

Exploring the Role of Students' Achievement Goals and Learning Approaches in Academic Performance

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Abstract

How students approach learning could be indicative of their cognitive engagement with the learning tasks they encounter in their engineering programs. Their cognitive engagement with learning tasks could have implication for actual performance and whether they continue to feel motivated to deeply engage with learning, or become disengaged, disinterested and eventually consider dropping out of their engineering program. However, students' approach to learning engineering material could be deeply ingrained in their achievement goal orientation – meaning that efforts at helping students to become better learners might benefit from helping them set and realize achievement goals that orientate them towards adopting productive learning habits. In this study, we examined the relationships between the achievement goals that students adopt, their approach to learning and performance in an engineering classroom. Participants included 87 students enrolled in an introductory Fluid Mechanics course. Students participated in classroom activities and exam scores as well as took measures of achievement goal and learning approach. We conducted correlational analysis of three goal types: task-related, self-related and other-related, and two learning approaches: deep learning and surface learning strategies and student's final performance in the class. Lastly, we conducted multiple regression analysis to determine the relative contribution of each variable to predicting students' academic performance. Implications of these findings for student engagement in engineering classrooms will be discussed.

Introduction

The way students engage with learning or the learning-related tasks they encounter in school are often rooted in the achievement goals they embrace [1]. The *Achievement Goal Orientation (AGO)* theory proposes that how students engage with learning is motivated by the latent achievement goals that they embrace – these achievement goals determine the depth and quality of their learning engagement. Covington (2000) argues that “all actions are given meaning, direction, and purpose by the goals that individuals seek out, and that the quality and intensity of behavior will change as these goals change” [2]. The AGO theory posits that students' motivation to engage with learning may be informed by task-related motives, in which case they seek to attain *mastery* of the learning material. Task-related goals are referred to as *mastery goal orientation* because the students who embrace such goals are mostly motivated by an aspiration to gain mastery of the material [3]. Alternatively, students' motivation to learn may be informed by ego-centric achievement goals. For example, they may be motivated by aspirations to outperform themselves (either to achieve better, or no less than their earlier performance) or other students (either to look academically better than others or to save face) [3]. The latter two types of goal motives are referred to as *performance goal orientation* [3]. Hence, performance goal orientation maybe categorized as self-focused or other-focused depending on whether achievement goal is directed towards the self or others. Students who embrace mastery goals are intent on achieving competence by seeking ways to deepen their understanding of course material, while students who are motivated by performance goals focus more on the optics of looking not-smart or performing poorer than their peers. Research has shown that students' goal orientation has implications towards their academic performance [3]. Besides goal orientation, some researchers

have proposed that the how students approach study reflects on their cognitive engagement with academic material, and may affect their performance in school [3].

The *Students Approach to Learning* (SAL) theory proposes two major levels of cognitive processes that characterizes students approach to studying: surface-level strategy approach and deep-level strategies approach [4]. Surface approach to studying is associated with rote memorization and the reproduction of facts, without making any deep cognitive connection with the learning material [5]. Deep approach describes an approach to studying or learning that is characterized by active knowledge construction and critical thinking [4]. Building on the SAL, other researchers have suggested a third approach to learning, referred to as strategic learning approach. They argue that besides surface or deep cognitive engagement, self-regulated learners are strategic about how they approach learning, and their strategy may depend on their objectives for studying a particular subject [6, 7].

Objective of the current study: Some studies have indicated that students who embrace mastery goal orientation employ the adaptive learning strategies required to master the content of a material. On the contrary, student who are motivated by performance goals tend to engage in maladaptive learning practices [1]. Because achievement motivation may inform how students study, we anticipate that students' achievement goal orientation could also reflect on study habits and consequently their academic achievement. Being able to document the relationship between students' achievement goal orientations and their learning approaches could highlight the degree to which instructional or academic coaching interventions geared towards motivating students to adopt adaptive learning strategies could promote meaningful learning.

In the current study, we examine the relationship between achievement goal orientation, learning and study approaches and student performance in an engineering classroom. Secondly, we explored the relative contributions of different goal orientations and study approaches in predicting students' achievement. Our primary objective was to understand the relative salience of goal orientation and learning approaches in determining learning outcomes. We explore the following research questions:

1. What is the nature of the relationships between students' goal orientation, learning approach and their academic achievements?
2. What is the relative contribution of goal and learning approach towards academic achievement?

