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”Is it Going to be on the Test?” An Introductory Study of the Factors Influencing Engineering Technology Student Motivation

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Introduction

Anyone teaching college students has likely been subjected to questions such as, "Is this going to be on the test?" or excuses for why students did not want to complete the homework assignments that are so vital to student learning. In the experience of the authors as well as anecdotal evidence from their colleagues, this lack of motivation seems to be on the rise. As faculty members, we may have theories about the cause for this lack of motivation with little data to support them. For example, Southern Polytechnic State University (SPSU; the site of this study) has been moving from a largely non-traditional student body to a more typical college demographic. This is seen by many as one of the causes of unmotivated behavior many see more frequently in recent years. Though the causes may be less understood, many studies indicate the consequences of low motivation are serious and include low persistence in engineering majors[1,2]. The study outlined below focuses on two specific research questions. First, what demographic factors (e.g., age, sex) are most closely tied to high levels of motivation? We are considering levels of motivation to be manifest in points earned on low point-value assignments, typically an "un-motivating" assignment. Second, are these factors different for engineering technology students than the rest of the college population?

Motivation Theory in the Classroom

There is a rich body of literature on motivation theory, including motivation theory in the college classroom. Much of that focuses on how students' needs, expectations, and other factors lead to motivation and what learning interventions can be used to increase motivation. A common theory is that student motivation is "heavily influenced by their thinking about what they perceive as important and what they believe than can accomplish"[3]. McMillan and Forsyth model motivation as a function of both needs and expectations, and hypothesize that if student needs are present and if students believe they are able to satisfy the needs, then they will be motivated to behave in ways that meet the needs.

This argument falls under the broader heading of expectancy theory[4,5]. Expectancy theory posits that motivational force derives from a combination of expectancy, instrumentality and valence. In other words, one performs a given behavior because one feels capable of performing it (expectancy), one views the behavior as leading to success or reward (instrumentality) and one values that reward (valence). Some would distinguish between intrinsic (self-determined or autonomous) and extrinsic (externally-regulated or controlled) motivation[6], which may be influenced by other variables, including interest in the subject matter, perceptions of its usefulness, general desire to achieve, self-confidence and self-esteem, patience, and persistence[7]. However, it is possible a single behavior is driven by more than one motivator; expectancy theory subsumes both intrinsic and extrinsic motivation, though potentially at different points in the motivational process.

Additionally, students' perception of success or reward may differ depending on their desired outcome. A student's boundary goal is set by their perception of what minimum performance is required for them to feel successful[8]. It is important to note that this boundary goal is not necessarily what the student *hopes* to achieve, it is merely what they would find an *acceptable* achievement. These could be approach goals (i.e., the student would like to have a 4.0 GPA) or avoidance goals (i.e., the student would like not to fail a particular class), and potentially vary according to the class and/or circumstance. It is possible students' boundary goals may be higher in classes within their major, and lower in core classes.

Research suggests that, among American students evaluating math and science courses, these three types of motivations—self-concept (instrumentality), affect (expectancy) and value (valence)—are significantly positively related, and are separately related to indicators of future behavior, including the self-reported likelihood of the student taking another course in the discipline and self-reported achievement in the discipline[9]. These data indicate these variables are correlated, yet may independently influence motivation and achievement.

Others have focused on boredom in the classroom, though this is a less investigated phenomenon. Pekrun[10] and colleagues argue that boredom is a negative/unpleasant, deactivating achievement emotion resulting from students failing to feel control over or to find value in an assignment or task. Importantly, these authors theorize students' cognitive resources, motivation and cognitive strategies and self-regulation impact the link between boredom and academic performance. The results of their study supported that theory, with significant negative correlations between boredom and perceived task value, effort, self-regulation, performance and control (rs = -.70, -.45, -.26, -.26 and -.24, respectively). Perceived performance also was significantly positively related to perceived control and perceived task value (rs = .55 and .33, respectively). However, their paper is limited in that the variables assessed were all student self-report, thus limiting the generalizability and ecological validity of their study.

