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Modeling the Motivation of Mechanical Engineering Students: Productive Perceptions for Present and Future Success*

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In the United States and around the world, engineering programs face issues of demotivation and attrition. Many small studies have examined a few motivational characteristics in engineering education, generally treating variables as discrete and using simple correlational analyses. Given the complex, interactive nature of motivation for learning and development, the field of engineering education needs studies that model interactions among multiple variables informed by a multi-theory approach to motivation. Once demonstrated, these relationships and model can be tested for similarities or differences in more diverse groups. To address this gap, we present a systematic approach to model and validate interactions of multiple motivational characteristics. This study assessed the motivational profiles of 80 junior and senior students in mechanical engineering design, and tested the data for correlations to verify the strength of their overall relationships. Then, the researchers created an interactive, directional model informed by theory and precedent in the literature, and further tested the relative influence of the interrelated factors, to identify those most influential on key outcomes, using multiple regression. Correlations indicated 28 possible paths, which were built into the hypothetical model, and the multiple regressions eliminated 15 of those pathways, leaving the 9 most influential factors and 13 most significant predictive pathways modeling the course engagement and the career efficacy and success expectations of these advanced engineering students. This approach of modeling the influences among different constructs helps to reduce the noise and confusion from multiple, sometimes conflicting findings, and refine understanding of students' motivation that can contribute to more effective engineering education.

Keywords: motivation; retention; mechanical engineering

1. Introduction

Motivation predicts academic success, retention and completion across schools, groups and levels of education [1]. Engineering is facing problems of attrition, and challenges in recruiting minority groups such as women [2]. Understanding the motivations that drive successful (junior and senior) engineering students can provide information to support recruitments and the alignment of course and programs to meet students' needs. However, motivation for learning is not simple or linear. Educational research on motivation has moved beyond single-theory frameworks and dividing cognitive from affective and social factors, into a more integrative conceptualization of human motivation for learning and change [3].

Students experience different motivational characteristics, some productive, promoting engagement, attention and development, and others unproductive, reducing and deterring engagement and success [4]. In the short term, productive motivation predicts and supports students' course attendance, engagement and completion, as well as educational program retention and completion [5]. In the long term, productive motivation supports students' investment in deep learning, the development of professional competencies, and persistence in overcoming challenges and innovating throughout their careers [6]. Motivation is critical for student retention across disciplines and competency development across professions [7]. Engineering education research can benefit from including motivation as a key component in predicting student retention and success, particularly in engineering design courses that have been highlighted to engage and motivate students. An understanding of the complex interactions among different motivational characteristics is needed to develop competencies and increase student retention.

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Consequently, the research question being addressed in this study is: What are the most significant predictors among individual goal orientations, beliefs about the profession (success depending on basic abilities or hard work), course content perceptions (value, relevance & utility), course climate perceptions (support of teacher and peers), and developmental motivational characteristics (course efficacy & success expectations) on the productive motivations (course engagement and career efficacy & success expectations) of mechanical engineering seniors in a design course?

Addressing this research question involved first identifying a comprehensive set of relevant motivational characteristics along with relevant construct measures, from the existing research literature in engineering education. Second, these measures were contextualized for the engineering context and administered to advanced engineering design students. Third, after reliability of the measures for the participant group and purpose were verified, correlations were computed to determine significant relationships among the characteristics under study, and to develop an initial hypothetical model based on these interactions. Fourth, a regression analysis was used to refine and validate the model. The resulting model of engineering students' motivation can be used to improve productive motivation for engineering design students.

2. Literature review

2.1 Motivational issues in engineering education

Research in engineering education from around the world underscores the need for motivation research. The US, in particular, is falling short of market needs for skilled engineers [8]. Engineering schools evidence low student success rates, as reflected in retention (degree completion) and graduation [2, 9–11], with estimates that half of engineering students change to different majors in their first and second years [12–13]. While attrition is high, only about 10% of students leave because of failure [14], which suggests that the problem of retention is not primarily cognitive, but motivational.

Beyond current trends in higher education, the hands-on nature of engineering and its integration of math and science into concrete activities have made it the focus of programs for elementary and secondary students and their teachers. Engineering activities have been demonstrated to promote early interest in engineering itself, as well as broader interest in math and science, for secondary students (e.g., [15–16]). If younger students are to be interested in, and prepared for, engineering careers, then their teachers must also have engineering-related knowledge and skills [17–18]. Funding agencies and researchers have invested in many projects and studies demonstrating both learning and motivational effects of engineering-based teacher professional development experiences (e.g., [19–20]). Thus, understanding motivation for engineering education reaches back from undergraduate programs into the secondary recruiting pipeline.

A better understanding of students' motivations can help engineering educators and curriculum designers address attrition and quality issues. Given the role of engineering programs to prepare students for specific career goals, the scope of relevant motivations include those directly linked to course experiences, as well as those related to success in their future professional roles [2, 21].