Methods

Participants and Design

Participants were 86 undergraduate students enrolled in Introduction to Fluid Mechanics course in a public research institution. Their ages ranged between 19 and 41 ($M = 21.08$, $SD = 2.86$) years old. They comprised 76.3% male and 22.4% female students who are in the Sophomore (25%), Junior (50%) and Senior (23.7%) years of their undergraduate engineering program. About 22% of the participants transferred into the program from other schools. The study is based on correlational and regression analysis of three goals: task-related, self-related and other-related; and two learning approaches: deep learning and surface learning strategies and student's final exam performance (score) in the course.

Material and measures

The Revised Two-Factor Study Process Questionnaire (R-SPQ-2F): The R-SPQ-2F questionnaire is a 20-item instrument comprising 4 factors (deep motive, deep strategy, surface motive, and surface strategy) intended to measure deep and surface dimensions of student approach to learning. Participants responded using a 5-point Likert-type scale ranging from 1 (being ‘rarely true of me’) and 5 (being ‘always true of me’). The R-SPQ-2F is a revision of the earlier 43-item Study Process Questionnaire SPQ. Internal reliability coefficients for study processes scales used in this study are reported in Table 2.

Achievement Goals Questionnaire (AGQ): Students’ achievement goal orientation was measured using the 3 x 2 version of the AGQ. The instrument comprises of 18 items that measure three dimensions (Task, Self, and Other) of students’ achievement goal orientation. Items on the task orientation measured student mastery-focused goals (6 items). Self-orientation measured ego-centric goals that are focused on self-improvement (6 items), while other-orientation measured student’ ego-centric goals that informed by the desire to outperform other students in the class (6 items). Items on the sub-scales are captured on a 5-point scale ranging from 1 (not at all true) to 5 (very true). Internal reliability coefficients for achievement goal scales used in this study are reported in Table 2.

Data Collection

Students received links to complete the questionnaire online. Besides items that assessed goal orientation and learning approaches, the survey also included items to capture demographics information: age, gender, ethnicity and major. Assessment of student performance was based on their final exam on the course.

Data Analysis and Result

Preliminary analysis was conducted to explore the distribution and normality of the data. Descriptive statistics of each constructs are reported in Table 1. We conducted Pearson correlations to determine the strength and directions of the relationships between study processes, students’ achievement goal orientation and performance on the course. Correlation coefficients and internal reliability coefficients Cronbach’s alpha for each construct are reported in Table 2 below.

Table 1: Descriptive statistics of Study Constructs

	Score	Deep Learning Approach	Surface Learning Approach	Self-Related Goal	Others Related Goal	Task Related Goal
Mean	81.53	28.33	24.17	24.74	21.05	26.90
SD	8.79	5.93	5.41	4.22	5.99	3.35
Skewness	-0.26	0.37	-0.08	-1.09	-0.65	-1.13
Kurtosis	-0.53	-0.11	-0.13	1.25	-0.09	1.18

Table 2: Correlation and internal reliability coefficients of study constructs

	Performance Score	Deep Learning Approach	Surface Learning Approach	Self-Related Goal	Others Related Goal	Task Related Goal
Performance Score	1					
Deep Learning Approach	.39**	1				
Surface Learning Approach	-.33**	-.32**	1			
Self-Related Goal	-.33**	-0.01	0.21	1		
Others Related Goal	.28*	0.15	0.09	0.02	1	
Task Related Goal	.25*	0.20	-0.07	.32**	0.11	1
Cronbach		0.79	0.72	0.87	0.920	1

