A Comparison of Statistical Methods for Examining Persistence in Engineering

Daniel Kuzbary, William C. Bridges
Department of Mathematical Sciences
Clemson, University
Clemson, SC, USA

Julia L. Sharp
Department of Statistics
Colorado State University
Fort Collins, CO, USA
jlsharp@colostate.edu

Catherine McGough, Lisa Benson
Department of Engineering & Science Education
Clemson University
Clemson, SC, USA

Abstract**—***This paper compares three methods for examining the relationship of multiple factors related pertaining to student motivation on the degree outcome (persistence in an engineering major). A study was conducted in which all first year engineering students at one institution were invited to complete a survey designed to measure students' motivations and attitudes towards engineering. The survey was based on Future Time Perspective (FTP) theory, which considers how students' perceptions of the future impact their perceptions of present tasks, and their goal orientation. The survey was distributed early in students' first semester (n=979, 82% response), and the current major of these students was collected two and a half years later (Spring 2016). Three statistical methods were used to determine what factors have a significant effect on the likelihood that a student will persist in engineering: two sample t-tests, simple logistic regression analysis, and multiple logistic regression analysis with all factors and pairwise interactions in the model. When considering all factors simultaneously, there is evidence that students with positive perceptions of the future are more persistent toward their goals, indicating that FTP is a relevant theory for examining interactions between student motivation and persistence in engineering.* ***Keywords— future time perspective; persistence; statistical methods***

I. INTRODUCTION

Quantitative studies in engineering education research often examine effects of multiple factors on an outcome, for example motivational factors on student persistence in engineering. The Motivation and Attitudes in Engineering (MAE) survey [1] is designed to measure students' dispositions towards their coursework and the field of engineering, as well as learning outcomes of perceived metacognitive strategy use and problem solving self-efficacy. Attitudinal attributes are based on the theoretical frameworks of Goal Orientation (GO),Expectancy-Value Theory (EVT), and Future Time Perspective (FTP) [2].Items related to metacognitive strategies are adapted from work by Shell and Husman [3]. Problem solving self-efficacy placed problem solving strategies in engineering [4] on a self-efficacy scale [5]. The eight factors that were considered in this survey are described in Table 1. This paper compares three methods for examining the relationship of multiple factors related to student motivation and the degree outcome (engineering major or not), including an exploration of descriptive statistics.

II. METHODS

The MAE survey was given to first-year engineering students in Fall 2013. The MAE factor scores were calculated on a seven-point Likert scale, except for PS which is on a scale from 0 to 100. The current majors of these students were collected in 2016, and they were divided into two groups: engineering majors (n=783) and non-engineering majors (n=196).

Three methods were used to examine the relationship of the factors related to student motivation and the degree outcome. Two-sample tests of means were used to compare the mean of the factors between engineers and non-engineers (Method 1). Simple logistic regression was used to consider the probability that students will be engineering majors in 2016 for each of the factors (Method 2). Multiple logistic regression was used to consider the probability that students will be engineering majors in 2016 with all of the factors in the model, including the pairwise interaction terms among the factors (Method 3).

Factor Name	Definition
Performance Approach (PA)	The student's academic goals include wanting to receive favorable evaluation on tasks compared to their peers.
Mastery Approach (MA)	The student's academic goals include wanting to master, or learn the concepts, on tasks.
Work Avoid (WA)	The student's academic goals include wanting to complete the task with as little effort as possible.
Expectancy (E)	The student believes they are competent at their engineering coursework.
Perceptions of the Future (F)	The student is certain about being an engineer.
Perceived Instrumentality (PI)	The student perceives their engineering coursework to be important to achieving their future goals.
Metacognitive Strategies (MC)	The student believes they use specific metacognitive strategies of knowledge and regulation.
Problem Solving Self-Efficacy (PS)	The student is confident in their ability to solve problems.

Table 1: Description of the factors measured in the MAE survey, their abbreviations and definitions of what a high score in this factor indicates.

For the two-sample t-test (Method 1), we tested whether each mean factor score of engineering majors is equal to the mean factor score of non-engineering majors (H_0: $\mu_1 = \mu_2$ against H_1: $\mu_1 \neq \mu_2$). We use the Welch two-sample t-test to accommodate for potential heterogeneity of variances. [6]

While the two sample t-tests are useful for determining a difference in the means, more analysis is required to determine the relationship between a student's factor scores in 2013 and persistence in an engineering major in 2016. In the simple logistic regression analysis (Method 2), we consider a statistical model in which a student's factor score is the predictor and the probability that a student is an engineering major as the response. Since the response is a probability, it must take values from zero to one. Therefore, a simple logistic regression model is an appropriate choice for this study.