2.2 Studies of motivation for engineering

While America's gaps in skilled engineering have been most broadly publicized, motivation studies conducted around the world focus on engineering education, moving beyond content and activities, to promoting maximum engagement and integrative learning (e.g., [22–23]). This body of work has begun to illuminate the importance of various motivational characteristics, both personal (general) and context or discipline-specific (experiential). Among these characteristics are: intrinsic interest and success expectancies [24–25] perceived relevance and value through identification with engineering generally [26] and with engineering subdisciplines (e.g., [27]). Research also demonstrates that motivation improves student engagement, learning and completion for traditionally content-heavy foundational courses such as Statics [28], as it does for completion in general (previously "gatekeeper") math and science courses (e.g., [29]); and that it promotes more general college success among engineering students (e.g., [30–31]). Among the most often-used motivational constructs are several types of self-efficacy, all found to promote engineering learning and performance: general or personal self-efficacy [32], field or domain-specific self-efficacy [26] and project or task-specific self-efficacy [25]. Linking course and program effects are findings that long-term commitment to the major promotes short-term motivation to learn in the course [25]. On the negative, or unproductive side of motivation, some engineering students experience high levels of performance pressure and anxiety, which reduce learning and performance quality [24]; and productive motivations of students decrease during the first year of engineering study [26], and may continue to fall over years of progress toward degree [23]. Learning environments, operationalized in course climates, can motivate and engage students individually [23], as well as promote peer collaboration and student-instructor interaction [29].These studies illustrate the influential power of motivation in engineering education, for better or worse.

Given that motivation is so influential, it is important that it is also malleable, that instructional strategies can explicitly promote productive individual and environmental characteristics. Self-efficacy for engineering (like other subjects) can be promoted by the combination of personal success experiences and explicit verbal encouragement, supported by communicating skill and task value; and in the absence of direct success, providing role modeling and vicarious success [32]. Course climates that promote productive motivation depend primarily on instructor support, including: accessibility and openness; motivationally appropriate instructional strategies; and prompt, meaningful feedback to students [29]. Service learning projects offer potential to promote perceptions of outcome value which supports skill development [33]. Engineering students' productive motivational perceptions for both course and careers can be enhanced by systematic integration of motivating strategies [34]. Engineering design courses are often used for such motivational effects studies (e.g., [10, 34]), because they present the elements of creativity and problem-solving which are so critical to the valued professional outcomes of design thinking and innovation [21]. Recent studies have found both learning and motivational benefits from interdisciplinary education [35], e-learning environments [36], and fully problem-based curricula [37]. These studies form a foundation on which additional research can be built, to inform engineering education.

2.3 Frameworks for modeling engineering motivation

Educational studies, outside of engineering, have used regression and other modeling methods to show that maximizing motivation depends on the relative contributions and dynamic interactions of multiple personal and experiential variables [38]. The importance of modeling these contributory variables together is that it tests their relative influences on the same individuals' motivations, providing a clearer picture of what factors are most influential for this group [39–41]. Engineering studies have identified a range of productive motivational characteristics for the domain and tasks of engineering, as identified in the previous review.

A few modeling studies have demonstrated more complex and interactive relationships among motivational variables and outcomes in engineering education. Burtner [12] used discriminant analysis to examine the expectations and perceptions of professional subject matter, along with personal attributes, as characteristics of students who dropped out or changed majors versus remained and completed their programs. Jones [42] modeled similar relationships among expectations, values, achievement and career plans. Lent and others [25] focused on the predictive role of self-efficacy on outcome expectations, interest and major choice. However, a more comprehensive set of variables have not been tested together to more clearly identify their nuanced contributions to global motivational outcomes for engineering students.

2.4 Method for modeling relationships among motivational characteristics for engineering

To model the relationships among a complex set of motivational characteristics for advanced undergraduate engineering students, this study was conducted in a senior-level mechanical engineering design course.

2.4.1 Participants

Study participants were 80 university mechanical engineering undergraduates in a senior-level engineering design course. The group was: 75 (94%) male and 5 (6%) female; ages 19-37 (M = 22.79). As to ethnicity, they identified as: 6 (8%) Hispanic or Latino; 54 (68%) Non-Hispanic/White; 10 (13%) Asian/Asian American; 3 (4%) Black/African American; 3 (4%) American Indian/Alaska Native; and 4 (5%) Multi-racial. All participants were seniors majoring in mechanical engineering, with similar prior knowledge and experience, taking the same requisite courses (but not all together), and preparing for similar future careers. All had earned (required) high math and science aptitude scores (SAT math 600-700 & composite M= 1280; ACT math 32-25 & combined M = 28.3), with (self-reported) GPAs: 2.52-4.08 (M = 3.35).

2.4.2 Measures

A set of multi-scale questionnaire instruments assessed participants' perceptual and motivational characteristics. These constructs were chosen because they had been demonstrated as influential on independent or dependent variables related to engineering motivation (as illustrated in the previous review). All were multi-item quantitative scales (7-pt Likert-type; anchored: 1 = "strongly disagree" to 7 ="strongly agree"). The instruments were contextualized for this study, by making the questions specific to the course and discipline. All construct measures demonstrated adequate inter-item coherence, indicating scale reliability, using the Cronbach's *alpha* reliability statistic, at a target level of *alpha* $\geq$ 0.80 (see [43–44]). The full set of questionnaires was administered at one time, near the end of the pre-capstone design course, to control for order effects, and to the same group of students, to control for individual differences. The constructs and subscales are described below.

Individual goals: Goal orientations frame students' tendencies toward particular reasons for learning and performance.

