THE ROLE OF NON-COGNITIVE FACTORS IN THE INTRODUCTORY STATISTICS CLASSROOM

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ABSTRACT

The current study aimed to understand not only students' attitudes towards statistics, but also their beliefs about their ability to perform statistical tasks (self-efficacy), the value they place on carrying out course and statistical tasks (task value), and the level of effort they perceive when engaging in these tasks (cost) across a semester in an undergraduate introductory statistics course. Findings indicated that students viewed statistics as more difficult, less valuable, and more costly to engage in as the semester progressed. Further, students also reported an increase in avoidant help-seeking behaviors (e.g., not seeking help when needed). Non-cognitive factors were not found to predict course retention. Variables of affect and self-efficacy, however, were shown to predict overall course grade.

Keywords: Statistics education research; Attitudes towards statistics; Value; Self-efficacy; Student outcomes; Student retention

1. INTRODUCTION

Understanding statistical information or results (statistical literacy), making sense of statistical ideas and information (statistical reasoning), as well as understanding why and how statistical investigations are conducted (statistical thinking) (Ben-Zvi & Garfield, 2004) are highly valued skills in a current climate that requires information-based decision making (Ben-Zvi & Garfield, 2004; Rumsey, 2002; Tishkovskaya & Lancaster, 2012).

Introductory statistics courses provide students with their first college level experiences in statistics. Commonly, these courses provide foundational information necessary for degree progression for a number of majors outside of statistics (Qian, 2011). While it has been acknowledged that introductory statistics educators face a population with varied statistical backgrounds with respect to their literacy, reasoning, and thinking (Ben-Zvi & Garfield, 2004; Murray & Gal, 2002; Tishkovskaya & Lancaster, 2012), the structure of introductory courses may be one factor leading to students' lack of statistical

literacy and inability to apply statistics to their everyday lives (Ben-Zvi & Garfield, 2004; Tishkovskaya & Lancaster, 2012).

Over the last two decades statistics education has shifted to a focus on statistical literacy, reasoning, and thinking (Ben-Zvi & Garfield, 2004; Carver et al., 2016). As a result, introductory statistics courses have been going through major pedagogical changes, moving from primarily emphasizing the use of rote memorization to promoting active learning in the classroom and providing students with applied real-world statistical problems (Ben-Zvi & Garfield, 2004; Carver et al., 2016; Qian, 2011).

Early research in measuring student outcomes and success in statistics education has focused primarily on cognitive skills (i.e., development of skills and knowledge), with little attention given to non-cognitive factors such as student attitudes, beliefs, or expectations (Eichler & Zapata-Cardona, 2016; Gal & Ginsburg, 1994). Now that course structure is shifting, research is expanding to focus more on non-cognitive factors.

Researchers advocating for the measurement of non-cognitive factors commonly cite the main goals of introductory statistics as to: 1) prepare students for future use of statistics both inside and outside of the classroom, and 2) promote initial success in statistics at the college level (Carnell, 2008; Gal & Ginsberg, 1994). Fostering non-cognitive factors such as positive attitudes and perceptions of statistics, as well as instilling their value in the real world, is viewed as crucial for promoting students' engagement in further statistical experiences after course completion (Gal & Ginsberg, 1994; Garfield et al., 2002). Further, by examining these factors, instructors are able to adopt a student lens and understand how the course structure and materials affect students' feelings towards the use of statistical skills, ideas, and techniques (Garfield et al., 2002; Zieffler et al., 2008).

Unfortunately, student perceptions of introductory statistics courses are negative. Students view them as demanding and irrelevant to their career goals (Kirk, 2002), with some students exhibiting course-related anxiety (Mvududu, 2003; Tishkovskaya & Lancaster, 2012). Further, student attitudes have been shown to become more negative over the course of a semester (Carnell, 2008). Our study focuses on four non-cognitive factors, trying to understand not only student attitudes towards statistics, but also their beliefs about their ability to perform statistical tasks (self-efficacy), the value they place on carrying out course and statistical tasks (task value), and the level of effort they perceive when engaging in these tasks (cost). We chose to examine these variables based on both the instructors' experience as well as prior literature that has outlined interest, competence beliefs, and cost as influencing success in the STEM classroom (Robinson et al., 2019). As limited research has been conducted in these areas in the context of the introductory statistics classroom, the current review was drawn from the wider literature to inform the research questions.