The simple logistic model can be represented in terms of the probability P_i that student i will be an engineering major in 2016 (e.g., let $P_i = 1$if student i is an engineering major in 2016, and let $P_i = 0$ if student i is not an engineering major in 2016).The simple logistic regression model is written as

$$P_i = \frac{e^{\beta_0+\beta_1 x_i}}{1+e^{\beta_0+\beta_1 x_i}}, \tag{1}$$

where x_i is the 2013 factor score of student i. A Wald z-test was performed to test the significance of the relationship of the specified factor with the response by testing the hypotheses H_0: $\beta_1 = 0$versus H_1: $\beta_1 \neq 0$. The marginal effect of the specified factor $\frac{dP_i}{dx_i} = \beta_1 P_i(1-P_i)$ was estimated using the parameter estimate $\hat{\beta}_1$and the proportion of students who are engineering majors ($\hat{P}=0.80$) as an estimate for $\beta_1$and P_i, respectively.

We fit eight simple logistic regression models to the data, each using a single factor as the sole predictor. The simple logistic regression models provide information about the relationship between a particular factor score and the probability a student will be an engineering major. However, we are not able to consider the relationship of several factors simultaneously on the response in a simple logistic regression model. In a multiple logistic regression model, we can consider the relationship a particular factor has on the probability a student will be an engineering major given that the other factors are also in the model.

In addition to considering the relationship of all factors simultaneously with the probability a student will persist in an engineering major in 2016, we may wish to consider the relationship combinations of factor scores have with this probability. To this effect, we will add pairwise interaction terms to the multiple logistic regression model (Method 3). This model takes the form

$$P_i = \frac{e^{\beta_0 + \sum_{j=1}^{8} \beta_j (x_{ji}-\bar{x}_j) + \sum_{k=1}^{7}\left(\sum_{j=k+1}^{8} \beta_m (x_{ji}-\bar{x}_j)(x_{ki}-\bar{x}_k)\right)}}{1+e^{\beta_0 + \sum_{j=1}^{8} \beta_j (x_{ji}-\bar{x}_j) + \sum_{k=1}^{7}\left(\sum_{j=k+1}^{8} \beta_m (x_{ji}-\bar{x}_j)(x_{ki}-\bar{x}_k)\right)}} \tag{2}$$

where x_{ji} is the score student i has in factor j, $j=1,2,\ldots,8$, and $m=9,10,\ldots,36$ is the index of the parameter $\beta_m$associated with each interaction term. The variables in the multiple logistic regression model are centered to reduce the effect of correlation between the terms in the model.