** Correlation is significant at the 0.01 level (2-tailed); * Correlation is significant at the 0.05 level (2-tailed)

Lastly, we conducted stepwise regression analysis to determine the relative contribution of students' typical study approach and achievement goal orientations in predicting their performance on the course. Four models of variables predicting students' performance were examined. The first model indicated that deep processing was the main predictor of students' performance $\beta = 0.39$, $t = 3.58$, $p = 0.001$. But deep processing alone only explained 15% of variance in students' performance scores, $R^2 = .15$ ($F(1, 73) = 12.81$, $p = .001$; Adj. $R^2 = .14$). The second model includes deep processing, $\beta = 0.39$, $t = 3.79$, $p < 0.001$, and self-related goal, $\beta = -0.33$, $t = -3.30$, $p = 0.002$, as explaining 26% of the variance in students' performance scores ($R^2 = .26$, Adj. $R^2 = .24$, $F(2, 72) = 12.79$, $p = .001$). The model was significant. Task-related goal was included as a significant predictor ($\beta = 0.32$, $t = 3.11$, $p = 0.003$) of students' performance on the course in the third model. The model explained 35% of the variance in students' performance ($R^2 = .35$, Adj. $R^2 = .32$, $F(3, 71) = 12.62$, $p < .001$). The fourth, and most comprehensive of the models, indicated that all three achievement goal orientations and deep processing were significant predictors of students' performance. The fourth model explained a total of 39% of the variance in students' performance ($R^2 = .39$, Adj. $R^2 = .35$, $F(4, 70) = 11.11$, $p < .001$). Regression coefficients are reported in Table 3 below.

Table 3: Regression coefficients of predictor variables in the study

		B	Std. Error	β	<i>t</i>	Sig.	R	R²
<i>Model 1</i>	Deep	0.57	0.16	0.39	3.58	0.001	.39 ^a	0.15
<i>Model 2</i>	Deep	0.57	0.15	0.39	3.79	0.000	.51 ^b	0.26
	Self - Goal	-0.69	0.21	-0.33	-3.26	0.002		
<i>Model 3</i>	Deep	0.47	0.15	0.32	3.25	0.002	.59 ^c	0.35
	Self - Goal	-0.91	0.21	-0.44	-4.29	0.000		
	Task - Goal	0.85	0.27	0.32	3.11	0.003		
<i>Model 4</i>	Deep	0.43	0.14	0.29	3.04	0.003	.62 ^d	0.39
	Self - Goal	-0.90	0.21	-0.43	-4.37	0.000		
	Task - Goal	0.80	0.27	0.30	2.99	0.004		
	Other - Goal	0.30	0.14	0.21	2.16	0.035		

Discussion and Scholarly Significance

These results show that the correlations between learning approaches and goal orientations were consistent with extant theoretical propositions of motive-as-goal theories. Deep learning strategy was positively correlated with task-related goals and other-related performance goals. It was however negatively correlated with self-related performance goals. Conversely, surface learning strategy was negatively correlated with Task-related goals and positively correlated with self-related performance goals. However, these correlations were not significant and may not express very much about the relationship between the students' learning strategies and achievement goal orientation. Besides, students' learning approaches and achievement goal orientations may be situational – that is, they may change, depending on the learning contexts. On the contrary, both SAL and AGO had significant correlations with achievement. Deep learning approach to learning was positively correlated with achievement. The direction of the relationship suggests that adopting deep approaches to learning may increase academic achievement, while adopting a surface approach could negatively reflect on academic achievement. Similarly, self-related goal orientation could negatively reflect on achievement.

The data also suggests that being motivated by the goal to outperform others has about the same effect on achievement as being motivated by the goal of achieving mastery. The finding suggests that, like being motivated by mastery, being motivated by competition may not be harmful to achievement. However, adopting self-related performance goal is negatively correlated with achievement. Subsequently, it would be interesting to examine how self-related goals impact

students' self-believe and self-efficacy.

The regression analysis suggests that four of the variables explained 39% of the variance in the achievement scores of the students who participated in this study. Deep learning approach, task-related and other-related goals were significant predictors of students' performance in the course. Their effects accounted for 30% of the variance in participants' course performance (deep learning approach accounted for 15% and task- and other-related goals explained 13% of the variance observed). The result suggests that the negative effect of self-related achievement orientation goal was substantial, at 11%, its relative effect was comparable to the other significant predictors. These findings suggest that as students are challenged towards seeking mastery through the use of deep learning strategies, instructional or coaching efforts that direct students towards adopting adaptive learning strategies and away from focusing on their failings success could be productive.

Direction for future work

We are in the process of collecting more data to investigate if these results are isolated and to determine the strength of the relationships between the variables examined in the study reported in this paper. In the future, we will use factor scores derived from factor analysis to evaluate the mediation relationships between the variables in our study, and we will employ learning and motivation theories to further explore these relationships.

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