Engagement as a Mediator of the Relationship Between

Motivation and Academic Achievement

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Abstract

Most researchers have studied self-regulated learning (SRL) in contrived lab settings or during brief windows of time, but SRL is temporal, sequential, and adaptive, meaning that it is best understood in situ, over an extended period of time. However, there are few research studies of SRL in this longitudinal context. Researchers have found that motivation is a strong predictor of academic achievement, but there are other variables that may play a role in this relationship. In the present study, I conducted secondary data analysis on a large-scale dataset, collected from undergraduate biology students who participated in a semester-long study that monitored course progress. Specifically, I ran mediation analyses to determine whether engagement acts as a mediator in the relationship between motivation and academic achievement. The results suggested that engagement acts as a partial mediator between motivation and academic achievements for students who reported high levels of mastery and performance approach motivation goals. Additionally, findings suggested that early semester engagement may be an indicator of final exam performance. In the future, researchers might further investigate the role of engagement behaviors in SRL, as well as its relationship to motivation.

Introduction

Studies show that students' motivation is a strong predictor of their school achievement (Grant & Dweck, 2003; Kriegbaum et al., 2018). Some researchers have found that motivation is as important as, if not more important than intelligence for predicting academic achievement (Steinmayr & Spinath, 2009). Despite this, many students lack the motivation to make use of successful learning tactics (Greene, 2018; Richardson et al., 2020). Amid dissatisfaction with their education (Schnettler et al., 2020) and under a variety of pressures, some students may resort to less-productive learning tactics (e.g., cheating or avoiding challenging tasks). Other students may stop using learning tactics at all (e.g., skipping class, not completing assignments; Greene, 2018). On the other hand, some students continue to perform well in their classes by self-regulating their learning (i.e., the processes in which learners personally activate and sustain cognitions, affects, and behaviors that are systematically oriented toward the attainment of personal goals; Zimmerman & Schunk, 2011) throughout the semester.

Persisting through challenges requires a significant amount of productive motivation. There is existing literature on the topic, but important questions remain regarding the type of motivations that help some students persist through such challenges, yet others struggle to persist or give up altogether. Cognitive engagement, investment to understand content and master relevant skills, may play a role in students' persistence in SRL throughout the semester (Fredricks et al., 2004). Additionally, the roles of persistence and engagement as they relate to motivation in academic achievement have not been thoroughly examined (Zeiser et al., 2014).

By better understanding what kinds of motivations are sustaining students' engagement in SRL, future psychologists and educators may be able to help students who struggle to engage in their learning. To do that, it is important to measure what types of productive motivations students report as helping them to sustain their motivation. In this study, I explored the relationships between students who show high levels of motivation, measured through self-reports, and digital trace data representative of engagement throughout the semester. Then, I investigated whether engagement operates as a mediator between motivation and academic achievement.

Self-Regulated Learning (SRL)

Researchers have suggested using SRL processes, like monitoring and managing one's learning, can lead to students using more effective learning strategies, exerting productive effort, and persistence (Ben-Eliyahu & Bernacki, 2015; Greene, 2018; Martin et al., 2021; Tse et al., 2022; Zimmerman, 1990). Self-regulated learning can be thought of as an adaptive process through which students set goals for their learning then enact strategies while monitoring, controlling, and updating their cognition, motivation, affect, and environment toward achieving that goal. Generally, self-regulated learners are characterized as active participants in their own learning (Greene & Schunk, 2018).

Self-regulated learning as a process has been operationalized in a few different ways, helping to separate different phases or paths through learning. Winne and Hadwin's (1998) model has been used in much of the research on SRL. This model includes four main phases. Stage one is task definition, and can involve stating and explaining the assignments given. Stage two is the production of learning goals and the creation of plans to meet those goals. Stage three is the enactment of strategies during learning. Finally, stage four, which takes place after the majority of learning has taken place, involves the decision of whether to implement long-term changes to beliefs, strategies, and motivation. Each stage of this model includes the use of metacognitive monitoring and control. Metacognitive monitoring involves cognition that compares one's learning to their goal; determining whether the standard of knowledge desired has been reached. Metacognitive control involves determining how to move forward based on monitoring; continue as before, adapt cognition to the task, or abandon the attempt (Winne & Hadwin, 1998).

There is evidence that SRL interventions, in which students are taught techniques and given tools to help them regulate their learning, improve academic achievement (Jansen et al., 2019). Studies have also shown that SRL behaviors are a strong predictor of academic achievement specifically in online-learning environments (Xu et al., 2022). However, researchers also find that there are statistically significant levels of variance in the enactment and effect of SRL between individual students (Jansen et al., 2019; Xu et al., 2022). Some of this variance may be due to differences in individual students' motivations.

Achievement Goal Theory

Motivation is not a static process, determined by unchanging goals; instead, prior research supports the idea that motivation is fluid and situational (Pintrich, 2000). This research has helped to establish multiple theories regarding how motivation functions in particular contexts, including achievement goal theory (AGT; Pintrich, 2000). Achievement goal theory is one way to operationalize and conceptualize motivation in academic settings. An achievement goal represents one's aim, focus, or primary reason for a particular behavior. In postsecondary school, common achievement goals could be to get a degree, to get a good job, or to learn about topics of interest. Achievement goals are viewed as cognitive representations of desired outcomes, which then direct behaviors that differ by the individual's perception of competence.

Achievement goals were specifically developed to explain achievement motivation and behavior (Pintrich, 2000).

Achievement goal theory also represents a combination of other kinds of achievement, including striving towards mastery or competency, as well as specific targets or criteria that one can use to evaluate their learning. Specifically, students have a particular “goal-orientation,” which refers to students' beliefs about success, failure, competence, ability, effort, etc. (Pintrich, 2000). AGT models assume that achievement goals can be strongly influenced by personal characteristics, making the goals themselves relatively more stable (ex. I am a hard worker and I want to learn this content). AGT also assumes that achievement goals are heavily reliant on situations, such as classroom or home contexts (ex. If I do not do well on this exam, my parents will be disappointed; Pintrich, 2000).

The literature describes two main kinds of achievement goals: mastery goals and performance goals. Generally, mastery goals are those that are centered on developing competence, increasing understanding over time, and eventually mastering a task according to one’s own internal and external standards (Jaitner et al., 2019). Performance goals, however, are those that are more focused on outperforming other students, appearing competent, or demonstrating skills (Jaitner et al., 2019). This framework has been extended by the additional definition of behaviors or goals which *approach* a positive prospect or *avoid* a negative prospect. With these terms, achievement goals can be sorted into four categories: mastery approach, mastery avoidance, performance approach, and performance avoidance. Mastery approach goals, then, are striving towards achieving mastery, and mastery avoidance goals center on *avoiding losing* competencies. Students with performance approach goals seek to perform better than other students or appear competent, while performance avoidance goals aim to *not* perform *worse* than other students, or *not* appear *incompetent* (Jaitner et al., 2019; Jokwar et al. 2014; Urdan & Kaplan, 2020).

Previous literature shows that mastery approach goals are consistently linked to adaptive processes for students (Jaitner et al., 2019; Hulleman et al., 2010). There is little research on mastery avoidance goals, and that which is published remains inconclusive (Jaitner et al., 2019). Research on performance approach goals are somewhat inconclusive, however there is some support that they lead to positive outcomes. Performance avoidance goals, on the other hand, are related to maladaptive outcomes (Jaitner et al., 2019, Harackiewicz et al., 2002).

