of students’ math-preparedness, was a significant predictor in all math-biology task value models (interest and cost $p < 0.001$, utility value $p = 0.008$; Appendix 3). Pairwise comparisons demonstrated that students who completed Calculus in high school reported higher interest than students who

![Figure 1](https://example.com/fig1.jpg)

**FIGURE 1.** Overall means (± 1 SD) for life science majors’ math-biology task values (interest $n = 1,015$, utility value $n = 994$, cost $n = 991$).

![Figure 2](https://example.com/fig2a.jpg)

**FIGURE 2.** Effect of (A) gender and (B) first-generation status on life science majors’ math-biology interest ($n = 1,015$), utility value ($n = 994$), and cost ($n = 991$). Bars are marginal means (averaged over all other effects in each model) with 95% confidence intervals (**p < 0.001, *p < 0.01, *p < 0.05, ns = not significant; $p$ values based on modeled regression coefficients).
had completed only pre-Calculus ($\beta = -0.61$, $p < 0.001$), Algebra ($\beta = -0.93$, $p < 0.001$), or Statistics ($\beta = -0.97$, $p < 0.001$) (Fig. 4, Appendix 3). Students who completed Calculus in high school also reported higher utility value than students who completed only Algebra ($\beta = -0.48$, $p = 0.03$) and reported lower cost than those who completed only pre-Calculus ($\beta = 0.68$, $p < 0.001$), Algebra ($\beta = 1.47$, $p < 0.001$), or Statistics ($\beta = 0.80$, $p < 0.001$) (Fig. 4, Appendix 3). Students who completed pre-Calculus also reported lower cost than those who had completed only Algebra ($\beta = 0.79$, $p = 0.003$; Fig. 4, Appendix 3).

Year in college was also a significant predictor of students’ cost ($p = 0.04$), though the only significant difference was that students who were $\geq$ fourth year reported lower cost than students who were in their first year ($\beta = -0.42$, $p = 0.03$; Appendix 3). Students’ pre-professional status was not a significant predictor of any math-biology task value (Appendix 3).

The proportion of variance explained by fixed effects (marginal $R^2$) was 9% in the interest and cost models and 4% in the utility value model; adding in the random effect increased the proportion of variance explained (conditional $R^2$) to 10% for the interest model and 9% for the utility value model but did not affect the proportion of variance explained for the cost model (Appendix 3).

Predicting future course intentions from math-biology values

Students’ likelihood of taking a biomodeling course was positively related to their reported math-biology interest ($\beta = 0.63$, $p < 0.001$) and negatively related to their reported cost ($\beta = -0.18$, $p < 0.001$) (Fig. 5, panels A and C; Appendix 4). Students’ likelihood of taking a biostatistics course was positively related to their reported interest and utility value ($\beta = 0.45$ and 0.14, $p < 0.001$ and $p = 0.005$, respectively; Fig. 5, panels D and E; Appendix 4). The proportion of variance explained by fixed effects (marginal $R^2$) was 43% in the biomodeling model, and 26% in the biostatistics model; adding in the random effect did not affect the proportion of variance explained for either model (Appendix 4).

DISCUSSION

Consistent with our first hypothesis and recent findings (31), we found most life science majors in our study reported at least some cost associated with doing mathematics in their biology courses, and approximately one-third reported high cost ($\geq 6$ on the 7-point scale). However, we also found that, on average, students reported high utility value, which also supports our first hypothesis and is in line with multiple studies showing students generally find mathematics useful for their life science careers (26–30). In contrast to our first hypothesis, we found most students were at least somewhat interested in using mathematics to understand biology, and nearly one-third reported high interest ($\geq 6$ on the 7-point scale). Thus, while our findings lend some support to the belief that biology students are math-averse, we found that students are much more interested in using mathematics to understand biology than previously believed.
While students’ math-biology task values were on average near-neutral at worst, there was high variation among students, with many reporting low interest and high cost in particular. Some of this variability can be explained by students’ sociocultural and academic background (discussed more below), but the conditional $R^2$ for these models is low, suggesting that there are factors unaccounted for in our models. For example, perceived social support from parents (48, 49), peers (49), and instructors (50, 51) may all influence students’ mathematics attitudes and achievement. Future research on these and additional factors is needed to understand the unexplained variation in students’ math-biology task values.