Indicators of Motivation

Overall, the majority of investigations into this domain have used self-report measures as indicators of motivation[9-11], and other self-reported variables as outcome measures (e.g., likelihood of taking another course in the discipline in the future[9]). There are several potential problems with this methodology, including social desirability concerns in reporting and the consequent limitations in ecological validity an entirely self-reported dataset produces. However, some authors have operationalized motivation in behavioral terms, though inconsistently across studies.

For example, a recent study by Little-Wiles[12] and colleagues looked at various self-reported proxies for student motivation in an on-line course, including the frequency of logging in to the learning management stystem (LMS), use of various tools in the LMS, and frequency of communication. They also studied the correlation between course grade and actual use of the LMS and found significant correlation between use of the system and grades. Others have operationalized motivation in terms of obtained GPA and retention (vs. attrition; Robbins et al., 2004, as cited in Ackerman, Kanfer & Beier[13]). Meta-analytic data suggests that certain personality variables—Conscientiousness, Agreeableness and Openness—are consistently related to GPA, though with only small effects, indicating a potential personality-driven facet of motivation (Poropat, 2009, as cited in Ackerman, Kanfer & Beier[13]). Finally, high school GPA, SAT scores and AP exam scores have been considered "traditional predictors" and have been used in concert with gender, personality traits, and prior year college GPAs in the prediction of persistence in the STEM (science, technology, engineering and math) disciplines[13]. One could argue persistence itself is a proxy variable for motivation, as it is unlikely a student can persist without significant motivation.

Few studies have investigated differences in motivation across demographic variables. In one, college females were found to have significantly higher intrinsic motivation, better time and environment use, better effort regulation, as well as lower levels of procrastination than college males[6]. In another, the authors differentiated between performance (extrinsic) and mastery (intrinsic) motivation, as well as approach (desire toward a goal) and avoidance (desire to avoid a specific outcome) motivations[8]. Although, strangely, significance values were not reported, positive correlations were found between exam scores and both performance approach and mastery approach goals (*r*s = .25 and .16); performance avoidance goals also were negatively related to exam scores (r = -.18). Additionally, females were more likely to report having performance avoidance goals (r = -.28). A full investigation into the demographic correlates of low motivation or behaviors indicative of low motivation is lacking in previous research. One of the goals of the present paper is to address this lack in a diverse undergraduate sample.

Present Study

The above literature review highlights two issues in previous research. First, many of the variables assessed across these diverse studies were self-reported, and thus approach the question of motivation and performance from the standpoint of a student's perception. Although perception is important, it examines only one facet of a very large, very complicated construct. It is possible this methodology is limiting the conclusions one can draw about motivation. Second, the vast majority of these studies focus on a broad spectrum of students and do not look at discipline- or major-specific considerations. For example, as posited above, a student may have different levels of motivation and thus different achievement behaviors in a major course than in a core course. Similarly, students within the STEM disciplines may be a distinct subsample, with different behavioral tendencies than other students. We seek to address these limitations in previous research in the below study.

Specifically, our work does not approach the question from student perception standpoint. We believe investigating real-life performance, instead of student perceptions of their motivation, enhances the ecological validity of our project and decreases the potential for socially desirable responding. Although there are many possible indicators of motivation (e.g., including grades on low-point value assignments, attendance and punctuality, rates of non-instructional cell phone/laptop use during class), for this study, we focus on the grades obtained on low point-value assignments. We believe these assignments may be particularly unmotivating for many students because they may be seen as a nuisance, given they are such a small component of an overall class grade, and thus may be easy to dismiss. Our work also focuses on various demographic variables that may be potentially related to motivation behavior, including: gender, age, race, GPA, SAT score, major, course withdrawal rate, and course classification (in-major, core, other). Finally, it is the only work we are aware of that specifically reports results for Engineering Technology students. We approached this study with no specific hypotheses, as this is the first study of which we are aware to examine this question from this particular perspective.