Students' behavior is usually linked to multiple kinds of motivation simultaneously (Jaitner et al., 2019). For some students, certain motivations may be more dominant than others in determining students' behaviors towards school. Motivation researchers have suggested that students can fall into subgroups that each emphasize certain aspects of motivation over others, (i.e., some students may have more mastery goals than avoidance goals, while others have an equal amount, while still other have little of either, etc.) (Wijnia & Baars, 2021). These subgroups are often referred to as motivation profiles (Jaitner et al., 2019; Wijnia & Baars, 2021).

Cognitive Engagement

School engagement is an emerging topic in educational psychology research (Fredricks et al., 2004). Engagement in the literature is often defined in three ways; behavioral engagement, emotional engagement, and cognitive engagement (Fredricks et al., 2004). *Cognitive engagement* in the research literature is based on investment and willingness to exert effort to understand content and master relevant skills. Cognitive engagement is also often defined in terms of self-regulation; students who plan, monitor, and evaluate their learning may be described as “self-regulated” or “cognitively engaged” interchangeably. Much of the literature on cognitive engagement is definitionally similar to that of motivation. Overlapping constructs between the two include learning goals, valuing learning, and striving for mastery in academia. Additionally, cognitive engagement tends to be more closely related to mastery goals, rather than performance goals (Fredriks et al., 2004).

There are some difficulties with measuring cognitive engagement in students. As cognition is an internal process, it is not readily observable (Fredricks et al., 2004; Winne & Perry, 2000) and so it must be inferred through measurements of behaviors or self-reports. One type of behavioral measurement emerging in the field is digital trace data. Digital trace data is a record created by software that can “trace” and record a learner's actions during a digital task (Bernacki, 2018). Digital traces create large-scale rapidly collected records of participants’ data using a variety of software and technology. Online learning software such as Blackboard, Canvas, Google Classroom, or Sakai record the behaviors of students with time stamps, creating a set of data that can be examined in multiple ways (Arizmendi et al., 2022; Krumm et al., 2014).

Digital trace data from LMS has been positioned as a tool complementary to traditional methods of data collection in psychology, recommended for use in addition to traditional psychological methodology to glean insight into large, more diverse, less biased datasets that include less human error (Arizmendi et al., 2022). Digital trace data shows promise as a method for predicting student success through variables that measure students’ prior knowledge and early assignment grades (Arizmendi et al., 2022; Rafaeli et al., 2019). This data is descriptive in nature; it shows what a student *did,* but not what they were thinking when they did it, and thus does not illustrate internal cognitive processes. However, it does give a detailed overview of behaviors that are related to engagement with the course material.

Present Study

I investigated the relationships between motivation, engagement behaviors, and academic achievement throughout the semester. There is literature that supports both motivation and engagement behaviors as important factors in academic achievement, but the relationship between the two, as well as how they relate to each other and achievement, has not been thoroughly researched. Perhaps motivation leads to an increase in engagement, which subsequently leads to an increase in academic achievement. I ran multiple linear regressions to determine if engagement behaviors act as a mediator in the relationship between motivation and academic outcomes.

Hypothesis 1: First, I tested whether there were differences in academic outcomes (measuring with exam grades and course grade) between different motivation profiles. I expected that students with motivation profiles that report a high level of mastery approach and/or performance approach goals would receive higher exam and course grades than students who report low levels of mastery and/or performance approach goals and high levels of performance avoidance.

Hypothesis 2: I tested whether there were differences in engagement behaviors across the semester between different motivation profiles. I hypothesized that students with a high level of mastery approach motivations would enact more engagement behaviors than those who report a low level of mastery approach motivations. I also expected that those who report a high level of avoidance motivations would enact less engagement behaviors. Finally, I expect that performance approach motivations would not be related to engagement behaviors.

Hypothesis 3: I tested how students' engagement behaviors during the 4 units of the course related to their academic outcomes. I expected that students with higher amounts of engagement behaviors would receive higher grades for each unit exam as well as final course grade.

Hypothesis 4: Last, I tested how students' engagement behaviors mediated the relationship between their motivation profile and their academic outcomes. I expected engagement behaviors to mediate the relationship between motivation and academic outcome for students, specifically those who report high levels of mastery approach motivations.

Method

Participants

In this study, I analyzed data collected as part of an intervention study on SRL during the spring and fall semesters of 2020. Participants were students enrolled in BIO101, an introductory biology class recommended for students in a range of majors. Participants consisted of 575 students from the University of North Carolina Chapel Hill, of which 67.4% were female. Most of the students categorized themselves as white (68.3% white versus 31.7% non-white). Of the 575 students, 23.8% were first generation college students. 22.3% reported that they were either a biology major or a biology minor. Seven students were missing a grade for the final exam. Though these students had a final course grade reported, these may be "false grades" calculated by the grading software even if the student dropped the class. As there was no way to determine whether these students dropped the class or not, I decided to omit the data of these 7 students.

Procedure

During the second week of the semester, BIO101 students who consented to participate in the study completed a pre-survey containing questions related to motivation, as well as demographics and other supplemental information. The researchers conducting the intervention study also collected digital trace data from these students, which tracked their interactions with online software and other online tools used in the course. During the four units in the semester, students took three unit exams directly related to the content from that unit, and one final exam that was cumulative. As part of the initial intervention study, some students were assigned to an experimental group and others to a control. The students in the experimental group were given additional instruction on SRL and ways to monitor their learning. However, early analysis has shown that there is not a statistically significant difference in the academic behaviors or performance between the two groups. Therefore, I used data from all students, regardless of their experimental or control treatment, and did not control for condition in the analyses.

Measures

Motivation. Students completed a pre-survey in which they were asked to respond to a variety of questions about their demographics, previous knowledge of biology, and motivations. There were nine questions related to achievement goal theory, which were sourced from The Achievement Goals Questionnaire-Revised (Elliot & Murayama, 2008). There were three questions each related to relevant subscales: mastering approach, performance approach, and performance avoidance. Mastering approach items included "My aim is to completely master the material presented in this class", "My goal is to learn as much as possible", and "I am striving to understand the content in this course as thoroughly as possible." Performance approach items included "I am striving to do well in comparison to other students", "My aim is to perform well relative to others", and "My goal is to perform better than the other students." Performance avoidance items included "My goal is to avoid performing poorly compared to others", "I am striving to avoid performing worse than others", and "My aim is to avoid doing worse than other students."

Students responded to each question on a 7-point Likert-type scale. For each student, I totaled their responses to the Mastering Approach (MAP), Performance Approach (PAP), and Performance Avoidance (PAV) questions. Scores for each category ranged from 3 (selecting 1 for each prompt) to 21 (selecting 7 for each prompt). After I reviewed the distribution of the data, I grouped students post hoc into six groups based on their totals for each category (see fig. 1).