Influence of student characteristics on math-biology task values

We found significant gender-related differences in math-biology task values, with men reporting higher interest and lower cost than women, partially supporting our second hypothesis. Mathematics is frequently stereotyped as a male domain (32–35) and thus gender is predicted by expectancy-value theory of achievement motivation (12, 13) to influence mathematics task values. Despite decreasing or disappearing gender-related gaps in mathematics achievement (20, 52, 53), it is still common for women to report more negative attitudes toward mathematics than men (31, 35), in particular, lower interest (37) and higher anxiety (20).

First-generation students reported lower interest and utility value than continuing-generation students, also partially supporting our second hypothesis. Lower interest may be due to cultural stereotypes related to socioeconomic status, though we would expect that negative cultural stereotypes related to academic ability would also influence cost (as discussed below for race/ethnicity). Alternatively, lower interest and utility value in first-generation students may be a result of a lack of cultural capital. As their parents never attended college, first-generation students are less likely than continuing-generation students to receive guidance from their parents on connections between curriculum and career expectations (54). This may explain their comparatively lower perception of the usefulness of mathematics for their life science career, which in turn may explain their lower interest in using mathematics to understand biology. Given our relatively small sample size (< 150) of first-generation students and the paucity of other research...
on their mathematics attitudes, additional research on larger populations of these students is necessary. Similar to others who have found differences in mathematics attitudes by race (19, 41, 44) or ethnicity (25), we found that in comparison with White students, Asian, Hispanic/Latinx, and multiracial students reported higher math-biology cost, also partially supporting our second hypothesis. While post-hoc comparisons using a p value correction showed no significant differences, we do not want to dismiss the possibility that this is a real finding that our study was underpowered to detect. Negative cultural stereotypes related to academic ability (43) could explain higher cost among Hispanic/Latinx students. However, Asian students are perceived as the model minority, with high academic aptitude in mathematics and science (55), and thus would not be predicted to report higher cost based on negative cultural stereotypes. One possible explanation for this unexpected result may lie in our broad race categories that likely mask important differences between ethnic groups. Our category of Asian encompassed all people originating from anywhere on the Asian continent, yet Southeast Asian students are stereotyped as academically inferior to White students, while East Asian students are stereotyped as academically superior to White students (55). Thus, aggregating Asian data by ethnic groups may reveal nuances that could explain the observed results. Similarly, students selecting more than one race or ethnicity were binned into a single “multiracial” category; thus, the many different cultural backgrounds represented by this category make it difficult to speculate on why we see higher perceived cost in these students compared with White students. Finally, although we sought a diverse sample of students, we had a small sample size for Black or African American students (< 70). Further research utilizing much larger sample sizes of students from diverse cultural backgrounds is necessary before drawing conclusions about how race or ethnicity influences life science majors’ math-biology task values.

Although we found significant differences in math-biology task value scores related to gender, first-generation status, and race/ethnicity, these differences were small (Figs. 2 and 3; Appendix 3). However, subsequent regression analyses suggest the small differences observed between women and men and between first-generation and continuing-generation students may impact students’ academic-related choices. We re-ran the biomodeling and biostatistics regression models without task values and found that gender significantly predicted students’ likelihood of taking a biomodeling course ($β = -0.51, p < 0.001$) and first-generation status significantly predicted students’ likelihood of taking a biostatistics course ($β = -0.51, p = 0.003$). When task values were originally included in these regression models, neither gender nor first-generation status were significant (Appendix 4; discussed below). Thus, gender and generation differences in the likelihood of including quantitative biology courses appear to be mediated by gender and generation differences in task values, though additional research is needed to explore this possibility (e.g., path analysis). Further research should also determine whether the small differences in task values between groups differentially affects student performance on quantitative biology tasks.

In addition to relationships with students’ sociocultural background, we found that math-biology task values were significantly related to students’ math-preparedness, measured as their highest high school mathematics course completed. Students who completed Calculus in high school reported higher interest and lower cost, which is consistent with expectancy-value theory (12, 13) and empirical research showing that students’ math-preparedness influences their mathematics task values (18, 19, 24). Collectively, as predicted by expectancy-value theory (12, 13), our findings demonstrate that undergraduate life science majors’ math-biology task values are informed by their sociocultural and academic backgrounds. However, it should be noted that most students in our study came from research institutions. In particular, it is likely that community college students may have very different math-biology task values than students from research institutions. Further research on populations of students from community colleges and primarily undergraduate institutions is necessary to understand the math-biology task values of students attending these institution types.

