Mathematics Motivation in Students Enrolled in an Introductory Biology Course

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Over the last two decades, the field of biology has become increasingly more quantitative leading to more mathematics being integrated into biology education curriculum (Brewer & Smith, 2011). However, students enrolled in biology courses often report having negative feelings towards mathematics, resulting in them being resistant to learning course material (Thompson et al., 2013). To understand these negative feelings, this study focuses on identifying patterns of mathematics motivation among undergraduate students enrolled in a gateway biology course. To do this, the study utilizes Expectancy Value Theory (EVT; Eccles et al., 1983), which proposes that an individual's expectancy for success and their subjective task values are predictors of academic choice, persistence, and performance. Subcomponents of values are (1) utility value, or how useful the task is for future goals, (2) interest value, or the intrinsic interest of a task, (3) attainment value, or the importance of doing well, and (4) cost, or the accumulated negative aspects of engaging in the task. This study looks at two dimensions of cost: emotional cost and effort required to complete the task (Wigfield & Eccles, 2000).

Participants include 538 students in an introductory biology course at a large research-intensive university. At the start of the course, students completed a 7-point Likert Scale survey that examined six variables including self-efficacy, emotional cost, effort cost, intrinsic value, mathematics attainment value, and utility value. Self-efficacy was measured as an indicator of expectancy of success (Eccles & Wigfield, 1995). Each subscale was taken or modified from previously validated surveys (Andrews et al., 2017; Flake et al., 2015; Gaspard et al., 2015; Glynn et al., 2011). The study used Confirmatory Factor Analysis, with "lavaan" R package (Rosseel, 2012) with maximum likelihood robust estimation (Knekta et al., 2019) to verify the factor structure of the variables. All fit indices (CFI, TLI, RMSEA, SRMR) were within suggested cutoff values as suggested by Hu & Bentler (1999) and Steiger (2007).

This study used hierarchical cluster analysis (Wards method and Euclidean distance), to find students with similar motivation characteristics based on task values (mathematics attainment, utility, and intrinsic value), cost (emotional and effort) and self-efficacy (expectancy of success). Using the "NbClust" package (Charrad et al., 2014), we found three different patterns of mathematics motivation within the data: low, moderate and high. The low group includes 45 students that place low value on mathematics (range of task value means: 1.76 - 3.91) and do not feel confident to complete the mathematics required in the course (self-efficacy mean: 2.93). Also, low motivation students felt that mathematics had high costs (emotional and effort cost means > 5.55). In contrast, the high group (164 students) place high value on mathematics and are more confident in the subject (task values and self-efficacy means > 5.60). In addition, students believe mathematics in the course has low costs (means < 2.50). The final group, moderate, is composed of 319 students who are moderately motivated to do mathematics. In this group, mathematics attainment value and utility value had higher means of 5.42 and 5.18, respectively. All other variable means were relatively close to 4. The findings show that students in the introductory biology course can be clustered into three groups (low, moderate, and high), with over half in the moderate cluster. For future analysis, we plan to further examine each cluster, with more of a focus on the moderate cluster.

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Mathematics Motivation in Students Enrolled in an Introductory Biology Course

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Introduction

- ❖ Over the last two decades, the field of biology has become increasingly more quantitative leading to more mathematics being integrated into the biology curriculum (Brewer & Smith, 2011).
- ❖ However, students enrolled in biology courses often report having negative feelings towards mathematics, resulting in them not fully engaging in quantitative tasks (Thompson et al., 2013).

Research Questions:

1. What are the mathematics motivational patterns among undergraduate students who are enrolled in a gateway biology course?
2. To what extent is gender and pre-professional status related to these motivational patterns?

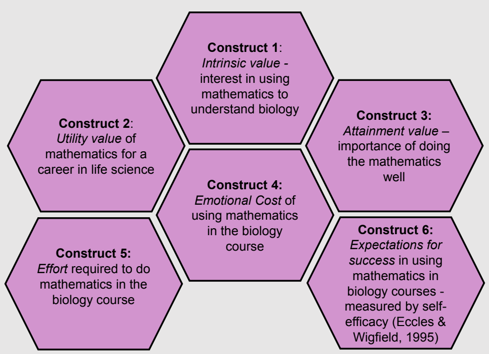
Data

Setting and Participants

- ❖ Course: Introductory biology course
  - ❖ Six sections over 2 years
- ❖ Data consists of 473 student survey responses who were life-science majors enrolled in the course.
  - ❖ Gender: Male = 121 & Female = 352
  - ❖ Pre-Professional Status: Pre-Professional = 211 & Non-Pre-Professional = 262
  - ❖ Highest math class taken in High School: Algebra, Geometry or Trigonometry = 70, Pre-Calculus = 202, & Calculus = 201