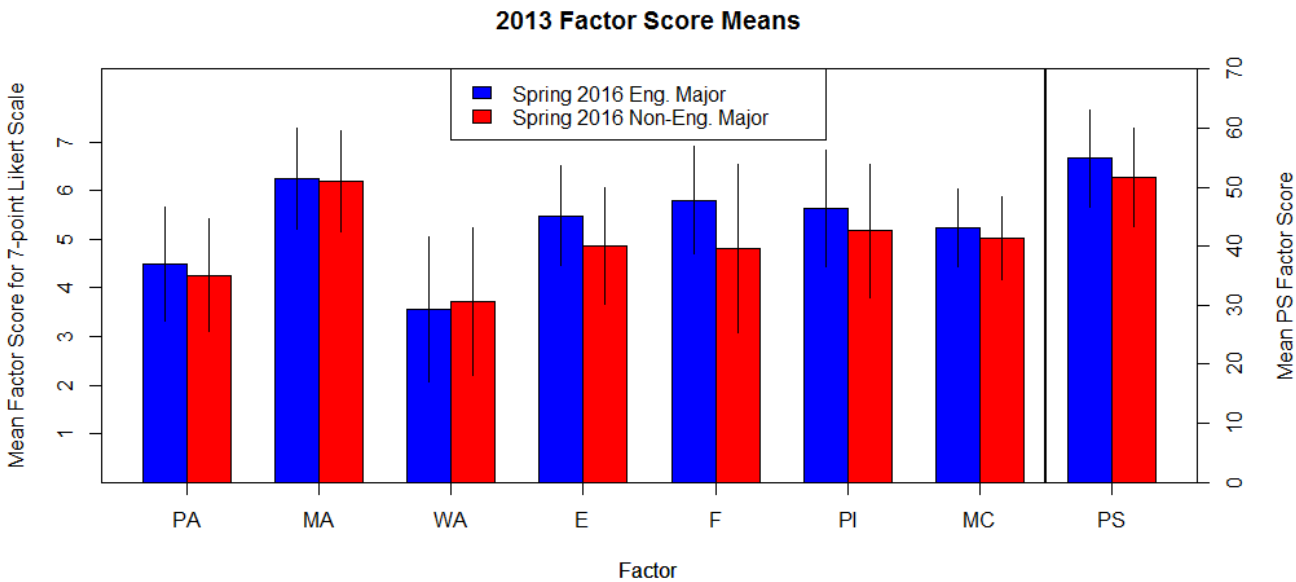

Fig.1: Mean factor scores and standard deviation bar for engineering majors (n=783) and non-engineering majors (n=196). The first seven factors are on a 7-point Likert scale; PS is on a scale from 0-100.

III. RESULTS

The means and standard deviations of the engineering and non-engineering major factor scores are provided in Fig. 1. Overall, Engineering majors have higher sample mean factor scores than non-engineering majors, with the exception of WA. The PA, MA, WA, PI, MC, and PS means are similar between engineering and non-engineering majors while the E and F factor scores each appear to be significantly larger for engineering majors than non-engineering majors

The results from the two sample t-tests, given in Table 2, indicate that the true mean of the engineering major E scores is significantly different from that of non-engineering majors (95% CI: 0.44,0.80; $p<0.001$). The true mean of F for engineering majors is significantly different than that of non-engineering majors (95% CI: 0.73,1.25; $p<0.001$). There are also significant differences between engineering majors and non-engineering majors in average PA (95% CI: 0.06, 0.42; $p=0.011$), in PI (95% CI: 0.25,0.67; $p<0.001$), in MC (95% CI: 0.06, 0.33; $p=0.006$), and in PS (95% CI: 1.64,4.79; $p<0.001$). There was not a significant difference between engineering and non-engineering majors in the average MA scores ($p=0.496$) or in the average WA scores ($p=0.219$).

The results for each of the eight simple logistic regression models are summarized in the respective rows in Table 3.The fitted model with the E score as the sole predictor gives the coefficient estimate $\hat{\beta}_1=0.52$. The z-test shows that E is a significant predictor of whether an engineering student in 2013 will be an engineering student in 2016 ($z=6.85$, $p<0.001$). Further, under this model, a one-unit increase in the E score increases the probability that a student will be an engineering major by $\hat{\beta}_1\hat{P}(1-\hat{P}) = 0.52(0.80)(0.20) = 0.083$.

When considered individually, other scores that are significant predictors of whether an engineering student in 2013 will be an engineering student in 2016 include PA ($p=0.011$), F ($p<0.001$), PI ($p<0.001$), MC ($p=0.004$), and PS ($p<0.001$). The probability that a student will be an engineering major increases by 0.028 with a one-point increase in PA, by 0.082 with a one-point increase in F, by 0.044 with a one-point increase in PI, by 0.047 with a one-point increase in MC, and by 0.006 with a one-point increase in PS. When considered individually, neither MA ($p=0.494$) nor WA ($p=0.212$) have a significant relationship with the probability a student will remain an engineering major.

Factor	Test statistic (t)	df	p-value	95% CI for $\mu_{eng} - \mu_{non}$
PA**	**t = 2.56**	**294.30**	**0.011**	**(0.06,0.42)**
MA	t = 0.68	296.76	0.496	(-0.11,0.22)
WA	t =-1.23	293.93	0.219	(-0.39,0.09)
E**	**t = 6.69**	**268.69**	**<0.001**	**(0.44,0.80)**
F**	**t = 7.56**	**231.65**	**<0.001**	**(0.73,1.25)**
PI**	**t = 4.25**	**269.81**	**<0.001**	**(0.25,0.67)**
MC**	**t = 2.79**	**273.97**	**0.006**	**(0.06,0.33)**
PS**	**t = 4.02**	**258.38**	**<0.001**	**(1.64,4.79)**

Table 2: Results of two-sample t-tests comparing the mean scores of engineering and non-engineering majors. **Bold rows indicate statistically significant mean differences at significance level α=0.05.