Math-biology task values predict future course intentions

Interest was the strongest predictor of students’ likelihood of taking advanced biomodeling and biostatistics courses, which supports our third hypothesis and is consistent with expectancy-value theory (12, 13) and the findings of others (21–23). However, students’ perceptions of the usefulness of mathematics for their life science career were only positively related to their likelihood of taking a biostatistics course. This may be a result of students’ perceptions of the types of mathematics useful to life science careers. The use and interpretation of statistics is often stressed throughout the undergraduate life science curriculum. Therefore, when life science majors report high math-biology utility value, they may be primarily thinking about the importance of statistics. If so, utility value would be expected to predict the likelihood of taking a biostatistics course but would not necessarily predict the likelihood of taking a biomodeling course. Moreover, when evaluating the likelihood of taking an elective biostatistics course, students may have weighted its perceived usefulness more than the costs of taking the course, which would explain the lack of significance of cost in the model. In contrast, students may have put significant weight on cost when evaluating their likelihood of taking the biomodeling course due to the less familiar, and potentially more intimidating, nature of the course. Future research could utilize an explanatory sequential mixed-methods study, in which selected students...
are interviewed based on their survey responses, to better understand students’ motivational reasons underlying their likelihood of taking particular quantitative biology courses. Additionally, as we only measured students’ likelihood of taking hypothetical quantitative biology courses, future research could longitudinally track students to determine actual advanced quantitative biology courses they enroll in during their undergraduate life science career.

While further research linking math-biology task values to students’ mathematics achievement in biology contexts is still needed, we believe that engendering positive math-biology attitudes in students is in itself a worthy goal of quantitative biology instruction. Thus, instructors incorporating quantitative skills into their courses can design more effective quantitative instruction by implementing strategies that may lead to more positive math-biology task values. Although students generally perceived mathematics to be useful for their life science career, first-generation students may benefit from a utility value intervention, in which students make connections between course topics and their lives or other interests (56, 57). This type of intervention has also been successful in increasing interest in a topic (16, 56), and thus could also be beneficial for women and mathematically underprepared students. Student-centered learning methods focused on solving authentic problems (57–59) can also promote student interest in quantitative biology. Similar strategies have been shown to be successful at reducing mathematics anxiety, along with providing encouragement and positive reinforcement and making testing environments less intimidating (60). Based on our findings, anxiety-reducing strategies could be beneficial for women, first-generation, minority, and mathematically underprepared students. Student-centered learning methods focused on solving authentic problems (57–59) can also promote student interest in quantitative biology. Similar strategies have been shown to be successful at reducing mathematics anxiety, along with providing encouragement and positive reinforcement and making testing environments less intimidating (60). Based on our findings, anxiety-reducing strategies could be beneficial for women, first-generation, minority, and mathematically underprepared students. Student-centered learning methods focused on solving authentic problems (57–59) can also promote student interest in quantitative biology. Similar strategies have been shown to be successful at reducing mathematics anxiety, along with providing encouragement and positive reinforcement and making testing environments less intimidating (60). Based on our findings, anxiety-reducing strategies could be beneficial for women, first-generation, minority, and mathematically underprepared students.

CONCLUSION

Our findings suggest that, on average, undergraduate life science majors perceive some cost associated with doing mathematics in their biology courses and are therefore somewhat math-averse. However, students also generally see mathematics as useful for their life science career and are much more interested in using mathematics to understand biology than previously believed. As predicted by expectancy-value theory (12, 13), aspects of students’ sociocultural background and their math-preparedness informed their math-biology task values, which predicted their likelihood of choosing to take advanced quantitative biology courses.

SUPPLEMENTAL MATERIALS

Appendix 1: Additional methodology and details on the survey (instructions, items, and response options)

Appendix 2: Correlations among all variables used in the study

Appendix 3: Unstandardized regression coefficients, standard error, and p values for fixed effects used in interest, utility value, and cost linear mixed-effects models

Appendix 4: Unstandardized regression coefficients, standard error, and p values for fixed effects used in likelihood of taking a bio-modeling and bio-statistics course linear mixed-effects models

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