Instrument & Variables Measured

- ❖ The survey is made up of 28 7-point Likert-type items taken or modified from previously published surveys (Andrews et al., 2017; Flake et al., 2015; Gaspard et al., 2015; Glynn et al., 2011).
- ❖ The instrument contains items that relate to six constructs:



- ❖ Confirmatory Factor Analysis with maximum likelihood robust estimation (Knekta et al., 2019) verified that all fit indices (CFI, TLI, RMSEA, SRMR) were within suggested cutoff values as suggested by Hu & Bentler (1999) and Steiger (2007).

Expectancy Value Theory (Eccles et al., 1983; Wigfield & Eccles, 2000)

Task Values

- ❑ Intrinsic Value
- ❑ Utility Value
- ❑ Attainment Value
- ❑ Emotional Cost
- ❑ Effort Cost

Expectancy of Success

- ❑ Self-Efficacy

Achievement Motivation & Task Completion

Data Analysis

What are the mathematics motivational patterns among undergraduate students who are enrolled in a gateway biology course?	❑ Agglomerative Hierarchical Clustering using Wards method as the algorithm and Euclidean distance as the distance measure. ❑ Bootstrapping was used to determine the optimal number of clusters.
To what extent is gender and pre-professional status related to these patterns?	❑ Multinominal Logistic Regression Analysis ❑ Outcome Variable: Cluster ❑ Independent Variables: Gender (male or female) and Pre-Professional Status (pre-professional or non-pre-professional) ❑ Control Variable: Highest Mathematics Course Taken in High School (Algebra/Geometry/Trigonometry, Pre-Calculus, or Calculus)

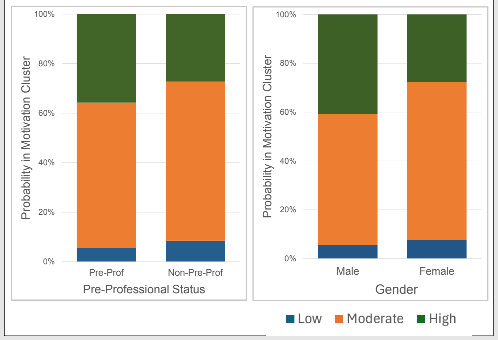
Cluster Analysis Results

Table 1: Means and Standard Deviations of the six affective variables in each motivation cluster.

Variable \ Cluster	Low Motivation N = 45	Moderate Motivation N = 319	High Motivation N = 164
Intrinsic Value	1.76 (± 0.65)	3.56 (± 1.23)	5.62 (± 0.77)
Utility Value	3.76 (± 1.23)	5.42 (± 0.99)	6.20 (± 0.81)
Mathematics Attainment Value	3.91 (± 1.07)	5.18 (± 1.02)	6.13 (± 0.77)
Emotional Cost	6.11 (± 0.60)	4.32 (± 1.05)	2.33 (± 0.91)
Effort Cost	5.55 (± 0.76)	3.74 (± 0.98)	2.10 (± 0.72)
Self-Efficacy	2.93 (± 1.17)	4.72 (± 1.05)	5.98 (± 0.84)

Multinominal Logistic Regression Results

Figure 1: Percent chance each predictor variable category is in low, moderate and high motivation cluster.



Conclusions

- ❖ Students in the introductory biology course can be clustered into three groups of motivation (low, moderate, and high), with over half in the moderate cluster.
- ❖ Gender and pre-professional status were not statistically significant in predicting motivational patterns.
- ❖ Controlling for highest mathematics course taken in High School, the probability that a female will be in the high motivation cluster is 27.8%. In comparison, the probability that a male will be in the high motivation cluster is 40.9%.
- ❖ Pre-Professional majors have a 35.7% chance of being in the high motivation cluster while non-pre-professional majors have a 27.3% of being in the high motivation cluster while controlling for highest mathematics course taken in High School.
- ❖ Next Steps: Investigate whether students' motivational patterns change as they complete the biology course?

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