Learning and future goals [45–47]. This subscale assessed the degree to which students' desire to learn engineering for personal interest or to contribute to personally-valued future career goals (7 items; *alpha* = 0.93). Higher values on the scale indicate internal or intrinsic reasons. Sample item: "I do my work in this course because I want to understand the ideas".

Performance goals [45–47]. This scale assessed the degree to which students' desire to learn engineering to impress others (group members, teacher, etc.), to avoid appearing incompetent to others or for grades (9 items; *alpha* = 0.95). Higher values indicate external or extrinsic reasons for learning. Sample item: "I do my work in this course to make others proud of me".

Beliefs about the Profession: Items in this scale assess students' beliefs about aptitude and characteristics that are needed to be successful in the field of engineering. These original scales were added by the engineering experts on the research team, in consultation with an assessment expert. These types of perceptions had been discussed generally in previous engineering studies (e.g., [37]), but coherent scales to assess them were not available, so the team created them for this project.

Requires learning, teamwork and creativity. This subscale assessed students' belief that success in engineering as a career depended on a learning diverse skills (continuous learning, teamwork, creativity) (3 items; *alpha* = 0.89). Sample item: "You have to be creative to be a mechanical engineer".

Math-science aptitude. This subscale assessed students' belief that success in engineering as a career depends on natural aptitudes in math and science (3 items; *alpha* = 0.86). Sample item: "To be successful as an engineer, you really have to be good at math and science".

Hard work/challenge. This subscale assessed students' belief that success in engineering as a career depended on hard work and effort, learner-controlled factors (4 items; *alpha* = 0.80). Sample item: "It takes a lot of hard work to be good at mechanical engineering".

Perceptions of the course: Student's perceptions that course content has motivating characteristics for both in and outside of class use, in the near and distant future, and that the class social climate is supportive of success.

Content—value [19, 38]. This subscale assessed students' perceptions that the course content is valuable (9 items; *alpha* = 0.95). Sample item: "I seriously value what I am learning about engineering in this course".

Content—relevance [19–38]. This subscale assessed students' perceptions that the course content is relevant to the student's life and career needs (7 items; *alpha* = 0.93). Sample item: "When we learn something new in this course, it is clearly linked to our career goals".

Content—utility [19, 38]. This subscale assessed students' perceptions that the course content is useful for the student's life and career needs (6 items; *alpha* = 0.93). Sample item: "The things we do in this course are really useful for us as engineers".

Climate—professor support [38, 46–47]. This subscale assessed students' perceptions that the climate provided by the professor was fair, supportive and encouraging (11 items; *alpha* = 0.91). Sample item: "When students make mistakes, the professor makes it a learning opportunity".

Climate—peer support [38, 46–47]. This subscale assessed students' perceptions that the climate provided by student peers was cooperative, supportive and respectful (7 items; *alpha* = 0.91). Sample item: "Students in this class support each other".

Course-level motivations and engagement: Assessments to measure success-related factors that predict investment in class, along with a scale for overall course engagement.

Self-efficacy—course [19–20, 46–48]. This subscale assessed students' beliefs that they could succeed in the course, even in the face of challenges (8 items; *alpha* = 0.88). Sample item: "If I do poorly on an assignment or project in this course, I have strategies to help me succeed the next time".

Success expectations—course [38, 46]. This subscale assessed students' beliefs that they would learn, achieve and be successful in the engineering design course (7 items; *alpha* = 0.80). Sample item: "I am sure that I will do well in this course".

Engagement and effort [49–50]. This subscale assessed students' self-reported effort to learn and engage in the course activities and tasks (a dependable and commonly-used proxy for overall motivation) (9 items; *alpha* = 0.93). Sample item: "I work very hard in this course".

Career-related motivations: These scales assess productive motivations for engineering as a career.

Self-efficacy—profession [19, 46–48]. This subscale assessed students' beliefs that they could succeed in their future engineering careers, even in the face of challenges (8 items; *alpha* = 0.90). Sample item: "I believe that I can manage most challenges that a mechanical engineer faces".

Success expectations—career [38, 46]. This subscale assessed students' beliefs that they would learn, achieve and be successful in their future engineering careers (7 items; *alpha* = 0.93). Sample item: "I expect to be successful in my engineering career".

2.4.3 Initial model building—Correlation analysis

The model-building design and testing procedure used a multiple regression approach [39–41, 51]. First, to confirm the coherence of the scales for this participant group, the scales were tested for internal consistency, using Cronbach's *alpha* (at the target level of *alpha* $\geq$ 0.80). Second, to confirm the general strength of relationships among these constructs for this participant group, scale mean scores were calculated and Pearson's product moment correlations computed, with the target of both a critical magnitude ($r \geq 0.40$) and a high level of significance ($p < 0.001$).

2.4.4 Model refinement—Multiple regression

Any variables not demonstrating the target level of correlation were dropped from the regression model test. Using the remaining variables, a hypothetical prediction model of engineering students' overall motivation and success expectations was constructed. The model consisted of the significantly-correlated predictor variables, ordered based on their theoretical relationships and previous research precedent. Finally, three phases of regression analysis were used to test the relative magnitude and power of influences on the theoretical sequence of factors (regression target level: $p < 0.01$). Multiple regression addresses the size of overall relationship between a group of predictor variables and a single outcome variable, and also parses out the individual contribution that each individual variable makes to that overall influence [41]. Any paths in the hypothetical model falling below the target level of significance would be dropped, leaving the most significant paths to explain prevalent influences on these engineering students' course engagement and career self-efficacy and success expectancies.