2. LITERATURE REVIEW

2.1. ATTITUDE TOWARD STATISTICS

Student attitudes towards statistics have been examined through several overlapping theoretical lenses (Dempster & McCorry, 2009; Nolan et al., 2012). The current study utilizes the framework of Schau et al. (1995), viewing student attitudes as a "multidimensional construct that stand for students' learned predispositions to respond positively or negatively with regard to statistics" (Emmioğlu & Çapa-Aydın, 2012, p. 95). Specifically, the construct of attitudes towards statistics has four components: 1) affect, 2) cognitive competence, 2) value, and 4) difficulty. The current study focuses on affect, or positive and negative feelings about statistics, and difficulty, attitudes about the difficulty of statistics as a domain (Hilton et al., 2004; Schau et al., 1995).

Prior research has shown student attitudes toward statistics to be important for explaining students' statistics achievement (Carlson & Winquist, 2011; Cashin & Elmore, 2005; Chiesi & Primi, 2015, 2018; Dempster & McCorry, 2009; Emmioğlu & Çapa-Aydın, 2012; Ramirez et al., 2012; Schau et al., 2012; Schutz et al., 1998; Sorge & Schau, 2002) as well as their use of learning strategies (Chiesi & Primi, 2018). Further, attitudes have also been found to be related to other motivational constructs such as self-efficacy (Perepiczka et al., 2011; Walker & Brakke, 2017), expectancies (Hood et al., 2012), anxiety and feelings of competence (Chiesi & Primi, 2010; Sorge & Schau, 2002), and accurate conceptions about statistics (Evans, 2007).

When exploring attitudes over time, findings have been mixed (Carlson & Winquist, 2011; Eichler & Zapata-Cardona, 2016). General analyses have evidenced attitudes to be relatively stable across the course of a semester (Evans, 2007). More targeted analyses, however, have found differences. For example, Chiesi and Primi (2010) observed that students with high math competence increased on all four attitudinal dimensions across a semester, whereas those with low math competence only showed increases in cognitive competence and value. Additionally, on average, attitudes stayed the same or had a small decrease for affect, cognitive competence, and difficulty while decreasing in magnitude for value, interest, and effort (Bond et al., 2012; Schau & Emmioğlu, 2012).

2.2. SELF-EFFICACY

Self-efficacy refers to a future oriented belief relating to an individual's ability to succeed in a task or accomplish a goal (Bandura, 1989; Schunk & Pajares, 2002; Zimmerman, 2000). Research has indicated self-efficacy to be predictive of student outcomes, including academic achievement (Ferla et al., 2010; Galyon et al., 2012; Kurtovic et al., 2019; Nasir & Iqbal, 2019; Sucuoğlu, 2018), GPA (Feldman & Kubota, 2015; Komarraju & Nadler, 2013; Richardson et al., 2012), and overall degree result (Trigwell et al., 2013). Positive relationships between self-efficacy and achievement (Zare et al., 2011) as well as engagement (Salim et al., 2018) have also been replicated in statistics education.

Alongside this, highly self-efficacious students have been found to persist through difficult material (Komarraju & Nadler, 2013), take a deep approach to learning (Ferla et al., 2010; Trigwell et al., 2013), engage in adaptive help-seeking (Chowdhury & Halder, 2019), set high standards for themselves, and show reduced levels of procrastination (Kurtovic et al., 2019). In contrast, those with low efficacy have been found to take a surface approach to learning (Trigwell et al., 2013), show lower levels of participation (Galyon et al., 2012) and higher levels of anxiety (Ferla et al., 2010), as well as hold the beliefs that they cannot meet the high standards they set for themselves (Kurtovic et al., 2019).

Due to the context-specific nature of self-efficacy, it is considered highly malleable and prone to changes over time (Honicke & Broadbent, 2016; Ouweneel et al., 2013; Schunk & Pajares, 2002). Researchers have observed increases in self-efficacy across academic semesters (Cheng & Chiou, 2010) as well as from first to final year of study (e.g., Cassidy, 2012). Further, the strength of the relationship between academic performance and self-efficacy has been shown to differ based on the time at which self-efficacy is measured. Multiple studies (Gaylon et al., 2012; Gore, 2006; Lane et al., 2004; Lawson et al., 2007) have observed measures taken during or at the end of the semester to correlate more highly with performance compared to those taken at the beginning of the semester.

2.3. EXPECTANCY VALUE (TASK VALUE AND COST)

Initially developed in the field of mathematics education (Wigfield et al., 2009), expectancy value theory (Wigfield & Eccles, 1992, 2000) encompasses students expectancies for success (how well they will do in an area or task), ability beliefs (evaluations of their current ability or competence in an area or task), and value based judgments (enjoyment, usefulness, or cost of engaging in a task). In general, the expectancies and values that students hold, have been shown to be related to their performance, effort, and persistence in a course (González et al., 2016). Further, both attitudes towards statistics (Hood et al., 2012; Ramirez et al., 2010) and self-efficacy (Wigfield & Eccles, 2000) are complementary to the expectancy value framework.