Method

The investigators approached professors and instructors at Southern Polytechnic State University (SPSU) for classroom data if it included, in the previous semester, low-point value assignments. Assignments were operationally defined as “low-point value” if each assignment was worth no more than 7% of a student’s grade (e.g., a single assignment worth 5% or a set of 10 homework assignments that totaled 30% of the classroom grade). These classes were classified as either within the student’s major, part of the core curriculum, or other.

To form the subsample for analysis, approximately 1 student was randomly selected (using a random number generator) for every 3 students enrolled in each class, leading to a subsample of 187 students from an original sample of 587 students. Table 1 includes demographic data for the selected subsample, as well as the ET majors from within that subsample. It is worth noting 116 of these students had GPAs from prior higher education institutions; the average of these prior GPAs was 2.96 (SD = .55). The average SAT scores in the sample were 559.56 for Verbal and 596.33 for Math (SDs = 75.55 and 79.41, respectively), though only 91 students had reported SAT scores.

Table 1: Summary demographics for full sample (n=186) and engineering technology subsample (n=34).

Demographics	**Full sample**	**ET students**
Gender		
Male	79%	88%
Female	21%	12%
Class standing		
Freshman	12%	9%
Sophomore	30%	24%
Junior	16%	12%
Senior	42%	56%
Race/Ethnicity		
White	56%	47%
Black	20%	24%
Hispanic	9%	12%
Other	15%	18%
Age		
<25	75%	71%
25-35	21%	26%
>35	4%	3%
GPA		
<2.5	26%	21%
2.5-2.99	24%	18%
3.0-3.49	32%	24%
>=3.5	18%	38%

For these students, data were collected from 9 professors and instructors. Courses ranged from lower-level core classes (e.g., Public Speaking, Psychology, Calculus) to upper-level, major-specific courses (including Engineering and Engineering Technology). Table 2 includes summary information about the types of courses and grading policies. As an indicator of class difficulty, the course withdrawal rate was calculated. Across all classes, the average withdrawal rate was 8% (SD = 8%). Finally, on average, the students obtained a B-/C+ in the assessed class (M = 2.52, SD = 1.27).

The low-point value assignments obtained were originally classified as: homework; quizzes; writings for discussion on the class website; participation points; weekly in-class assignments; and papers. For the purposes of the below analyses, these were further subdivided into: 1) quizzes and homework (116 students, or 62.0% of the total sample); 2) in-class assignments (weekly in-class assignments and participation points; 43 students, or 23.0%); and 3) writing assignments (discussion postings and papers; 27 students, or 14.4%). On average, these assignments summed to 18% of the total class points (SD = 8%), and the students earned 75% of these points (SD = 23%).

Table 2: Summary course information from the whole sample (n=186) and engineering technology subsample (n=34).

Course and assignment information	Full sample	ET students
Course category		
Major	45%	62%
Core	52%	38%
Other	3%	0%
Assignment classification		
HW or Quiz	62%	68%
Participation or in-class exercise	24%	9%
Writing assignment	14%	24%
Aggregate assignment percentage of total points		
<=10%	9%	6%
10-24.99%	80%	74%
>=25%	11%	21%

Results

Prior to the reported analyses, the distributions for each variable were examined and the data were re-coded and transformed if necessary to facilitate analysis. For four of the variables—points on assignment, age, course withdrawal rate, percentage of class points accounted for by the assignment—marked skews (> 1.0) were present in the distributions. The variable of points on assignment was negatively skewed due to the majority of students doing quite well on the assignments. Age was positively skewed due to the largely college-aged student population (i.e., 18-22 years old). The course withdrawal rates caused a positive skew because, in general, the rates were quite low. Finally, due to these being low point-value assignments, the percentage of class points for which these assignments accounted was low, leading to the positive skew in this variable. The latter two of these variables were log transformed to eliminate the skews. However, for the former two, the various transformations did not work to eliminate the skew. As such, the data were transformed into rank-ordered distributions, and these transformed variables were used in the subsequent analyses.