3. Results: Model of productive motivational characteristics of engineering students

The following sections report the results of the three-phase model-building and testing procedure (based on methods in [39–41, 51]).

3.1 Reliability analysis

First, to confirm the coherence of the scales for this participant group, the scales were tested for internal consistency, and all subscales demonstrated reliabilities at the target level of *alpha* $\geq$ 0.80 (Cronbach's *alphas* 0.80–0.95). Shown in Table 1 are the means, standard deviations and Cronbach's *alpha* reliability statistics for each of the subscales.

3.2 Correlation analysis

Second, to confirm the general strength of relationships among these constructs for this participant group, Pearson's product moment correlations were computed on scale means, with the target of both a critical magnitude ($r \geq 0.40$) and a high level of statistical significance ($p < 0.001$). In the correlation test, two clusters of the original variables correlated at an extremely high magnitude, ($r > 0.90$) and significance ($p < 0.000$), suggesting that they were essentially functioning as measures of the same constructs [43]. To further assess their coherence, a confirmatory factor analysis (CFA) was conducted using Principal Extraction [39]. These clusters, the three content perceptions (relevance, value, utility) and the two climate support perceptions (professor, peers) each loaded onto a single factor, indicating that they were functioning as one variable in this dataset [43]. Based on these analyses,

Table 1. Scale descriptive statistics

Scale/Construct Name	# of Items	Mean Score	Standard Deviation	Reliability (Cronbach's *alpha*)
Goals: Learning & Future	7	5.16	1.20	0.93
Goals: Performance	9	3.62	1.32	0.95
Beliefs: Profession Requires Learning, Teamwork, Creativity	3	6.25	0.64	0.89
Beliefs: Profession Requires Math & Science Aptitude	3	4.26	1.12	0.86
Beliefs: Profession Requires Hard Work	4	5.53	1.08	0.80
Content: Value	9	4.37	1.43	0.95
Content: Relevant	7	4.82	1.37	0.93
Content: Utility	6	5.32	1.21	0.93
Climate: Professor Support	11	5.48	0.86	0.91
Climate: Peer Support	7	5.53	0.95	0.91
Course: Self-Efficacy	8	5.59	0.84	0.88
Course: Success Expectations	7	5.82	0.92	0.80
Course: Engagement & Effort	9	5.58	0.86	0.93
Career: Self-Efficacy	8	6.08	0.79	0.90
Career: Success Expectations	7	5.79	1.01	0.93

Table 2. correlations among variables

	P-Seffic	L&FG	PrefG	C-Seffic	P-Succ	C-Succ	Value	Relev	Util	ProfS	PeerS	HWk	Ma-Sci	LTwC	C-Eng
P-Seffic	1														
L&FG	**0.40** **0.00**	1													
PrefG	–0.05 0.68	0.16 0.17	1												
C-Seffic	**0.65** **0.00**	**0.65** **0.00**	0.09 0.45	1											
P-Succ	**0.81** **0.00**	0.31 0.01	–0.02 0.89	**0.51** **0.00**	1										
C-Succ	**0.52** 0.00	**0.50** **0.00**	0.28 0.02	**0.45** **0.00**	**0.51** **0.00**	1									
Value	0.38 0.00	**0.74** **0.00**	0.26 0.03	**0.60** **0.00**	0.23 0.05	**0.48** **0.00**	1								
Relev	**0.44** **0.00**	**0.62** **0.00**	**0.45** **0.00**	**0.64** **0.00**	0.36 0.00	**0.46** **0.00**	**0.83** **0.00**	1							
Util	**0.41** **0.00**	**0.70** **0.00**	**0.44** **0.00**	**0.62** **0.00**	0.30 0.01	**0.50** **0.00**	**0.84** **0.00**	**0.85** **0.00**	1						
ProfS	**0.51** **0.00**	**0.54** **0.00**	0.26 0.03	**0.70** **0.00**	0.38 0.00	**0.48** **0.00**	**0.66** **0.00**	**0.68** **0.00**	**0.66** **0.00**	1					
PeerS	**0.55** **0.00**	**0.46** **0.00**	–0.01 0.92	**0.62** **0.00**	**0.48** **0.00**	0.33 0.01	**0.57** **0.00**	**0.52** **0.00**	**0.44** **0.00**	**0.66** **0.00**	1				
HWk	0.35 0.00	0.36 0.00	–0.07 0.55	0.29 0.01	0.27 0.02	0.14 0.22	0.39 0.00	0.37 0.00	0.32 0.01	0.21 0.07	**0.50** **0.00**	1			
Ma-Sci	–0.06 0.59	0.18 0.14	0.31 0.01	0.14 0.23	0.02 0.86	–0.10 0.41	0.13 0.29	0.24 0.04	0.19 0.11	0.09 0.47	0.15 0.22	–0.10 0.40	1		
LTwC	**0.49** **0.00**	0.17 0.16	0.16 0.18	0.37 0.00	**0.46** **0.00**	0.36 0.00	0.27 0.02	0.36 0.00	0.31 0.01	0.36 0.00	**0.48** **0.00**	0.39 0.00	0.16 0.18	1	
C-Eng	**0.44** **0.00**	**0.75** **0.00**	0.18 0.12	**0.62** **0.00**	0.31 0.01	**0.50** **0.00**	**0.71** **0.00**	**0.66** **0.00**	**0.68** **0.00**	**0.54** **0.00**	**0.50** **0.00**	**0.44** **0.00**	0.17 0.15	0.27 0.02	1

Note: **bold text** indicates those correlations that met the dual standard of magnitude ≥ 0.40 and significance ≥ 0.001.

those two clusters of original variables were combined into single factors for the regression analysis.