The current study focuses on value, and in particular the constructs of task value and cost. Task (or attainment) value refers to how personally important it is to an individual that they do well on a task. Cost reflects the negative aspects individuals associate with engaging in a task, including anxiety or stress related to the task, the amount of effort needed to succeed in the task, as well as the lost opportunities that result from engaging in the task (Wigfield & Eccles, 2000). These constructs are considered independent but related (Hulleman et al., 2008), with changes in one construct influencing the development of the other (Perez et al., 2019). Research has observed that students enter college with relatively high levels of value, however, these decline over the first few years of college (Robinson et al., 2019).

Task value has been shown to predict test-taking effort and performance (Cole et al., 2008), GPA, and retention (Robinson et al., 2019), and to be associated with help-seeking (Karabenick, 2003).

Further, those with high levels of task value use of deeper cognitive and self-regulatory strategies (Neuville et al., 2007; VanZile-Tamsen, 2001), evidence heightened persistence (Hulleman et al., 2017), and increased effort and engagement (Guo et al., 2016).

A large majority of the research applying expectancy-values models of motivation has excluded the cost component (McCoach & Flake, 2018; Robinson et al., 2019). Research that has been carried out, however, has shown cost to have a negative association with achievement and retention (Guo et al., 2016; Johnson et al., 2016; Johnson & Safavian, 2016; Perez et al., 2018, 2019; Robinson et al., 2019). Further, cost influences attendance (Dietrich et al., 2017), as well as in-class behavior such as task planning and selection (Dietrich et al., 2017), use of self-regulatory strategies (Johnson & Safavian, 2016), and persistence in an activity (Conley, 2012; Flake et al., 2015).

2.4. STUDY AIM

The current study aimed to expand on the available literature and investigate the development of non-cognitive factors and their impact on course outcomes in an introductory statistics course. The current work builds from anecdotal feedback received by the instructors that mirrors prior research (e.g., Songsore & White, 2018) and suggests that students hold negative views of the course and do not view the content as important, with these negative attitudes towards the content developing as the course progresses.

Based on our review of the available literature, our study aims to address and expand upon current research by 1) examining a unique population, 2) measuring multiple non-cognitive factors simultaneously, and 3) exploring alternatives to traditional student outcomes such as grades and retention. Firstly, the majority of the studies on attitudes towards statistics have been conducted in social science settings such as psychology (e.g., Chiesi & Primi, 2015, 2018; Dempster & McCorry, 2009). Our study aims to expand current knowledge by investigating attitudes towards an introductory statistics course in a population (predominantly engineering students) underrepresented in the statistics attitudes literature (Sarikaya & Sarikaya, 2019) and vastly differing from that of social sciences. Social science populations commonly exhibit aversion or anxiety toward math as they enter introductory statistics courses (Dempster & McCorry, 2009). In contrast, mathematics is a primary aspect of engineering, and as such engineering students enter courses with a different background and higher level of exposure to mathematics. In the context of the sampled course, a 200-level calculus course was a prerequisite and the topics were taught using calculus. Conversely, the social science courses had algebra as a prerequisite course and the topics were taught from an algebraic perspective. Overall, this has led to a reduction in instructional efforts in the sample course aimed at enhancing student perceptions of their math ability, commonly cited as necessary in courses aimed at social science populations (e.g., Dempster & McCorry, 2009).

Second, although there is a large amount of research on motivational constructs such as attitudes, self-efficacy, task value, and cost, they are rarely investigated together or over time in a post-secondary environment (Robinson et al., 2019). Our study design allows us to account (at least in part) for the multi-dimensional nature of attitudes and motivation by measuring these constructs together and at multiple timepoints during the course.

Finally, the current research also adds to literature by not only looking at student performance but also at student tendency to seek out instructional support (help-seeking). In STEM-related disciplines, student levels of comfort in seeking help influence engagement in introductory courses (Gasiewski et al., 2012). Further, in general, motivational components such as self-esteem, self-efficacy, and self-regulatory behavior have been linked to help-seeking (Järvelä, 2011; Reeves & Sperling, 2015; Roll et al., 2011).

Based on the study aims and scope, addressed were the following research questions:

1) How do student attitudes, values, and beliefs change over time? and

2) How does student motivation predict help-seeking behavior and learning outcomes in the course?