Factor	Estimate $\hat{\beta}_1$	Std. Error	95% CI	Test Statistic z	p-value	Marginal Effect $\hat{\beta}_1\hat{P}(1-\hat{P})$	SE Marginal Effects	95% CI Marginal Effects
PA**	**0.17**	**0.07**	**(0.03,0.31)**	**2.53**	**0.011**	**0.028**	**0.004**	**(0.005,0.050)**
MA	0.05	0.07	(-0.10,0.19)	0.69	0.494	0.008	0.001	(-0.016,0.030)
WA	-0.07	0.05	(-0.17,0.04)	-1.25	0.212	-0.011	0.002	(-0.027,0.006)
E**	**0.52**	**0.08**	**(0.37,0.67)**	**6.85**	**<0.001**	**0.083**	**0.013**	**(0.059,0.107)**
F**	**0.51**	**0.06**	**(0.40,0.63)**	**8.69**	**<0.001**	**0.082**	**0.013**	**(0.064,0.101)**
PI**	**0.27**	**0.06**	**(0.15,0.39)**	**4.50**	**<0.001**	**0.044**	**0.007**	**(0.024,0.062)**
MC**	**0.29**	**0.10**	**(0.09,0.49)**	**2.87**	**0.004**	**0.047**	**0.008**	**(0.014,0.078)**
PS**	**0.04**	**0.01**	**(0.02,0.06)**	**4.49**	**<0.001**	**0.006**	**0.001**	**(0.003,0.010)**

Table 3: Results from fitting simple logistic regression models to the data, each using a single factor score as the sole predictor and the probability a student will be an engineering major as the response. **Bold rows indicate statistically significant parameter estimates as significance level α=0.05.

The results from fitting the multiple logistic regression model with pairwise interaction terms are given in Table 4. In this model, the relationship of a particular factor with the probability a student will be an engineering major is influenced by the value of other factor scores, as indicated by the significant interaction terms. When all factors and all pairwise interactions are included in the model, the main effects of MA, E, and F have a significant relationship with the probability that a student will remain an engineering major.

The inclusion of interaction terms in the multiple logistic regression model makes the interpretation of marginal effects of each factor more complicated. Let $\hat{\boldsymbol{\beta}}$ denote the vector of parameter estimates from our interaction model. We will denote the entries of $\hat{\boldsymbol{\beta}}$ by the predictor for which each estimate is associated, rather than a numeric index (e.g. $\hat{\beta}_F=\hat{\beta}_5$ is the parameter associated with the F factor score). The marginal effect of a given factor on the probability a student will be an engineering major is the partial derivative of P with respect to that factor. For example, the marginal effect of F on the outcome is given by

$$\frac{\partial P_i}{\partial x_F}=\frac{\partial}{\partial x_F}\left(\frac{e^{\beta_0+\sum_{j=1}^{8}\beta_j(x_{ji}-\bar{x}_j)+\sum_{i=1}^{7}\left(\sum_{j=i+1}^{8}\beta_k(x_{ji}-\bar{x}_j)(x_{ki}-\bar{x}_k)\right)}}{1+e^{\beta_0+\sum_{j=1}^{8}\beta_j(x_{ji}-\bar{x}_j)+\sum_{i=1}^{7}\left(\sum_{j=i+1}^{8}\beta_k(x_{ji}-\bar{x}_j)(x_{ki}-\bar{x}_k)\right)}}\right)$$

$$=\begin{pmatrix}\beta_F+\beta_{PA*F}x_{PA,i}+\beta_{MA*F}x_{MA,i}+\beta_{WA*F}x_{WA,i}+\beta_{E*F}x_{E,i}\\ +\beta_{F*PI}x_{PI,i}+\beta_{F*MC}x_{MC,i}+\beta_{F*PS}x_{PS,i}\end{pmatrix}*P_i*(1-P_i) \tag{3}$$

In this context, the marginal effect of a factor on P depends on the values of the other seven factors and interactions involving the factor of interest. The estimated marginal effects a factor are found by using the relevant parameter estimates from our interaction model and the proportion of students ($\hat{P}$=0.80) who are engineering majors as an estimate for P. Equations for the marginal effects of each factor are given in equations (4) through (11).