All but two of the variables demonstrated the target level of correlation, and those variables (performance goals, math & science aptitudes) were dropped from the regression model test. Given the goal of developing a directional model, the researchers excluded correlations indicating relational paths among variables in the same columns, which could not be clarified using regression analysis. This process yielded 25 possible directional paths, to build into the hypothetical prediction model.

Using the remaining significantly-related variables, a hypothetical, unidirectional prediction model of engineering students' overall motivation and success expectations was constructed. Positioning and sequential ordering were based on their theoretical relationships, along with previous research precedents both in engineering and more general education research studies [51]. They are presented in three sequential subsets (columns) in the hypothetical model, shown in Fig. 1: individual goal orientations and beliefs about the profession (column 1); course-based content perceptions, climate perceptions and course motivations (self-efficacy and success expectations) (column 2); and course engagement along with career-related motivations (self-efficacy and success expectations) (column 3).

3.3 Regression analysis and model test

Finally, three phases of simultaneous multiple regression analysis [39–40] were conducted to test the relative magnitude and power of influences on the theoretical sequence of factors (target level: $p < 0.01$). Multiple regressions were utilized to assess the relative significance of influences of the variables in each column in the hypothesized model, column 1 on column 2, column 2 on column 3, and column 1 on column 3 [41]. Any paths in the hypothetical model falling below the target level of significance would be dropped [51], leaving the most significant paths to explain the prevalent influences on these engineering students' course and career-related motivations. As a consequence, any variables that had significant correlations but did not demonstrate any significant predictive influences at the target level would also be dropped from the model.

As shown in the model summary statistics (Table 3), all of the multiple regressions demonstrated significant overall effects, showing the overall soundness of the hypothetical model as constructed.

As shown in the analysis of the model's unique variable coefficients (Table 4), there were one or more variables in each regression cluster of predic-

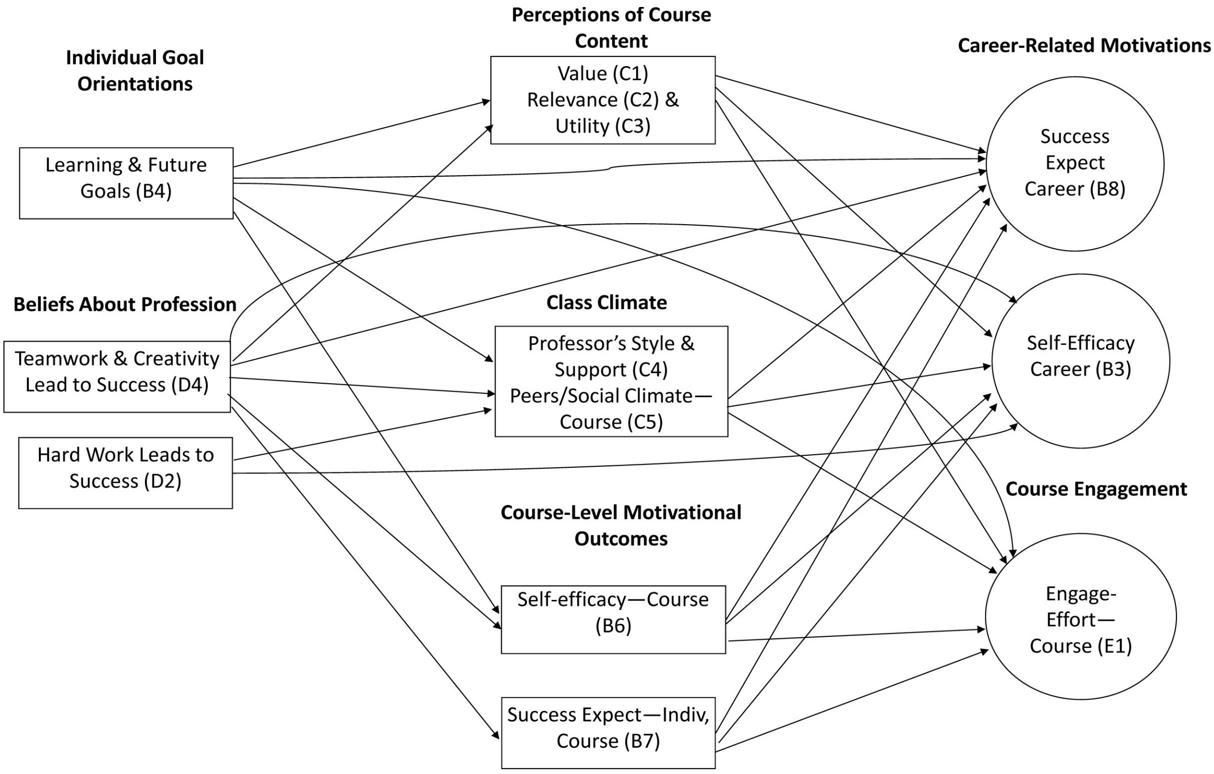

Fig. 1. Hypothesized Regression Model Predicting Engineering Students' Motivation.

tors that demonstrated a more highly significant influence on the outcome variable than the others ($p < 0.01$).