3. METHOD

3.1. PARTICIPANTS

A convenience sample of one hundred and eighty nine students from seven sections of a *Probability and Statistics for Engineers* course across the 2018–19 academic year (Fall 18: four sections, $n = 118$, Spring 19: three sections, $n = 71$) participated in the study. Surveys were administered via Qualtrics online survey software during (approximately) weeks 2–4 and 13–15 of the 16 week course. Study procedures followed human subjects guidelines and approval to conduct the research was given by our institutional review boards. Frequency analyses (via chi-square tests) revealed no differences in the demographic variables of ethnicity, gender, major, and age across semesters. For the purposes of the current paper, data were combined and presented as one sample.

Students were predominantly white (66.7% White, 12.7% Asian, 3.2% African American, 2.1% Hispanic, 8.5% identified as more than one race, 6.9% did not specify race), male (76.2% Male, 23.8% Female), and engineering majors (68.3% engineering majors, 31.7% other). Further, a large portion of students were Sophomores or Juniors (0.5% Freshmen, 40.2% Sophomores, 43.9% Juniors, 14.8% Seniors, 0.5% did not specify academic level). Student ages ranged from 18–40 (Mean = 20.28, $SD = 2.85$) and the average self-reported cumulative GPA for the sample was 3.16 ($SD = 1.02$). The current sample closely matches the average course enrollment in terms of race and gender. However, our sample is slightly younger than average (general course population age is 23.1 years) and contains more sophomores (general course population has 29.9% sophomores).

A large majority of students indicated that they had not taken a statistics course previously (70.9%; 24.9% 1–3 courses, 1.1% other—AP statistics, 3.2% missing), and had high expectations in regards to their overall course grade (79.2% indicated that they expected to receive an A in the course, 18.1% B grade, 2.1% C grade, 3.2% missing).

3.2. COURSE CONTEXT

Probability and Statistics for Engineers was a 3-credit course taken by approximately 1200 students each year, serving as a prerequisite for more than 50 courses across the university. The typical class size was approximately 90–100 students. The course was calculus-based and designed for students proficient in mathematics or from majors where mathematics/statistics skills were core competencies, commonly serving Computer Science, Computer Programming, Mathematics Education, and Engineering majors. An equivalent to the course was not offered in the college of engineering.

While every instructor has their own approach, the course was usually taught either via an exclusively chalk-and-talk lecture style or in a traditional lecture format with small group activities to promote active learning and engagement. Most of the faculty members' interactions with students occurred either during the small group activities, the asking of questions during lectures, or in office hour visits. At the sampled university, it was expected that each credit hour (unit) involved an input of approximately three hours per week from students.

The course required students to take a 200-level Calculus course as a prerequisite and covered the topics: principles of data collection (sampling methods, sampling bias, observational studies, designed experiments), probability (random variables, sampling distribution), inference (confidence intervals, hypothesis testing), one and two-way Analysis of Variance (ANOVA) and simple linear regression. By the end of the course, it was expected that students would (1) recognize and account for sources of variability and bias in experiments and observational studies, (2) determine and conduct valid statistical inference, and (3) draw appropriate real world conclusions given the sources of data.

Assessments in the course varied somewhat by instructor, but generally included group work or in-class activities (approximately 15% of overall grade), quizzes/homework assignments (approximately 25%), two midterm exams (approximately 35% of the overall grade), and a final and comprehensive exam (approximately 25% of the overall grade). Exams generally involved about 15 multiple-choice or true/false questions (accounting for about 50% of the overall exam score), followed by 4–6 short answer questions. The short answer questions involved solving problems and explaining statistical concepts. Almost all short answer questions involved some explanation such as, "Explain the meaning of the *p*-value found" or "Interpret your results in the context of the question."

Instructors who utilized homework assignments used a traditional textbook assignment, usually due weekly. These were graded by teaching assistants and returned to the students with comments and solutions provided. Instructors that used in-class activities (ICAs) generally included an ICA in every class. Most often these were done after an initial lecture period of about 40 minutes, with students being given the remaining class time (approximately 35 minutes) to work together in small groups of 2–5 in order to complete the assignment. ICAs were usually due by the start of the next class period, with solutions provided after the due date and graded ICAs returned to students.

3.3. MEASURES

Self-efficacy. Student beliefs about their ability to accomplish or complete the three main course learning objectives (LOs) were taken at both the beginning and end of the semester as a proxy for self-efficacy. Students rated their agreement that they could perform against each LO ("recognize and account for sources of variability and bias in experiments and observational studies", "determine and conduct valid statistical inference", and "draw appropriate real world conclusions given the sources of data") on a scale of 1 (Strongly disagree) to 5 (Strongly agree). A composite score across the three LOs was taken for analysis. Mean values were used due to the interconnection between LOs and the assumption that beliefs relating to one LO would impact general feelings of self-efficacy. Values ranged between 1 and 5.