Some of my groupings were clear from the students' frequencies of answers in each category. The majority of students (77.2%) had similarly high responses for the MAP and PAP categories, and so were differentiated by their responses to the PAV questions. I named the group with high MAP, PAP, *and* PAV the Approach and Avoidant Goal Setters (group 5; 38.6%), and the group with high MAP and PAP but *low* PAV the Approach Goal Setters (group 6; 38.6%). There were also 58 students (10.0%) who responded with the highest possible answer choice for every question – these students were sorted into a separate group for analysis. I called this group Maximal Goal Pursuit (group 1). To group the remaining 85 students (14.78%), I used an exploratory approach based on the interquartile ranges of each category.

18 students (3.1%) had a score for MAP, PAP, *and* PAV that was in the lower quartile of each group. I named this group Minimal Goal Pursuit (group 4). 41 students (7.1%) had scores in the middle of the range for MAP and PAP, with a PAV score that was within 2 points of their MAP score. I named this group Mid-Low Goal Pursuits (group 3). The remaining 26 students (4.5%) had a low MAP score and a high PAV score, with a PAP score that differed from their MAP score by at least 2 points. I named this group the Avoidant Goal Setters (group 2). Figure 2 illustrates the average score on each valence for each motivation profile.

Motivation Profile Grouping

Group	N	MAP score	PAP score	PAV score
Maximal Goal Pursuit	58	21 only	21 only	21 only
Avoidant Goal Setters	26	< 18	> ± 2 MAP score	>17
Mid-Low Goal Pursuits	41	< 18	14-17	< ± 2 MAP score
Minimal Goal Pursuit	18	< 18	< 14	< 12
Approach and Avoidant Goal Setters	222	18-21	18-21	18-21
Approach Goal Setters	222	18-21	18-21	< 18

Fig. 1

Motivation Profiles by Valence Averages: MAP, PAP, and PAV

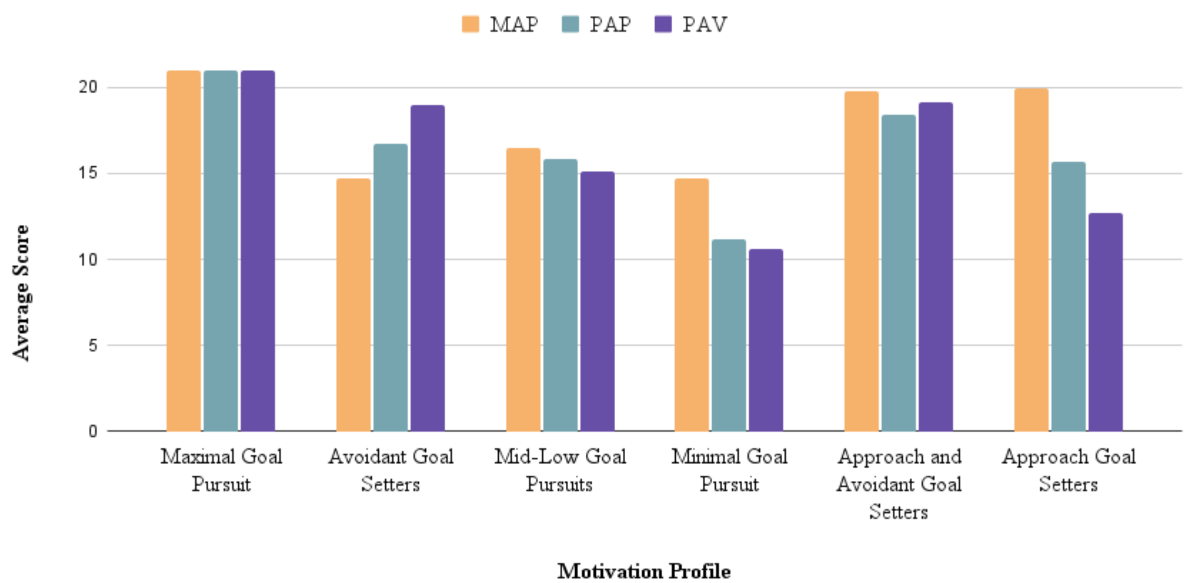

Fig. 2

Cognitive Engagement. I operationalized engagement by totaling digital trace behaviors related to the class. The digital traces captured the frequency of course related online activities, such as opening the syllabus, reading lesson pages, and downloading guided reading questions (see appendix for a full list of digital traces collected). For each student, I created a summation of their behaviors for each of the four units during the semester. This per-unit summation served as the measure of cognitive engagement for each student. Additionally, I totaled the summation of all behaviors over the semester to analyze in relation to course grades.

Academic Outcomes. I measured academic outcomes using the scores on three unit exams, the score on the cumulative final exam, as well as the final course grade. Each grade was reported as a percent out of 100. In the calculation of the final course grade, the lowest grade of the three unit exams was dropped. The calculation of the course grade consisted of the final exam grade (25%), the two highest exam grades (50%), homework average (9%), participation (7%), and quiz scores (9%).

Data Analysis Plan

Initially, I computed descriptive statistics and correlations to provide an overview of the sample. I ran ANOVAs with motivation as the predictor variable and exam grade as the outcome variable, to determine if there were statistically significant differences between groups. To determine whether a relationship between motivation and academic outcomes was mediated by engagement behaviors, I ran mediated regressions (see Figure 3), using SPSS version 28.

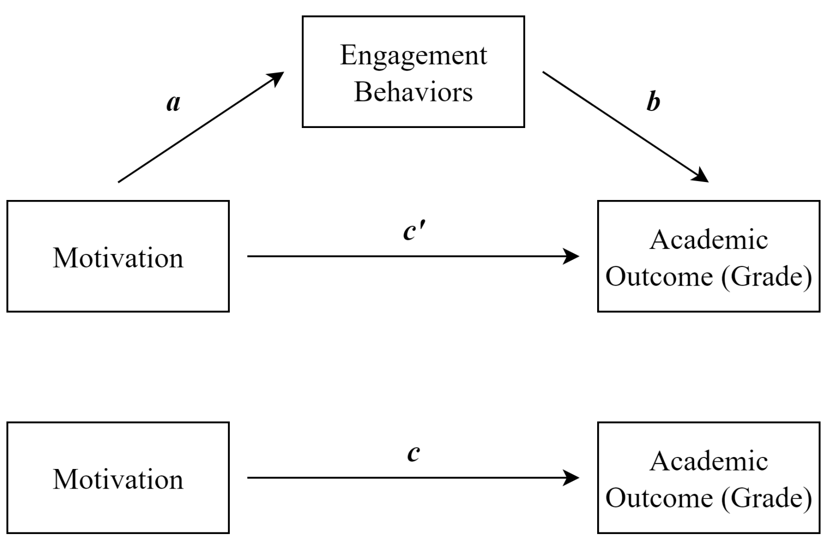

Fig. 3

First, to determine if statistically significant relationships exist between the variables for motivation, engagement, and academic outcomes, I ran multiple linear regressions. I organized my regression by outcome variables: exams 1-4 and final course grade. With each outcome variable as a dependent variable, I ran a linear regression comparing each of the six motivation profiles against the others to see if any one motivational group performed statistically significantly better or worse on the course outcomes (path *c*).

Then, I ran another regression with each outcome variable including both motivation *and* engagement behaviors as independent variables to determine the relationship between motivation groups and academic outcomes when accounting for engagement, as well as the relationship between engagement and academic outcomes (path *c'* and path *b*). Then, I ran a regression with motivation as an independent variable and engagement behaviors as the dependent variable to determine the relationship between motivation profiles and engagement (path *a*). Finally, I calculated the test statistic using an online version of the Sobel test via quantpsy.org to determine whether and how students' engagement mediated the relationship between their motivation profile and academic outcomes.