$$\frac{\partial P_i}{\partial x_{PA}}=0.013+0.017\,x_{MA}+0.010\,x_{WA}+0.012\,x_E-0.010\,x_F-0.005\,x_{PI}-0.001\,x_{MC}+0.001\,x_{PS}. \tag{4}$$

$$\frac{\partial P_i}{\partial x_{MA}}=-0.040+0.017x_{PA}+0.013x_{WA}-0.020x_E+0.032x_F-0.0004x_{PI}-0.019x_{MC}-0.001x_{PS}. \tag{5}$$

$$\frac{\partial P_i}{\partial x_{WA}}=-0.007+0.010x_{PA}+0.013x_{MA}+0.001x_E+0.020x_F-0.031x_{PI}+0.026x_{MC}-0.003x_{PS}. \tag{6}$$

$$\frac{\partial P_i}{\partial x_E}=0.072+0.012x_{PA}-0.020x_{MA}+0.001x_{WA}-0.018x_F+0.019x_{PI}-0.022x_{MC}+0.002x_{PS}. \tag{7}$$

$$\frac{\partial P_i}{\partial x_F}=0.048-0.010x_{PA}+0.032x_{MA}+0.020x_{WA}-0.018x_F-0.025x_{PI}+0.017x_{MC}+0.0004x_{PS}. \tag{8}$$

$$\frac{\partial P_i}{\partial x_{PI}}=-0.007-0.005x_{PA}-0.0004x_{MA}-0.031x_{WA}+0.019x_E-0.025x_F+0.014x_{MC}-0.002x_{PS}. \tag{9}$$

$$\frac{\partial P_i}{\partial x_{MC}}=-0.031-0.001x_{PA}-0.019x_{MA}+0.026x_{WA}-0.022x_E+0.0170x_F+0.014x_{PI}-0.001x_{PS}. \tag{10}$$

$$\frac{\partial P_i}{\partial x_{PS}}=0.002+0.001x_{PA}-0.001x_{MA}-0.003x_{WA}+0.002x_E+0.0004x_F-0.002x_{PI}-0.001x_{MC}. \tag{11}$$

Consider, for example, the marginal effect of F. From the equation given above $\left(\frac{\partial P}{\partial x_F}\right)$, the probability a student will be an engineering major increases by 0.048 – 0.010∗(PA score) + 0.033∗(MA score) + … + 0.0004∗(PS score) for a one point increase in the F score. For example, when a student's MA score is high with all other predictors constant, a one-point increase in the student's F has a greater impact on the probability that the student will be an engineering major than when the student's MA score is low.