The multiple regression analysis eliminated 13 of the 25 original, hypothetically predictive pathways, and one original factor (hard work), leaving the 9 most influential variables and 12 most statistically-significant influential pathways to course engagement, and to the career efficacy and success expectations of these advanced engineering students. The resulting final regression model is shown in Fig. 2.

3.4 Summary of findings

The final model suggests more complex relationships than are demonstrated by the regression results alone.

While personal goals and beliefs are strong predictors of both course-level factors (perceptions and motivations), they do not have significant direct paths to all of the outcomes. Thus, the data analyses indicate both direct effects on course engagement and career-related motivations, and indirect effects on the same outcomes, apparently mediated by the course-level perceptions and motivations.

Table 3. Results of Multiple Regression

Model Path	R^2 (Mult. Correl. Coefficient)	*F* Change	*df* (degrees of freedom)	Significance of *F* Change
Phase 1: Col 1 → Col 2	0.575	30.698	3	0.000**
Goals & Beliefs → Course Perc & Motiv				
Goals & Beliefs → Climate	0.447	18.556	3	0.000**
Goals & Beliefs → Course Efficacy	0.485	21.624	3	0.000**
Goals & Beliefs → Course Success Expect	0.206	6.052	3	0.001**
Phase 2: Col 2 → Col 3	0.393	10.511	4	0.000**
Course Perc & Motiv → Prof Succ Expect				
Course Perc & Motiv → Prof Self-Effic	0.469	14.370	4	0.000**
Course Perc & Motiv → Course Engage	0.594	23.730	4	0.000**
Phase 3: Col 1 → Col 3	0.278	8.993	3	0.000**
Goals & Beliefs → Prof Succ Expect				
Goals & Beliefs → Prof Self-Effic	0.342	12.153	3	0.000**
Goals & Beliefs → Course Engage	0.587	33.199	3	0.000**

Table 4. Influences of Individual Variables in Model

Model Paths	***B* Unstandardized Coefficient**	**Standard Error**	***t***	**Significance of Contribution**
Column 1 → Column 2	0.701	0.089	7.899	**0.000****
Learning & Future Goals → Content Perceptions				
Beliefs: Teamwork & Creativity → Content Perceptions	0.405	0.168	2.415	0.018
Beliefs: Hard Work → Content Perceptions	0.081	0.105	0.771	0.433
Learning & Future Goals → Class Climate	0.307	0.066	4.665	**0.000****
Beliefs: Teamwork & Creativity → Class Climate	0.425	0.119	3.584	**0.001****
Beliefs: Hard Work → Class Climate	0.076	0.078	0.978	0.331
Learning & Future Goals → Course Self-Efficacy	0.436	0.066	6.569	**0.000****
Beliefs: Teamwork & Creativity → Course Self-Efficacy	0.380	0.120	3.176	0.002*
Beliefs: Hard Work → Course Self-Efficacy	–0.023	0.078	–0.295	0.769
Learning & Future Goals → Course Success Expect	0.094	0.089	1.050	0.279
Beliefs: Teamwork & Creativity → Course Success Expect	0.601	0.162	3.716	**0.000***
Beliefs: Hard Work → Course Success Expect	–0.024	0.106	–0.222	0.825
Column 2 → Column 3	0.012	0.111	0.108	0.915
Content Perceptions → Career Success Expectations				
Class Climate → Career Success Expectations	0.053	0.187	0.284	0.778
Course Self-Efficacy → Career Success Expectations	0.320	0.117	1.815	0.074
Course Success Expect → Career Success Expectations	0.418	0.121	3.462	**0.001****
Content Perceptions → Career Self-Efficacy	0.027	0.083	0.323	0.748
Class Climate → Career Self-Efficacy	0.128	0.140	0.914	0.364
Course Self-Efficacy → Career Self-Efficacy	0.351	0.132	2.651	**0.010***
Course Success Expect → Career Self-Efficacy	0.218	0.091	2.410	0.019
Content Perceptions → Course Engagement & Effort	0.569	0.102	5.552	**0.000****
Class Climate → Course Engagement & Effort	–0.095	0.172	–0.552	0.583
Course Self-Efficacy → Course Engagement & Effort	0.199	0.163	1.225	0.225
Course Success Expect → Course Engagement & Effort	0.161	0.111	1.446	0.153
Column 1 → Column 3	0.214	0.019	2.342	0.022
Learning & Future Goals → Career Success Expectations				
Beliefs: Teamwork & Creativity → Career Success Expectations	0.614	0.165	3.712	**0.000****
Beliefs: Hard Work → Career Success Expectations	0.019	0.109	0.174	0.862
Learning & Future Goals → Career Self-Efficacy	0.188	0.068	2.748	**0.008***
Beliefs: Teamwork & Creativity → Career Self-Efficacy	0.481	0.124	3.884	**0.000****
Beliefs: Hard Work → Career Self-Efficacy	0.065	0.081	0.799	0.427
Learning & Future Goals → Course Effort & Engagement	0.606	0.075	8.091	**0.000****
Beliefs: Teamwork & Creativity → Course Effort & Engagement	0.166	0.136	1.223	0.225
Beliefs: Hard Work → Course Effort & Engagement	0.157	0.089	1.763	0.082