Results

Descriptive Statistics

The average final course grade of my sample was an 85.19 (SD = 8.63), which is reported as a B on the transcript (see Table 1). The average scores on exams 1, 2, and 4 were similar with means of 77.12 (SD = 12.55), 79.60 (SD = 14.63), and 78.84 (SD = 13.44) respectively. The average score on exam 3 was slightly higher, at 85.00 (SD = 10.26). Unit 1 engagement behaviors were the highest of the four units, with a mean of 622.33 behaviors (SD = 151.03). Unit 2 engagement behaviors decreased to a mean of 291.32 behaviors (SD = 50.60), and unit 3 engagement behaviors further decreased to a mean of 188.21 behaviors (SD = 37.41). Unit 4 engagement behaviors then increased to a mean of 319.82 behaviors (SD = 62.75). Exam and course grades were all highly correlated with one another (see Table 3). Every correlation was statistically significant at the 0.01 level, suggesting that performance on each exam was a strong predictor for performance on the other exams, as well as course grade.

Q1: Are There Differences in Academic Outcomes Between Different Motivation Profiles? (Path *c*)

When testing the direct effect of motivation profile on exam 1 grade, regression findings suggested some statistically significant differences. When compared to the Mid-Low Goal Pursuits group, both the Approach and Avoidant Goal Setters group (β = 0.257, p = 0.002) and the Approach Goal Setters group (β = 0.274, p = 0.001) had statistically significantly higher exam 1 scores. (See figure 4).

Exam 1 Grades by Motivation Profile

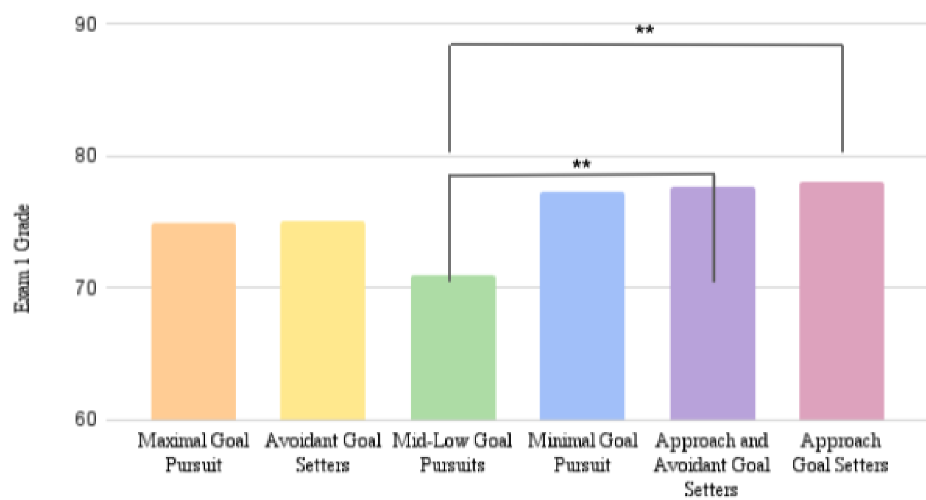

Fig. 4

On exam 2, the Approach Goal Setters had statistically significantly higher scores than the Maximal Goal Pursuit group. ($\beta = 0.176$, $p = 0.016$; see figure 5).

Exam 2 Grades by Motivation Profile

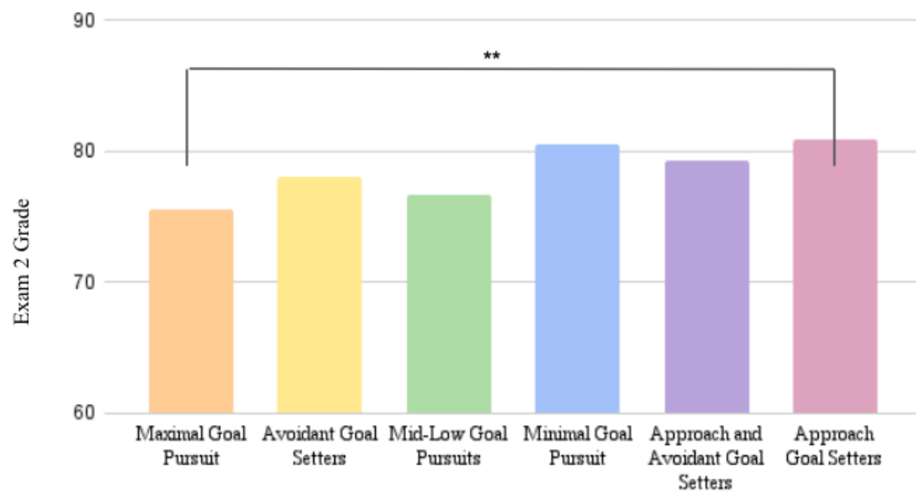

Fig. 5

On exam 3, the Approach Goal Setters group had statistically significantly higher grades than the Mid-Low Goal Pursuits group ($\beta = 0.201$, $p = 0.020$), which was also statistically significant in the exam 1 regressions (see figure 6).

Exam 3 Grades by Motivation Profile

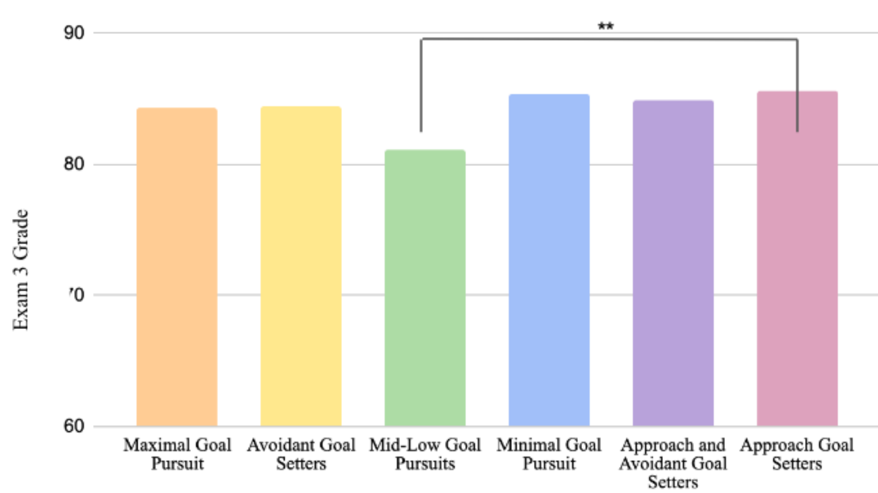

Fig. 6

On exam 4, the Approach and Avoidant Goal Setters group (β = 0.228, p = 0.008) and the Approach Goal Setters group (β = 0.294, p = 0.011) earned statistically significantly higher grades than the Mid-Low Goal Pursuits group. Additionally, the Approach and Avoidant Goal Setters group received statistically significantly higher grades than the Minimal Goal Pursuit group (β = 0.237, p = 0.047). In addition, the Maximal Goal Pursuit Group earned statistically significantly higher grades than the Mid-Low Goal Pursuit Group (β = -0.103, p = 0.048).