The relations among achievement and motivation indicators (including the demographic variables) are presented in Table 3. The data including all students are below the diagonal; ET students only are above the diagonal. To determine the significance of Spearman rank-ordered correlations, *t*-values were calculated using the following formula: $t = \sqrt{(n - 2)}/(1 - r^2)$; *t*-values > 1.96, or $r > .15$, were significant at $p < .05$, two-tailed. For the full sample, only four variables were significantly related to the points obtained on low-point value assignments. Class grade, overall GPA and class rank were significantly positively related (*r*s = .62, .48 and .16, respectively), while course withdrawal rate was significantly negatively related ($r = -.17$). These data suggest that, in general, high achieving students further along in their degree program in courses where students tended not to withdraw performed the best on low-point value assignments.

In contrast, when the ET students were considered alone, four variables were significantly related to the points obtained on low-point value assignments. It is worth noting that none of the ET students were in an "other" categorized course. As such, the core and major courses are duplicates (though opposite). Similar to the total sample, class grade and overall GPA were significantly positively related (*r*s = .52 and .56, respectively). However, in the ET subsample, the indicator the course was within the student's major and the fact that the assignment was homework or a quiz were negatively related to the points obtained (*r*s = -.15 and -.15, respectively). Together, these data suggest that high achieving students performed well on low-point value assignments, whereas specific types of assignments and courses within with student's major were related to lower performance.

Table 3. Interrelations among achievement and motivation indicators.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Assignment Variables																	
1. Points on assgnmnt[a]		-.03	**.52**	**.56**	-.10	-.15	---	-.15	-.05	.19	-.03	.08	.07	.08	-.13	.07	-.02
2. Assignment %[b]	-.07		-.06	-.07	**-.40**	**.43**	---	**-.43**	.11	**.40**	**.35**	.29	-.10	.03	-.01	.08	-.10
3. Class grade	**.62**	-.04		.71	-.18	-.19	---	.04	.06	-.08	-.19	-.10	-.06	.22	-.14	-.01	-.12
4. Overall GPA	**.48**	-.08	.63		.11	-.08	---	.06	-.08	-.01	-.06	.05	.01	.15	-.21	.13	-.07
Course Variables																	
5. Withdrawal rate[b]	-.17	**-.37**	-.24	.00		.09	---	**.34**	**-.45**	-.08	.04	.08	**.33**	-.00	-.13	-.13	.26
6. Major course[c]	.07	.05	.18	.04	.12		---	.10	**-.40**	.15	**.51**	**.40**	.09	.01	.01	-.09	.05
7. Core course[c]	-.03	-.09	-.15	-.01	-.16	**-.93**		---	---	---	---	---	---	---	---	---	---
8. HW/Quiz[c]	-.10	-.24	-.10	.01	**.44**	.06	-.08		**-.45**	**-.80**	-.04	-.14	-.06	.02	-.06	-.14	.16
9. Weekly in-class[c]	.14	-.02	.10	-.04	**-.38**	.03	-.01	**-.71**		-.17	**-.33**	-.23	-.21	.12	.07	-.11	-.14
10. Writing[c]	-.03	**.35**	.03	.04	-.15	-.13	.13	**-.53**	-.23		.27	**.32**	.21	-.11	.02	.23	-.07
Demographics																	
11. Age[a]	.00	.17	.01	-.06	.10	**.51**	**-.52**	.09	-.14	.04		**.52**	.25	-.13	.07	-.15	.22
12. Class	.16	.07	.19	.16	.15	**.59**	**-.60**	.08	-.12	.03	**.69**		.14	-.19	.05	-.05	.23
13. Gender (M=1, F=0)	-.08	-.10	-.12	-.03	.08	-.13	.14	.10	-.14	.03	-.06	-.05		.16	-.01	**-.43**	.17
14. Caucasian[c]	.04	-.15	.01	.15	.07	-.10	.10	-.01	.06	-.06	-.10	-.08	.09		**-.52**	**-.34**	**-.44**
15. African American[c]	-.02	.17	-.05	-.25	-.08	.08	-.04	-.04	-.06	.13	.16	.10	-.09	**-.57**		**-.20**	-.26
16. Hispanic[c]	.07	.06	.14	.14	-.06	.05	-.06	-.10	.09	.03	-.14	-.08	-.06	**-.35**	-.16		-.17
17. Other ethnicity[c]	-.08	-.02	-.07	-.04	.04	.01	-.04	.14	-.09	-.09	.08	.06	.04	**-.47**	-.21	-.13	