Learning and future goals demonstrated significant direct effects on perceptions of course content, class climate, and course and career self-efficacy. Beliefs about the profession (importance of teamwork and creativity) demonstrated significant direct effects on perceptions of class climate, course self-efficacy and success expectations, as well as career self-efficacy and success expectations. Course content perceptions demonstrated significant effects on course engagement and effort, as course efficacy did on career efficacy, and course success expectations did on career success expectations. All of these are theoretically-consistent findings, and while some individual relationships have been found in previous engineering studies, the entire complex modeling of these relationships has not previously been demonstrated for mechanical engineering students.

3.5 Limitations

A limitation of this study, like so many others in this body of work, is that its scope is a relatively small sample (80) from one engineering subspecialty (mechanical). At the same time, the homogeneous sample controlled for many extraneous factors and allowed testing a model to clarify the relative contributions of many factors previously found correlated. Having demonstrated the benefit of modeling to clarify some of the relative influences invites extension to more diverse samples, to discover how much divergence exists among subgroups in the field.

4. Discussion

International research activity on motivation in engineering education provides ample evidence that motivation is an issue of concern in the global community of engineering educators and institutions. The better engineering educators understand their students' motivation, the more effectively they can address the needs of course-level success (vs. failure) [52], as well as program-level completion (vs. attrition) [9]. At the same time, the field of engineering education needs to position itself for globalization and change [53], future-oriented goals

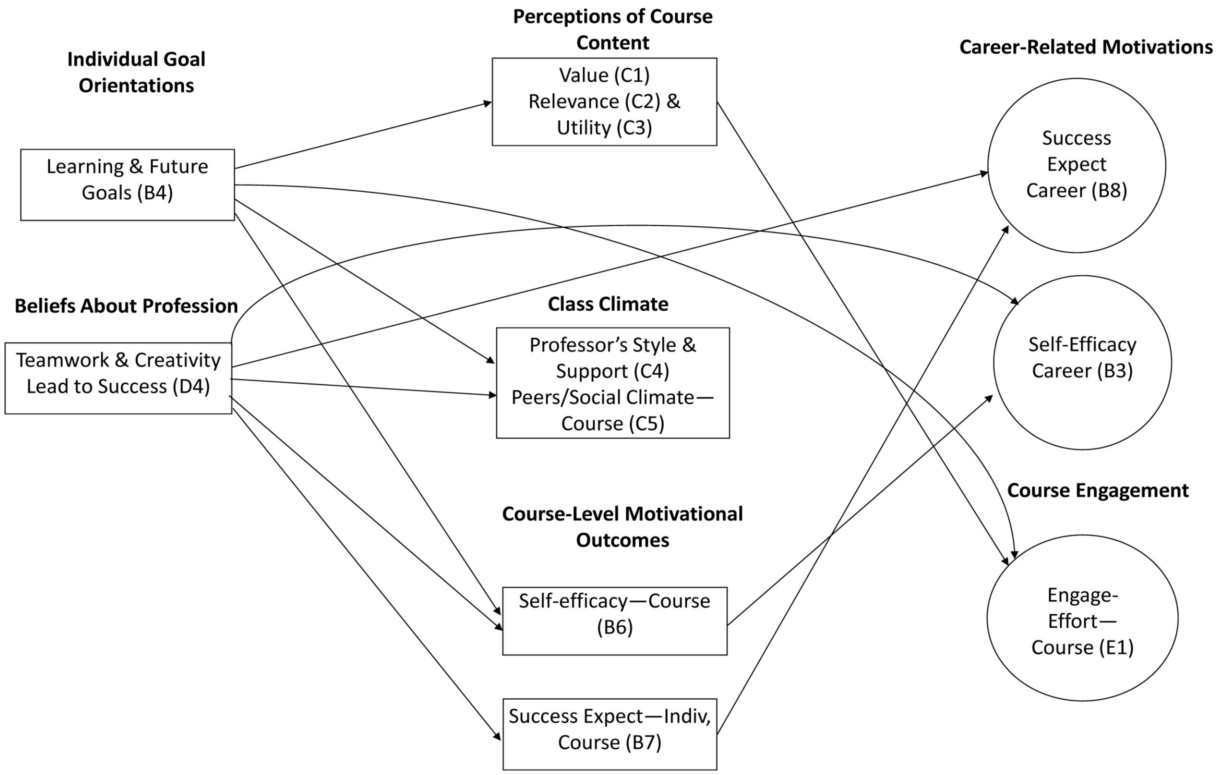

Fig. 2. Final Regression Model Predicting Engineering Students' Motivation.

that can be promoted by attending to motivation as well.