Attitudes towards statistics. General attitudes towards statistics were measured at the beginning and end of the semester using the Survey of Attitudes Toward Statistics (SATS-28; Schau et al., 1995). Two subscales of the attitude component of the scale, affect and difficulty, were measured. Students responded to items on a five point Likert scale (1-strongly disagree to 5-strongly agree). The affect scale (6-items) asked students about their positive and negative feelings concerning statistics (e.g., I am scared by statistics), whereas the difficulty scale (7 items) related to the perceived difficulty of statistics as a subject (e.g., Statistics is a complicated subject). Mean scores were taken for each scale, with values ranging from 1 to 5. Several studies have documented solid psychometric properties, reliability, and validity of SATS constructs (e.g., Chiesi & Primi, 2010; Hilton et al., 2004; Schau et al., 1995). Both scales showed sufficient reliability pre-post in the current study (Affect α = .82 and .87; Difficulty α = .73 and .75).

Task value. Six items from the Motivated Strategies for Learning Questionnaire (MSLQ) (Pintrich et al., 1991) were used to measure task value at the beginning and end of the semester. Items referenced the course (e.g., "Understanding the subject matter of this course is very important to me") and required individuals to rate their level of agreement for each statement on a scale of 1 (not at all true of me) to 7 (very true of me). Scores were summed across items, allowing total scores to range from 6 to 42. Pintrich et al.'s (1993) examination of the instrument revealed robust scale reliabilities, good factor structure, and reasonable predictive validity to actual course performance of students. A history of its use can be found in Duncan and McKeachie (2005). The scale showed a high level of reliability in the current study (α = .93 and .93).

Cost. Cost was measured using one subscale of the Flake et al. (2015) cost scale, task effort (TE) cost. Students were asked to respond to five items relating to work put forth to engage in the task (e.g., "This class demands too much of my time") on a scale of 1 (completely disagree) to 9 (completely agree). Scores were summed across items, allowing total scores to range from 5 to 45. Although limited in the number of studies that have investigated the psychometric properties of the scale, initial validation efforts by Flake et al. (2015) suggest adequate reliability and model fit. The scale showed a high level of reliability in the current study (α = .96 and .97)

Academic performance and help-seeking. In regard to student outcomes in the course, academic performance was measured using the students' overall course grade (%) and retention via letter grade (ABC/DFW). Further, student approaches towards seeking help were measured using scales from Reeves and Sperling (2015). Specifically, adaptive and avoidant help-seeking subscales were chosen. Adaptive help-seeking (5 items) relates to the tendency to seek help when needed, whereas avoidant

help-seeking (4 items) measures the tendency not to seek help when needed (Reeves & Sperling, 2015). Items in both subscales were measured on a five point scale (1-strongly disagree to 5-strongly agree). Scores were summed across items, allowing total scores to range from 5 to 25 for adaptive help-seeking and 4 to 20 for avoidant help-seeking. Items used in Reeves and Sperlings work were adapted from Ryan and Pintrich (1997; adaptive help-seeking) and Karabenick (2001; avoidant help-seeking). Both investigated the psychometric properties of the scale, with results suggesting adequate reliability and factor structure. Scales showed reasonable reliability pre-post in the current study (Adaptive help-seeking $\alpha = .70$ and .70; Avoidant help-seeking $\alpha = .88$ and .89).

3.4. ANALYSES

Analyses conducted in the current study consisted of three parts. Descriptive statistics were run to understand and summarize the variables, repeated-measures-ANOVAs were used to investigate changes over time in motivation (attitudes, task value and cost, help-seeking, self-efficacy), and regression models examined whether help-seeking behaviors at the end of the course and overall performance/retention could be explained by attitudes towards statistics (affect and difficulty), task value, cost, and self-efficacy measures at the beginning of the course, controlling for classroom effects. As the models run were a preliminary investigation, we chose to omit the inclusion of interaction terms. Classroom, entered as a random effect for all initial regression models, was removed as a predictor for final models due to convergence issues for models estimating help-seeking and retention, and an extremely low variance estimate for the model estimating overall performance.

Assumptions were checked for each repeated-measures model by visual inspection of the residual diagnostics and the models appear to fit well. Additionally, the independent variables in the regression model were checked for multicollinearity, which was found to be low (Field, 2013). It should be noted there are some methodological concerns cited in prior literature regarding the analysis of Likert scale data. Reviews of the literature, such as Carifio and Perla (2007), however, provide evidence that the *F*-test is robust to violations of the interval data assumption and moderate skewing and is therefore appropriate to use when analyzing Likert-type data. *SPSS 26* software was used to run descriptives and repeated-measures-ANOVAs and *JMP Pro 16* for regression analyses.