Note. All students are below the diagonal; ET students only are above the diagonal. [a] Indicates rank-ordered variable; [b] indicates log-transformed variables. [c] Indicates dichotomized variables (1 = yes, 0 = no). --- indicates a duplicate variable in the ET student subsample (Major and Core courses). For Class variable, 1 = Freshman, 2 = Sophomore, 3 = Junior, 4 = Senior. HW = homework. Underlined correlations are significant at $p < .05$, according to a two-tailed *t*-test for Spearman correlation coefficients. Correlations in **bold** > .30.

Discussion and Conclusion

The present study focuses on two specific research questions: First, what demographic factors are most closely tied to high levels of motivation? Second, are these factors different for engineering technology students than the rest of the college population? We operationalized motivation in behavioral terms, demonstrated by earned points on low point-value assignments. Overall, the data indicate that points on these assignments are significantly related to the grade obtained in a particular class, as well as students' overall prior GPA. The former is clearly expected, as the assignment contributes to the students' grade in the course (a part-whole correlation), but the magnitude of that relationship is still of interest. However, within the full sample examined, the only demographic variable significantly related to this indicator of motivation was class rank (e.g., Freshman, Sophomore, etc.). In contrast, within the ET student subsample, no demographic variables were related to earned points on low-point value assignments.

It is possible to consider this outcome in a positive light. For the full sample, with a single exception, there does not appear to be any particular demographic that appears to earn lower grades on low-point value assignments. Also with a single exception, there does not appear to be any particular type of class for which students are likely to not complete low-point value assignments. It is worth noting the two exceptions to this general conclusion are low correlations (rs < .20). Additionally, we sought to investigate if there were significant differences between the full sample and ET students. Two significant correlations were found between low-point value assignments and course variables, though again these correlations were low (rs < .20). The counterintuitive finding that students tended to perform worse on low point-value assignments in their major courses compared to their core courses is perhaps worth additional study. Taken together, it appears that if these assignments are indeed indicators of motivation (or the lack thereof), no specific group of students seems less motivated and no specific type of class appears to be un-motivating.

It is worth noting three limitations to our research design. First, it is possible that operationalizing motivation in behavioral terms, as done here, is illegitimate. This would necessarily limit the conclusions to be drawn from these data. However, anecdotal evidence from discussions with our colleagues would suggest that these are the types of assignments students are likely to "blow off", because these students feel able to make up the points elsewhere during the semester. Regardless, a subsequent study with a different behavioral indicator of motivation may find different results. Second, the student sample investigated in this study is unique. The demographic data outlined in Table 1 demonstrates this sample is heavily weighted toward males, and the ET subsample even more so. Previous research indicates gender differences in motivation (as outlined above), and it is possible the largely male sample investigated here reduced the variance in motivation that may be found in a more diverse sample. Finally, as noted earlier, there were significant skews in four of the variables analyzed; log transformations were able to address this for two of the variables, but these transformations did not work for the other two. This necessitated recalculating a continuous variable as a rank-ordered one, which required the use of a nonparametric test for analysis. It is common knowledge that nonparametric tests have less power than parametric ones, which may have limited the likelihood of drawing significant conclusions from the collected data.

Regardless, we believe the above results will enhance the conversation around student motivation. These data have the potential to educate faculty in factors that are related (or not) to motivation and to serve as a first step toward recognizing classes and/or assignments for which students may have inherently low motivation. Additionally, focusing on real-life behavior instead of perceptions of motivation provide faculty a baseline against which to judge improvements in student performance following interventions intended to increase motivation. In an era of increased emphasis on student success rates, we believe anything that can be done to increase motivation or manage low motivation is of value.

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