Previous studies have used a variety of motivational measures and constructs, mostly with item-level and correlational analysis; and while locally interesting, these methods contribute only modestly to the larger scope of data-driven change in the engineering field and engineering education practice. As a whole, they can present a cacophony of findings that may be more confusing than helpful. Modeling analysis, using well-designed scales and constructs from previous research precedent, assessed in one group and point-in-time, holds many extraneous variables constant, and also enables sorting out the shared variance to clarify influential relationships.

Previous studies have included beliefs in the motivational equation for engineering (e.g., [37]). The present study used perceptions of the course and beliefs about the profession to predict not only course engagement but also career motivations. Further, this study found some goal orientations and beliefs about the profession more positively influential on course motivation and engagement and on career-related motivation than others. Given their powerful predictive role across education and social science research, it is not surprising that learning and future goals demonstrated such dramatic influences among engineering students. They exerted the most significant influential effects on motivational characteristics, both proximal (current, course-related) and distal (long-term, career). Thus, fostering and supporting learning and future goals for individuals and groups may be the most important motivational investment that engineering education instructors and programs can make. While other beliefs about engineering as a profession did not demonstrate significant influential effects, the role of teamwork and creativity in success showed important influences on both course and career efficacy and success expectations, motivational factors that carry students through challenges and lead to completion and success. Notably, these beliefs tend to be more diverse and accessible, more malleable (learned and changeable) and more internalized (personally owned and enjoyed) than the others assessed (math & science aptitude and hard work). These characteristics place them in similar motivational frameworks as productive goals, but discipline-focused rather than learner-focused.

While performance goal orientations failed to achieve the target level of correlation with productive course and career-related motivations, learning and future goals emerged as one of the most powerful predictors in the model. While beliefs that the engineering profession required high math and science aptitudes failed to achieve adequate correlation, beliefs that it required learned skills (teamwork, creativity) and hard work correlated strongly, and belief in the need for those learned skills emerged as a powerful predictor of productive course and career motivations. Thus, among the important distinctions illuminated in this study was that more innate abilities and aptitudes (less malleable and learner-controlled factors) were *less predictive* of productive motivations than learned skills (more malleable and learner-controlled factors). This is consistent with research findings in other fields of education outside of engineering. It also presents research-based precedent for potential to enhance productive motivation among engineering students, because those more productive and influential factors are also malleable and amenable to instructional change.

Other recent modeling studies have explored the interrelationships of multiple motivational constructs and critical outcome characteristics (e.g., [26]). This study both confirms some of those predictive relationships and extends frameworks for understanding them into more multi-theory dimensions of motivation and beyond individual characteristics to include instructional climate (environmental supports). In addition, this study assessed the relative contributions of cognitive, affective-perceptual and contextual-social factors linked to motivation, based on the fully integrative conceptualization of motivation and learning [3]. In this particular sample of junior and senior engineering students, personal goal orientations and beliefs about the profession predicted content perceptions, class climate perceptions and course-level motivations (self-efficacy and success expectations). They also demonstrated both direct effects on course engagement and career-related motivations, and apparent indirect effects on the same outcomes, possibly mediated by course-level perceptions and motivations.

4.1 Future directions and extensions

Given the complexity and contextualized nature of human motivation, these influential relationships could vary across groups, so extensions across engineering subspecialties to illuminate convergence and divergence will further confirm and elaborate these findings. Opportunities for future extensions of this work include investigating similarities among a more diverse group of engineering students generally, and possible differences among subspecialties in engineering, as well as internationally. Such extensions are possible, in part, because the instruments used here provide standardized scales to assess multiple motivational constructs and related perceptions. In addition, given previous research demonstrating the links between motivation and intentions to drop out (e.g., [38]) and between intentions and actual dropout (e.g., [54]), an extension addressing the issue of dropout would be to include a measure of dropout intentions among engineering students.

4.2 Implications for engineering education

This motivational modeling research articulates and operationalizes some of the dynamics of engineering education relevant to current and urgent issues of the field, such as: the role of students' preconceptions about a subject, and the dynamic characteristics of effective and supportive teachers (e.g., [55]); priorities for understanding and evaluating teaching and learning that motivate students to remain and complete engineering programs (e.g., [56]); and the historic lack of adequate professional skills such as problem-solving, communication and teamwork among engineering graduates (e.g., [57]). Students' overall motivation impacts all of these individual and program outcomes, and has a residual influence on teaching, through teachers' reciprocal responses in teaching effort and expectations, based on students' motivational feedback (e.g., [58]). Better understanding the fully interactive dynamic of students' motivation offers potential for professors and programs to address long-standing issues of retention and completion [2, 21]. In addition, research that supports understanding of the productive motivational profile of students who succeed in engineering programs also offers potential to support recruitment and professional development that reaches into the secondary schools pipeline for recruiting future engineers [17].

5. Conclusions

For advanced engineering students, particular types of goals, beliefs and expectations predict their productive course and career-related motivations much more significantly than others. These findings demonstrate that, from students' perspectives, learned skills and malleable motivational characteristics (all things that teaching can influence) offer more motivational power to promote student success than do innate abilities or stable traits. Modeling these relationships reduces the noise from multiple, sometimes conflicting findings, enabling researchers and engineering educators to identify the strongest and most consistent influences on engineering students' course engagement and positioning for career success. A more refined understanding of these influences in the motivational dynamic supports focusing educational efforts, and using limited resources, to bring the greatest value-added to engineering programs and classrooms.

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