4. RESULTS

4.1. RQ1: HOW DOES STUDENT MOTIVATION CHANGE OVER TIME?

Attitudes towards statistics. RM-ANOVA analyses revealed decreases in both student reported affect ($F(1, 114) = 20.48$, $p < .001$, $\eta^2 = .15$) and difficulty ($F(1, 114) = 11.99$, $p < .001$, $\eta^2 = .10$) across the semester.

Task value and cost. Students reported lower value at the end of the course, with task value decreasing ($F(1, 113) = 25.70$, $p < .001$, $\eta^2 = .19$) and cost increasing ($F(1, 114) = 36.16$, $p < .001$, $\eta^2 = .24$) over time.

Help-seeking behavior. Strategic help-seeking behavior decreased over time, with reported adaptive help-seeking decreased ($F(1, 112) = 6.00$, $p = .016$, $\eta^2 = .05$), and avoidant help-seeking increasing ($F(1, 112) = 7.59$, $p = .007$, $\eta^2 = .06$) during the semester.

Self-efficacy (LOs). Students reported self-efficacy toward LOs remained stable over time ($F(1, 118) = 3. 29$, $p = .072$).

Table 1. Mean (M) and standard error (SE) based on RM-ANOVA

Construct	Beginning of semester		End of semester		Difference	
	M	*SE*	*M*	*SE*	*M*	*SE*
Affect	4.86	.10	4.38	.13	.48	.11
Difficulty	3.97	.07	3.67	.08	.30	.09
Task Value	29.80	.69	26.86	.82	2.94	.58
Cost	14.28	.52	17.63	.66	3.35	.56
Adaptive Help-seeking	19.56	.27	18.74	.30	.81	.33
Avoidant Help-seeking	8.92	.37	9.89	.37	.97	.35
Self-efficacy (LOs)	3.66	.07	3.44	.11	.23	.13

4.2. RQ2: HOW DOES STUDENT MOTIVATION PREDICT HELP-SEEKING BEHAVIOR AND LEARNING OUTCOMES IN THE COURSE?

Correlation analyses were undertaken as an initial step to understand the relationship between outcome and predictor variables in the model (see Table 2 below). In regard to the outcome variables, overall course performance (grade) was found to be positively correlated with task value ($r = 0.31$, $p < .001$) and affect ($r = 0.36$, $p < .001$) and negatively correlated with cost ($r = -0.20$, $p = .01$). Adaptive help-seeking was positively correlated with task value ($r = 0.26$, $p = .006$) and negatively correlated with cost ($r = -0.19$, $p = .042$), whereas avoidant help-seeking was only negatively correlated with task value ($r = -0.24$, $p = .012$).

When examining predictor variables, attitudes towards statistics (affect and difficulty) were found to be positively correlated with each other ($r = 0.35$, $p < .001$), self-efficacy ($r = -0.45$, $p < .001$ and $r = 0.23$, $p = .002$) and task value (affect only $r = 0.51$, $p < .001$) and negatively correlated with cost (affect only $r = -0.45$, $p < .001$). Task value was also found to be positively correlated with self-efficacy ($r = 0.15$, $p = .047$) and negatively correlated with cost ($r = -0.24$, $p < .001$).

Table 2. Correlations between performance, end of semester help-seeking, and beginning of semester non-cognitive factors

	1	2	3	4	5	6	7	8
1. Overall Grade (Percent)	—	.11 .233	-.26 .004	.31 < .001	-.20 .010	-.09 .212	.36 < .001	.04 .636
2. Adaptive HS (T2)		—	-.39 < .001	.26 .006	-.19 .042	-.05 .569	.17 .065	-.03 .792
3. Avoidant HS (T2)			—	-.24 .012	.09 .368	.17 .069	-.14 .129	-.04 .675
4. Task Value (T1)				—	-.28 < .001	.15 .047	.51 < .001	-.02 .801
5. Cost (T1)					—	-.06 .396	-.45 < .001	-.26 < .001
6. Self-efficacy (T1)						—	.34 < .001	.23 .002
7. SATS Affect (T1)							—	.35 < .001
8. SATS Difficulty (T1)								—

Note. HS = Help-seeking

Performance. A regression model revealed higher levels of affect were associated with higher student grades (%) in the course ($p < .001$) and high levels of self-efficacy were associated with decreases in student grades (%) ($p < .01$).