Exam 4 Grades by Motivation Profile

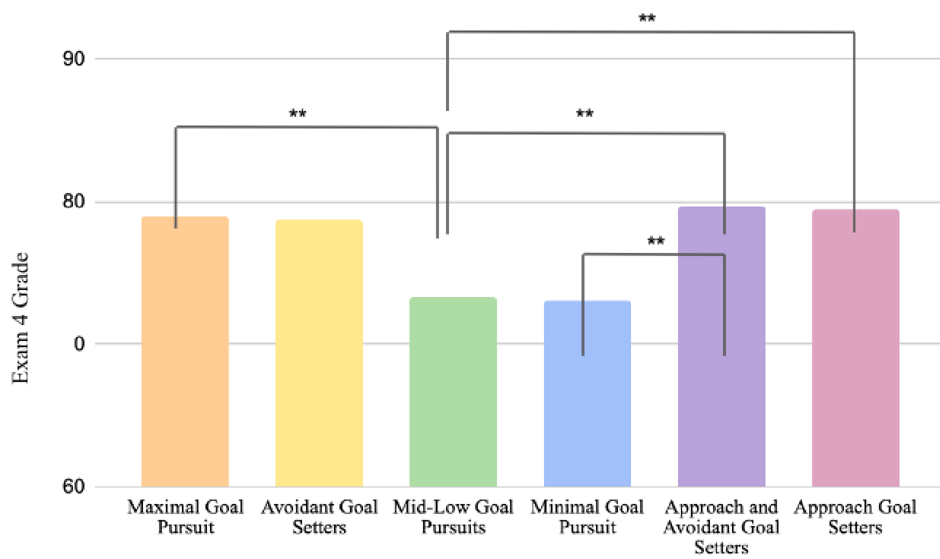

Fig. 7

The statistically significantly higher grades of the Approach Goal Setters group supports my hypothesis that those with high performance and/or mastery approach goals would receive better grades. The high achievement of the Approach and Avoidant Goal Setters group also supports this part of my hypothesis, though it is in contrast to my expectation that high avoidance would be linked to worse grades.

Q2: Are There Differences in Engagement Behaviors Across the Semester Between Different Motivation Profiles? (Path *a*)

When testing the relationship between the different motivation profiles and engagement behaviors for unit 1, regressions suggested that the Approach and Avoidant Goal Setters group engaged in statistically significantly more behaviors than the Maximal Goal Pursuit group (β = 0.193, $p = 0.007$).

Unit 1 Engagement Behaviors by Motivation Profile

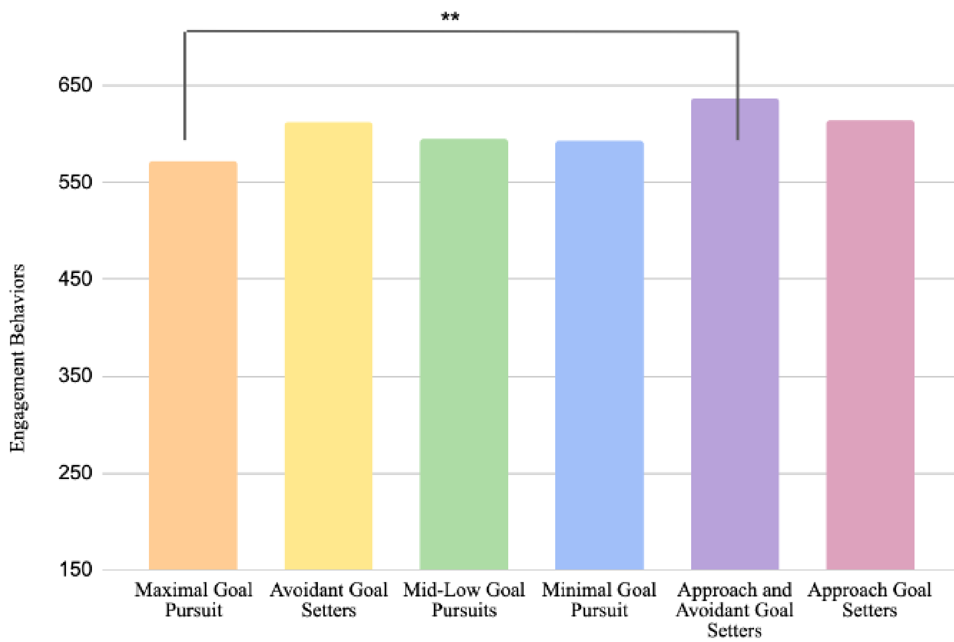

Fig. 8

For unit 2, the Approach and Avoidant Goal Setters group engaged in statistically significantly more behaviors than the Approach Goal Setters group (β = -0.110, $p = 0.017$).

Unit 2 Engagement Behaviors by Motivation Profile

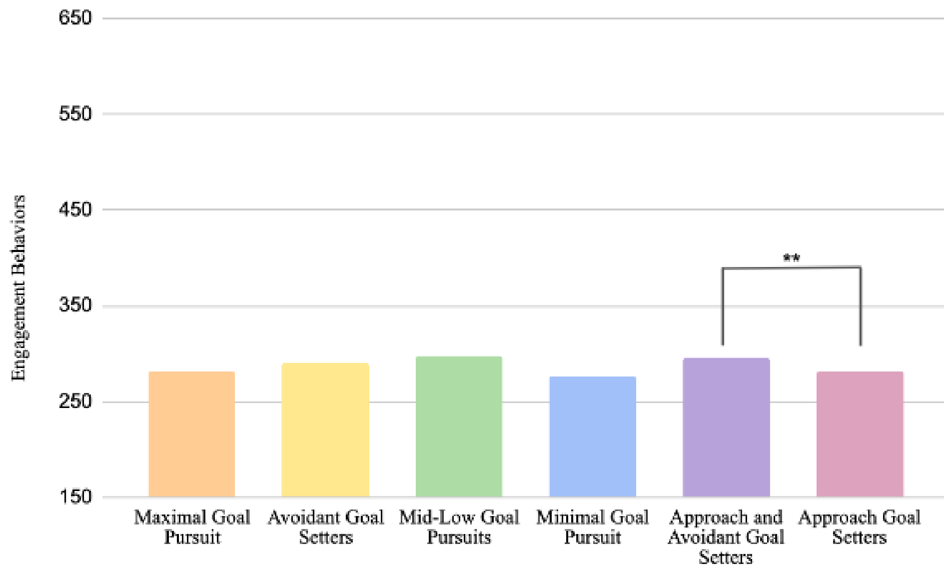

Fig. 9

For unit 3, regressions suggested that the Approach and Avoidant Goal Setters group engaged in statistically significantly more behaviors than the Minimal Goal Pursuit group (β = 0.234, p = 0.049).