Table 3. Regression predicting student overall grade (percent)

Effect	Estimate	SE	95% CI		t	p
			LL	UL		
Affect	3.44	.93	1.61	5.26	3.71	<.001
Difficulty	-.50	.98	-2.43	1.43	-.51	.607
Task Value	1.15	.68	-.20	2.50	1.69	.093
Cost	-.15	.67	-1.46	1.65	-.22	.823
Self-efficacy (LOs)	-2.42	.92	-4.23	-.60	-2.63	.009

Note. $R^2 = .19$. $R^2_{Adj} = .16$. $F(5,167) = 7.72$, $p < .001$. SE = Standard Error. CI = Confidence Interval; LL = Lower Limit; UL = Upper Limit.

Retention. Binary logistic regression model statistics revealed the addition of non-cognitive factors did not explain a significant amount of variance above the null model ($F(5,169) = 1.72$, $p = .13$).

Adaptive help-seeking behaviors. Regression model statistics revealed the addition of non-cognitive factors did not explain a significant amount of variance above the null model ($F(5,107) = 2.23$, $p = .057$).

Avoidant help-seeking behaviors. Regression analyses revealed lower task value and higher average self-efficacy at the beginning of the semester were related to higher levels of avoidant help-seeking behaviors at the end of the semester.

Table 4. Regression predicting end of semester avoidant help-seeking

Effect	Estimate	SE	95% CI		t	p
			LL	UL		
Affect	-.36	.49	-1.32	.61	-.73	.464
Difficulty	-.40	.52	-1.41	.67	-.71	.482
Task Value	-.72	.36	-1.43	-.02	-2.03	.045
Cost	-.10	.37	-.84	.64	-.28	.781
Self-efficacy (LOs)	1.14	.52	.12	2.17	2.20	.029

Note. $R^2 = .10$. $R^2_{Adj} = .06$. $F(5,107) = 2.33$, $p = .047$. SE = Standard Error. CI = Confidence Interval; LL = Lower Limit; UL = Upper Limit.

5. DISCUSSION

The current study investigated the development of student motivation and its impact on student outcomes in a calculus-based introductory statistics course. The study adds to the current literature through its investigation of an under-investigated population (engineering students) using multiple measures of non-cognitive factors (attitudes, self-efficacy, task value, and cost) over the course of a semester. Although the generalizability of our findings are somewhat limited due to the sampling method (convenience) and population (predominantly engineering students) and there is a need for broader follow up studies to solidify, confirm, and/or support these findings, the current work still

provides valuable insight to those investigating introductory statistics education at the undergraduate level.

Findings from our first research question appear to show that student motivation decreases over the course of a semester. Students viewed statistics negatively, perceiving it as more difficult, less valuable, and more costly to engage in as the semester progressed. Further, students also reported an increase in avoidant help-seeking behaviors (i.e., not seeking help when needed) by the end of the course. Negative perceptions towards statistics have been shown in introductory statistics classrooms previously (e.g., Ben-Zvi & Garfield, 2004), however, our findings provide mixed support for the prior literature conducted primarily with non-engineering populations, contradicting general research on ATS (e.g., Evans, 2007) that have shown attitudes to be relatively stable over time, and supporting previous research in value that has shown a decline over the first few years of college (Robinson et al., 2019).

There are two possible explanations for the current findings: 1) the shift in motivation represents students becoming more realistic in their judgments of their motivation, or 2) the traditional introductory statistics classroom is not motivating to the examined population of students. Research has shown students enter higher education with relatively high motivation levels (e.g., value; Robinson et al., 2019) as well as show miscalibration in their motivational beliefs (e.g., Talsma et al., 2019). It could be argued that these levels could resemble "overconfidence", or inflated value and attitudes, due to a lack of prior experience or disproportionate perceptions of what higher education statistics courses entail. The downward trend in motivation across the semester could therefore reflect students in the course becoming more familiar with college level statistics and being more realistic in their perceptions of the value of statistics, which potentially change attitudes towards it.

An alternate explanation is that the structure and course materials used in the examined introductory classroom were demotivating to students. Although the introductory statistics classroom has undergone significant pedagogical changes in recent years, it could be that these changes (as applied in the sampled course) may not be enough to impact students' perceptions of their motivation towards statistics Due to the use of questionnaires with Likert-type items we do not know why students provided their specific responses (Gal & Ginsberg, 1994). Based on this, it is difficult for us to know whether the decrease in motivation evidenced in the current study is related to students having unrealistic expectations, negative experiences with the course structure and instructional materials, or an interaction between these factors. We recommend that future research explore qualitative methods that allow students to provide interpretations of their own motivational changes across the course of a semester to both provide insight and minimize potential researcher bias when interpreting changes in motivational responses.