Unit 3 Engagement Behaviors by Motivation Profile

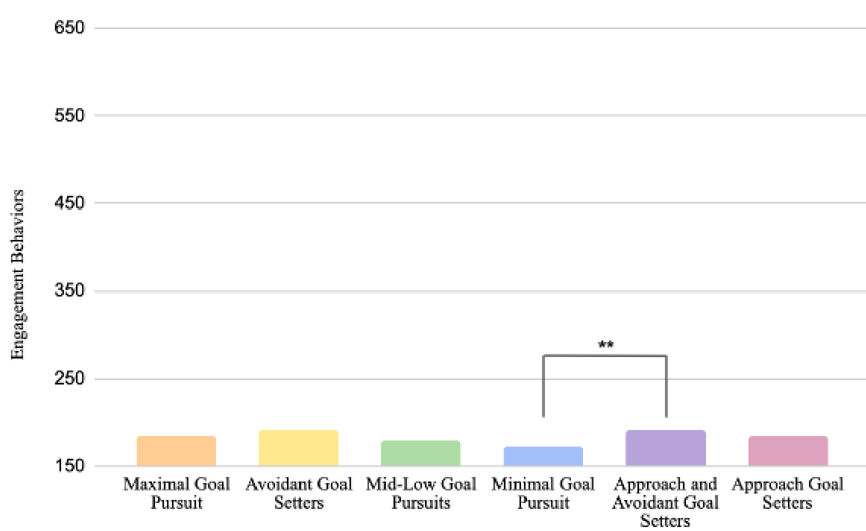

Fig. 10

For unit 4, the Approach and Avoidant Goal Setters group engaged in statistically significantly more behaviors than the Mid-Low Goal Pursuits group ($\beta = 0.210$, $p = 0.011$).

Unit 4 Engagement Behaviors by Motivation Profile

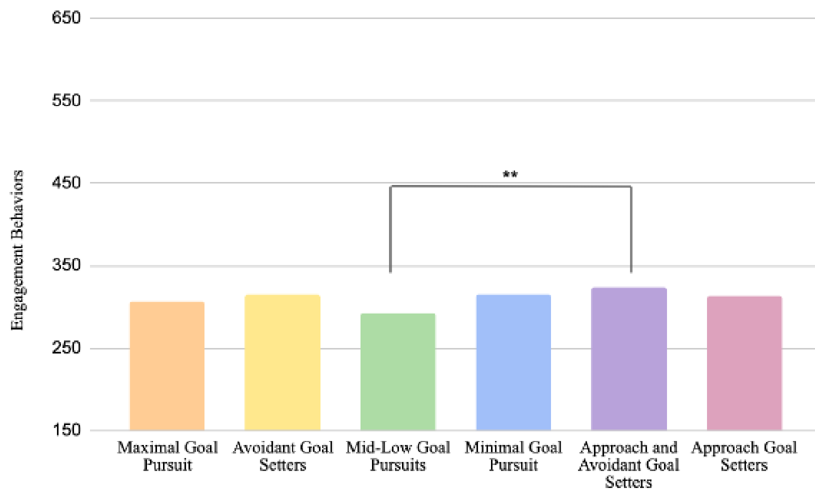

Fig. 11

When I totaled the engagement behaviors for the entire semester, regressions suggested that the Approach and Avoidant Goal Setters engaged in statistically significantly more behaviors than both the Maximal Goal Pursuit group ($\beta = 0.182$, $p = 0.011$), and the Approach Goal Setters ($\beta = -0.092$, $p = 0.046$).

The high performance of the Approach and Avoidant Goal Setters throughout supports my hypothesis that students with high mastery approach goals would enact more behaviors, while also refuting my hypothesis that students with high performance avoidance would enact less behaviors. For the final exam grade, the statistically higher amount of behaviors enacted by the Approach Goal Setters supports both parts of my hypothesis.

Q3: How Do Students' Engagement Behaviors Relate to Their Academic Outcomes? (Path *b*)

There were some statistically significant correlations between grades and engagement behaviors. Exam 1 grade was highly correlated with unit 1 behaviors, and exam 4 grade was correlated with unit 4 behaviors, but exams 2 and 3 were not statistically significantly correlated with their respective unit behaviors. Unit 1 behaviors were also statistically significantly correlated with exam 3 and exam 4, and unit 4 behaviors were statistically significantly correlated with both course grade and exam 1. This is unexpected, as unit 3 behaviors were not correlated with exam 3 grades, and there were few other cross-unit correlations (See table 4).

When testing the relationship between engagement behaviors and academic outcomes for each unit, regression findings suggested a statistically significant relationship for exam 1 ($\beta = 0.124$, $p = 0.003$), exam 4 ($\beta = 0.104$, $p = 0.013$), and final course grade ($\beta = 0.328$, $p < 0.001$). However, this relationship was not statistically significant for exams 2 and 3 (See tables 5-9).

The significance of the relationship between behaviors and academic outcomes for exams 1 and 4, as well as final course grade supports my hypothesis that higher behaviors would be linked to better grades. However, the lack of statistically significant relationship for exams 2 and 3 does not support my hypothesis.

Q4: How Do Students' Engagement Behaviors Mediate the Relationship Between Their Motivation Profile and Their Academic Outcomes? (Path *c'*)

According to the Sobel test, the difference in achievement scores between the Approach and Avoidant Goal Setters and the Maximal Goal Pursuit groups was mediated by engagement for both the Exam 1 (test statistic = 2.102) and the final course grade (test statistic = 2.374) outcomes. The mean grade on Exam 1 for the Approach and Avoidant Goal Setters was 77.65%, and the mean grade on Exam for the Maximal Goal Pursuit group was 74.96%. The mean final course grade for the Approach and Avoidant Goal Setters was 85.19% and the mean final course grade for the Maximal Goal Pursuit Group was 83.39%. Both the Exam 1 and final course grade analyses, neither the c path nor the c' path was statistically significant. However, both groups did have statistically significant differences on the mediator (path a) and the mediator did have a statistically significant relationship with the academic outcome (path b). Additionally, as shown by the Sobel test statistic, there was a statistically significant combined relationship between the group and each outcome, through the mediator. These analyses revealed a relationship between group members and academic outcomes that may not have been seen had the mediator not been collected and analyzed.

Discussion

Researchers have found that motivation is a strong predictor of students' academic achievement (Grant & Dweck, 2003; Kriegbaum et al., 2018). Furthermore, researchers have suggested that engagement is similar to motivation in the way that it relates to academic achievement (Fredricks et al., 2004). However, the role of motivation in the act of engagement, as well as whether engagement mediates the relationship between motivation and academic achievement, have not been thoroughly examined. The main aim of my study was to investigate these relationships between engagement, motivation, and academic outcomes. Specifically, I investigated whether engagement acts as a mediator in the relationship between motivation and academic achievement among students in an undergraduate introductory biology course.

In terms of my first research question, there were some differences in academic outcomes between different motivation profiles. My finding of differences between the Mid-Low Goal Pursuit group and the Approach and Avoidant Goal Setters and Approach Goal Setters on multiple academic outcomes suggested a relationship between motivation and academic outcomes. Specifically, the Approach and Avoidant Goal Setters and Approach Goal Setters both reported high levels of Mastery and Performance approach goals, and also earned higher grades than those in the Mid-Low Goal Pursuit group, which had relatively low levels of Mastery and

Performance approach goals. With my second research question, I asked whether there was a difference in the number of engagement behaviors between motivation profiles. I found that there were statistically significant differences. Specifically, once again, the Approach and Avoidant Goal Setters engaged in statistically significantly more engagement behaviors than at least one other group in each of the four units over the semester.