Our inclusion of multiple measures of motivation in models predicting student achievement, retention, and help-seeking in our second research question expands upon prior research findings that have commonly investigated motivational constructs in isolation (Robinson et al., 2019). Findings contradicted prior literature (e.g., Guo et al., 2016; Robinson et al., 2019), suggesting that student motivation does not predict course retention in the current course. This discrepancy could be due to the inclusion of multiple measures of motivation weakening the potential predictive power of individual constructs in the models.

Motivation in the form of affect and self-efficacy was shown to predict overall grade. These results would suggest that in the current course students' positive and negative feelings concerning statistics are more predictive than aspects of value (task value and cost). Our finding that the more positively a student views the field of statistics, the better they will perform replicates prior literature in the field (e.g., Emmioğlu & Çapa-Aydın, 2012). Alongside this, we found that the higher students rated their abilities in the course learning objectives at the beginning of the course, the worse they performed. This contradicts the commonly found relationship between self-efficacy and performance (e.g., Zare et al., 2011). Similar to RQ 1, a possible explanation for this finding is that students with high perceptions of their ability to complete course learning objectives were exhibiting a form of overconfidence and were overestimating their abilities. Overconfidence (in the form of high levels of self-efficacy) has been shown to be related to poor performance as a result of students feeling (incorrectly) that they do not need to put as much effort into their learning (e.g., Nasir & Iqbal, 2019). It could be that students in the current course focused their efforts on other tasks, rather than spending time engaging with course content. As noted previously, the use of qualitative methods may allow researchers to further understand students' thinking as they progress through the course and the reference points that guide their

perceptions. This could also be beneficial in understanding changes in students' study habits or engagement with course content because of their perceptions of statistics.

Findings for help-seeking tendencies were mixed, with non-cognitive factors predicting tendencies toward avoidant help-seeking but not adaptive help-seeking. In particular, lower task value and higher average self-efficacy at the beginning of the course were related to higher levels of avoidant help-seeking behaviors at the end of the course. The relationship observed with task value in our current population is in line with prior findings of negative correlations between the two constructs (Chowdhury & Halder, 2019; Karabenick, 2003). However, the general perspective that value (amongst other motivational variables) is a pre-requisite to asking for help (Black & Allen, 2019) cannot be fully supported as we did not see a replication of previously observed relationships between value and adaptive help-seeking (Chowdhury & Halder, 2019). The finding that students' lower value at the beginning of the course predicts increases in help-seeking suggests that as instructors we should try to increase students' perceived value as they enter the course. A possible line of research expanding from this work is the implementation of value-reappraisal interventions (Acee, 2023; Acee et al., 2018). These interventions involve embedding value-laden messages as to why academic tasks may be personally significant to students and/or including activities that help students to explore the potential value of academic tasks in the course content. This allows for investigation into whether the elevation of levels of task value in students may indirectly remediate higher levels of non-beneficial tendencies to seek help.

Two possible hypotheses have been cited in the literature as explaining the relationship between self-efficacy and help-seeking: the vulnerability hypothesis and the consistency hypothesis (Ng, 2014). The "vulnerability hypothesis" states that the refusal to ask for help is due to low academic self-efficacy students wanting to avoid being perceived as unable or dumb whereas the "consistency hypothesis" proposes that high efficacy students seek less help because it is not consistent with their self-perception of competence (Ng, 2014). The finding that higher average self-efficacy was linked to increase in avoidant help-seeking in the current study appears to support the consistency hypothesis, contradicting the "vulnerability hypothesis" and systematic reviews of the literature that has suggested non-adaptive help-seeking is related to low self-efficacy (Chowdhury & Halder, 2019). As the current study only measured tendencies towards help-seeking, it is unclear the extent to which student behaviors in the course matched the consistency hypotheses. It would therefore not only be beneficial for follow up studies to take a measure of help-seeking behavior in the course but also the reasons why students did (or did not) obtain help.

5.1. PRACTICAL IMPLICATIONS

Literature in the field of statistics education has been calling for reform in introductory statistics courses for more than two decades (e.g., Cobb & Moore, 1997). Updating courses to focus on concepts, reasoning, and thinking instead of formulas and mathematical calculations has long been associated with increases in student motivation and satisfaction (Garfield et al., 2002). Many of the papers written about this shift in focus are targeted at the general undergraduate population. The data collected from these calculus-based introductory statistics classes for engineers suggests that this pattern holds despite students' affinity for mathematics. The relative simplicity of the math in an introductory statistics course could lead this population to be overconfident, which then negatively impacts their grades. Focusing on concepts as opposed to formulas may serve to differentiate statistics from mathematics (Cobb & Moore, 1997) and help students understand the importance of statistical thinking specifically in engineering.

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