For my third research question, I asked how students' engagement behaviors related to their academic outcomes. Here, I found some unexpected results. Unit 1 behaviors were most strongly correlated with exam 4 grades, followed by exam 1. This was surprising, especially considering the time difference between unit 1 and the unit 4 exam. This suggests that engagement behaviors at the beginning of the semester may be important predictors of subsequent performance throughout the whole semester and may serve as a predictor of final course grade. These findings align with the adaptive and contextual nature of self-regulated learning, in which effective self-regulating learners do not necessarily need to be highly engaged in all learning behaviors at all times, but rather may need to be adaptively engaged in the most helpful learning behaviors at the right time (Ben-Eliyahu & Bernacki, 2015; Greene, 2018). These findings may also suggest that engaging more at the beginning of the semester, and then making use of a timely adaptation to a less engaged approach, may be necessary for sustaining productive engagement that enhances academic outcomes throughout the semester (Rakovic et al., 2022).

Finally, in my fourth research question, I asked how students' engagement behaviors mediated the relationship between motivation and academic outcomes. I found evidence that engagement functions as a mediator when comparing the academic performance of the Approach and Avoidant Goal Setters and the Maximal Goal Pursuit group. However, these results were only statistically significant for Exam 1 and the final course grade. These findings may suggest that engagement functions as a mediator at some points during the semester, but not at all times. Interestingly, this is related to my findings in the correlations between engagement behaviors and performance: the engagement in a specific unit may not necessarily relate to the academic outcome of that unit, but it may be related to the outcome of another unit, or the final course grade for the whole semester.

Limitations and Future Directions

One notable limitation of this study was the timeframe during which data was collected. I utilized data from spring and fall semesters of 2020, during which the Covid-19 pandemic significantly impacted college students' learning experience. Data collection as well as class content delivery was interrupted by a shift from in-person learning to virtual learning during both semesters. Because of this unique circumstance, these findings can not be extrapolated broadly to students in years other than 2020. Also, initially, I planned to control for potential differences between the two semesters by running analyses separately for the two semesters, however, the sample sizes when separated by semester were too small to provide meaningful results.

Another limitation was the small range of motivation responses of my sample. Most of the students responded to the motivation survey items with high levels of motivation. Ideally, when investigating differences among motivations, I would have been able to collect a sample that included students who reported a wider range of motivations. Similarly, because of the number of regressions conducted, it is possible that some of my statistically significant findings are due to Type 1 error.

Conclusion

Overall, I found data suggesting that engagement partially mediated the relationship between motivation and academic outcomes, in particular for students with lower goals compared to those with higher levels of mastery and performance approach goals. However, more research is needed to determine the practical significance and implications for practice of these relationships. In the future, it will be important to study the relationships among motivation, engagement, and academic achievement with different populations of students, because the population used in this study skewed towards high levels of motivation. Future analysis of the role of engagement may further understanding of the relationship between motivation and academic achievement. An understanding of the role of engagement in the relationship between motivation and academic achievement may be specifically helpful for educators as they structure their assignments (Pintrich, 2000).

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Tables

Table 1: ***Descriptive Statistics***

Variable	Minimum	Maximum	Mean	Std. Deviation
Course Grade	44.43	99	85.1851	8.627
Exam 1 Grade	39.4	101.02	77.1232	12.546
Exam 2 Grade	31	100	79.603	14.643
Exam 3 Grade	42	100	85.002	10.259
Exam 4 Grade	1	101	78.839	13.439
Unit 1 Engagement Behaviors	0	1134	622.33	151.027
Unit 2 Engagement Behaviors	0	549	291.32	50.604
Unit 3 Engagement Behaviors	0	362	188.21	37.418
Unit 4 Engagement Behaviors	0	595	319.82	62.746

Table 2: ***Descriptive Statistics by Motivation Profile: Means***

Variable	MV1*	MV2	MV3	MV4	MV5	MV6
Course Grade	83.39	84.07	79.19	82.12	85.19	85.37
Exam 1 Grade	74.96	75.05	70.97	77.31	77.65	78.09
Exam 2 Grade	75.57	78.12	76.70	80.56	79.34	80.93
Exam 3 Grade	84.27	84.37	81.16	85.41	84.85	85.65
Exam 4 Grade	78.99	78.75	73.35	73.11	79.65	79.40
Unit 1 Engagement Behaviors	572.28	613.18	594.20	594.06	636.23	614.17
Unit 2 Engagement Behaviors	282.00	291.42	298.22	277.44	295.16	282.31
Unit 3 Engagement Behaviors	184.40	190.92	179.34	171.83	191.27	184.61
Unit 4 Engagement Behaviors	305.71	314.35	293.17	314.67	324.23	314.08

* Motivation Profiles 1-6, refer to *Motivation Profile Grouping*

Table 3: ***Correlation Coefficients: Grades***

Grade	Course Grade	Exam 1	Exam 2	Exam 3	Exam 4
Course Grade	1.000**	.698**	.768**	.752**	.819**
Exam 1		1.000**	.566**	.454**	.561**
Exam 2			1.000**	.488**	.561**
Exam 3				1.000**	.543**
Exam 4					1.000**

* correlation is significant at the 0.05 level
** correlation is significant at the 0.01 level

Table 4: ***Correlation Coefficients: Grades and Behaviors***

Engagement Behaviors	Course Grade	Exam 1 Grade	Exam 2 Grade	Exam 3 Grade	Exam 4 Grade
Unit 1	0.018	.113**	0.008	-.138**	.124**
Unit 2	0.005	-0.027	-0.003	-0.065	-0.075
Unit 3	.179**	0.076	0.029	0.034	0.035
Unit 4	.253**	.132**	0.06	0.072	.103*

* correlation is significant at the 0.05 level
** correlation is significant at the 0.01 level

Table 5: ***Exam 1 Regression Coefficients***

Motivations	a path	b path	c path	c' path	Sobel statistic
mv1 x mv2	.053	.124**	.002	-.002	1.043
mv1 x mv3	.035	.124**	-.079	-.081	0.657
mv1 x mv4	.023	.124**	.032	.032	0.499
mv1 x mv5	.193**	.124**	.104	.087	2.102*
mv1 x mv6	.127	.124**	.121	.113	1.567
mv2 x mv3	-.031	.124**	-.081	-.078	-0.484
mv2 x mv4	-.021	.124**	.031	.034	-0.399
mv2 x mv5	.068	.124**	.100	.093	0.662
mv2 x mv6	.001	.124**	.117	.118	0.011
mv3 x mv4	.000	.124**	.087	.088	-0.003
mv3 x mv5	.127	.124**	.257**	.244**	1.402
mv3 x mv6	.060	.124**	.274**	.269**	0.717
mv4 x mv5	.127	.124**	.013	-.002	1.023
mv4 x mv6	.061	.124**	.030	.023	0.507
mv5 x mv6	.067	.124**	-.017	.025	1.331

Table 6: ***Exam 2 Regression Coefficients***

Motivations	a path	b path	c path	c' path	Sobel statistic
mv1 x mv2	.034	0.073	.035	.034	0.654
mv1 x mv3	.073	0.073	.019	.009	1.095
mv1 x mv4	-.014	0.073	.059	.061	-0.294
mv1 x mv5	.113	0.073	.123	.117	1.171
mv1 x mv6	.003	0.073	.176*	.179*	0.037
mv2 x mv3	.031	0.073	-.024	-.032	0.462
mv2 x mv4	-.042	0.073	.029	.032	-0.732
mv2 x mv5	.032	0.073	.040	.037	0.314
mv2 x mv6	-.078	0.073	.092	.099	0.314
mv3 x mv4	-.063	0.073	.045	.055	-1.040
mv3 x mv5	-.026	0.073	.086	.099	-0.313
mv3 x mv6	-.136	0.073	.139	.161	-1.202
mv4 x mv5	.151	0.073	-.040	-.053	1.032
mv4 x mv6	.042	0.073	.012	.009	0.344
mv5 x mv6	-.110*	0.073	.052	.062	-1.413

* correlation is significant at the 0.05 level
** correlation is significant at the 0.01 level

Table 7: ***Exam 3 Regression Coefficients***

Motivations	a path	b path	c path	c' path	Sobel statistic
mv1 x mv2	.033	.050	.002	-.001	0.599
mv1 x mv3	-.032	.050	-.071	-.073	-0.550
mv1 x mv4	-.054	.050	.018	.021	-0.839
mv1 x mv5	.083	.050	.026	.024	0.839
mv1 x mv6	.003	.050	.062	.064	0.036
mv2 x mv3	-.073	.050	-.073	-.072	-0.821
mv2 x mv4	-.082	.050	.016	.022	0.292
mv2 x mv5	.004	.050	.021	.027	0.197
mv2 x mv6	-.076	.050	.058	.067	0.494
mv3 x mv4	-.032	.050	.067	.071	0.899
mv3 x mv5	.144	.050	.165	.169	1.025
mv3 x mv6	.064	.050	.201*	.208*	1.077
mv4 x mv5	.234*	.050	-.025	-.036	-0.205
mv4 x mv6	.154	.050	.011	.004	0.088
mv5 x mv6	-.080	.050	.036	.040	0.655

Table 8: ***Exam 4 Regression Coefficients***

Motivations	a path	b path	c path	c' path	Sobel statistic
mv1 x mv2	.025	.104*	-.004	-.008	0.500
mv1 x mv3	-.045	.104*	-.103*	-.104*	-0.808
mv1 x mv4	.022	.104*	-.076	-.074	0.455
mv1 x mv5	.135	.104*	.024	.021	1.417
mv1 x mv6	.057	.104*	.015	.019	0.753
mv2 x mv3	-.075	.104*	-.099	-.094	-1.059
mv2 x mv4	.001	.104*	-.073	-.067	0.015
mv2 x mv5	.067	.104*	.032	.041	0.642
mv2 x mv6	-.002	.104*	.023	.040	-0.018
mv3 x mv4	.052	.104*	-.003	0.009	0.971
mv3 x mv5	.210*	.104*	.228**	.227**	1.745
mv3 x mv6	.141	.104*	.219*	.226**	1.397
mv4 x mv5	.065	.104*	.237*	.227	0.531
mv4 x mv6	-.004	.104*	.228	.226	-0.033
mv5 x mv6	-.069	.104*	-.009	-.001	-1.269

* correlation is significant at the 0.05 level
** correlation is significant at the 0.01 level

Table 9: ***Final Course Grade Regression Coefficients***

Motivations	a path	b path	c path	c' path	Sobel statistic
mv1 x mv2	.050	.328**	.014	-.003	1.015
mv1 x mv3	.019	.328**	-.103*	-.113*	.369
mv1 x mv4	.009	.328**	-.021	-.019	.185
mv1 x mv5	.182*	.328**	.086	.038	2.374*
mv1 x mv6	.090	.328**	.094	.078	1.240
mv2 x mv3	-.042	.328**	-.120	-.110	-.663
mv2 x mv4	-.033	.328**	-.033	-.017	-.625
mv2 x mv5	.065	.328**	.053	.045	.641
mv2 x mv6	-.027	.328**	.062	.085	-.271
mv3 x mv4	-.004	.328**	.050	.059	-.090
mv3 x mv5	.145	.328**	.285**	.258**	1.707
mv3 x mv6	.054	.328**	.294**	.298**	.649
mv4 x mv5	.158	.328**	.146	.092	1.304
mv4 x mv6	.066	.328**	.155	.132	0.554
mv5 x mv6	-.092*	.328**	.009	.040	-1.911

* correlation is significant at the 0.05 level
** correlation is significant at the 0.01 level

Appendix

I. Digital Traces

Description of process enacted	Inference about SRL
Starting the assessment	doing assigned work
Resuming a previously started assessment	completing started work
Submitting assessment answers	submitting assigned work
Review results of a submitted assessment	metacognitive monitoring
Viewing page in Sakai where syllabus is hosted	task knowledge acquisition
Downloading the syllabus from syllabus page or resources	task knowledge acquisition
Course documents like group assignments and accessing MasteringBio	task knowledge acquisition
Embedded tool for viewing course reserves	resources knowledge acquisition
Viewing the gradebook page in Sakai	metacognitive monitoring
Link to learning center page	help seeking
Read announcement in the Sakai (Additional instances occur via email)	diligence keeping up with course information
Use of the Piazza forum website to pose a question	help seeking
Viewing calendar events in Sakai	course information gathering
Editing calendar events	time and effort planning
Requesting a time slot during office hours	help seeking
Loading of a Lessons page in Sakai	course information gathering
Attending a session of class as recorded in Learning Catalytics	content knowledge acquisition
Class outlines are questions intended to be answered during class	goals
Slides presented during lecture that are posted after class	content knowledge acquisition
Supplemental readings provided for some lessons	content knowledge acquisition

Downloading the GRQ word doc	task knowledge acquisition
View assignment instructions	task knowledge acquisition
Start a new submission	submitting assigned work
Save a pending submission	submitting assigned work
Revise an existing pending submission	revising
Finalize and submit a response	submitting assigned work
Review a previously submitted response	monitoring for accuracy
Use hint within MasteringBio coursework	help seeking
View an item within MasteringBio coursework	help seeking
Provided the solution of an item within MasteringBio coursework	help seeking
Submit a correct answer to an item within MasteringBio coursework	submitting assigned work
Submit an incorrect answer to an item within MasteringBio coursework	submitting assigned work
Provided the solution of an item during a MasteringBio quiz	submitting assigned work
Submit a correct answer to an item during a MasteringBio quiz	submitting assigned work
Submit an incorrect answer to an item during a MasteringBio quiz	submitting assigned work
Course specific review session provided by the Learning Center	help seeking
Review sessions provided by bio department TAs and Peer Mentors	help seeking
Attending an office hours appointment with the instructor	help seeking
Attending a one-on-one peer mentoring session with bio department tutors	help seeking
Attending one-on-one academic coaching at the learning center	help seeking
Attending one-on-one writing coaching at the learning center	help seeking

Download study guide	task knowledge acquisition
Download example exam from previous semesters	task knowledge acquisition
Download example exam key from previous semesters	content knowledge acquisition
Download current semester exam file	reflection on past performance
Download key to current semester exam	reflection on past performance
Starting the practice exam	self-testing
Resuming a previously started practice exam	self-testing
Submitting practice exam answers	self-testing
Review results of a submitted practice exam	metacognitive monitoring
Downloading the reflection prompt file	task knowledge acquisition
Starting a submission of the reflection assignment	submitting assigned work
Resuming a previously started self reflection submission	completing started work
Submitting self reflection answers	submitting assigned work

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