Parameter β_m	**Estimate $\hat{\beta}_m$**	**Std. Error**	**95% CI**	**Test Statistic z**	**p-value**	**Conditional Probability $\hat{\beta}_m\hat{P}(1-\hat{P})$**	**SE Cond. Prob.**	**95% CI Cond. Prob.**
Intercept	1.64	0.11	(1.42,1.87)	14.49	<0.001	0.263	0.018	(0.227,0.299)
PA	0.08	0.09	(-0.10,0.25)	0.90	0.369	0.013	0.014	(-0.016,0.040)
***MA**	**-0.25**	**0.14**	**(-0.53,0.01)**	**-1.81**	**0.071**	**-0.040**	**0.022**	**(-0.085,0.002)**
WA	-0.04	0.07	(-0.18,0.10)	-0.57	0.571	-0.007	0.011	(-0.029,0.016)
****E**	**0.45**	**0.12**	**(0.22,0.68)**	**3.78**	**<0.001**	**0.072**	**0.019**	**(0.035,0.109)**
****F**	**0.30**	**0.09**	**(0.12,0.48)**	**3.21**	**0.001**	**0.048**	**0.014**	**(0.019,0.077)**
PI	-0.04	0.11	(-0.26,0.16)	-0.40	0.690	-0.007	0.018	(-0.042,0.026)
MC	-0.19	0.16	(-0.50,0.11)	-1.23	0.217	-0.031	0.026	(-0.080,0.018)
PS	0.01	0.01	(-0.02,0.04)	0.77	0.441	0.002	0.002	(-0.003,0.006)
PA*MA	0.1	0.10	(-0.09,0.31)	1.03	0.304	0.017	0.016	(-0.014,0.050)
PA*WA	0.06	0.05	(-0.04,0.17)	1.20	0.230	0.010	0.008	(-0.006,0.027)
PA*E	0.07	0.09	(-0.11,0.26)	0.79	0.432	0.012	0.014	(-0.018,0.042)
PA*F	-0.06	0.07	(-0.21,0.08)	-0.83	0.407	-0.010	0.011	(-0.034,0.013)
PA*PI	-0.03	0.08	(-0.19,0.13)	-0.37	0.710	-0.005	0.013	(-0.030,0.021)
PA*MC	0.00	0.13	(-0.27,0.26)	-0.03	0.973	-0.001	0.021	(-0.043,0.042)
PA*PS	0.00	0.01	(-0.02,0.03)	0.32	0.748	0.001	0.002	(-0.003,0.005)
MA*WA	0.08	0.08	(-0.08,0.25)	0.98	0.325	0.013	0.013	(-0.013,0.040)
MA*E	-0.12	0.15	(-0.42,0.16)	-0.82	0.410	-0.020	0.024	(-0.067,0.026)
****MA*F**	**0.20**	**0.10**	**(0.01,0.40)**	**2.06**	**0.039**	**0.032**	**0.016**	**(0.002,0.064)**
MA*PI	0.00	0.11	(-0.21,0.22)	-0.02	0.980	<-0.001	0.018	(-0.034,0.035)
MA*MC	-0.12	0.15	(-0.42,0.17)	-0.82	0.412	-0.019	0.024	(-0.067,0.027)
MA*PS	0.00	0.01	(-0.03,0.02)	-0.31	0.758	-0.001	0.002	(-0.005,0.003)
WA*E	0.00	0.08	(-0.15,0.15)	0.04	0.969	0.001	0.013	(-0.024,0.024)
****WA*F**	**0.13**	**0.06**	**(0.02,0.24)**	**2.27**	**0.023**	**0.020**	**0.010**	**(0.003,0.038)**
****WA*PI**	**-0.19**	**0.07**	**(-0.33,-0.06)**	**-2.81**	**0.005**	**-0.031**	**0.011**	**(-0.053,-0.010)**
WA*MC	0.16	0.11	(-0.05,0.38)	1.52	0.127	0.026	0.018	(-0.008,0.061)
****WA*PS**	**-0.02**	**0.01**	**(-0.04,-0.0021)**	**-2.16**	**0.031**	**-0.003**	**0.002**	**(-0.006,-0.0003)**
E*F	-0.11	0.08	(-0.28,0.05)	-1.32	0.189	-0.018	0.013	(-0.045,0.008)
E*PI	0.12	0.10	(-0.08,0.32)	1.14	0.253	0.019	0.016	(-0.013,0.051)
E*MC	-0.13	0.16	(-0.45,0.19)	-0.82	0.413	-0.022	0.026	(-0.072,0.030)
E*PS	0.01	0.01	(-0.02,0.04)	0.72	0.471	0.002	0.002	(-0.003,0.006)
****F*PI**	**-0.16**	**0.06**	**(-0.28,-0.05)**	**-2.64**	**0.008**	**-0.025**	**0.010**	**(-0.045,-0.008)**
F*MC	0.11	0.12	(-0.13,0.35)	0.86	0.389	0.017	0.019	(-0.021,0.056)
F*PS	0.00	0.01	(-0.02,0.02)	0.23	0.815	<0.001	0.002	(-0.003,0.003)
PI*MC	0.09	0.17	(-0.25,0.43)	0.52	0.605	0.014	0.027	(-0.040,0.069)
PI*PS	-0.01	0.01	(-0.04,0.02)	-0.70	0.482	-0.002	0.002	(-0.006,0.003)
MC*PS	0.00	0.02	(-0.03,0.03)	-0.19	0.848	-0.001	0.003	(-0.005,0.005)

Table 4: Results from fitting a multiple logistic regression model with pairwise interaction terms to the data, using the probability a student will be an engineering major as the response. Bold rows indicate statistically significant parameter estimates (* significant at α=0.10, ** significant at α=0.05).

MA/E	1	2	3	4	5	6	7
1	0.062	0.044	0.026	0.009	-0.009	-0.027	-0.045
2	0.094	0.076	0.059	0.041	0.023	0.005	-0.012
3	0.126	0.109	0.091	0.073	0.055	0.038	0.020
4	0.159	0.141	0.123	0.105	0.088	0.070	0.052
5	0.191	0.173	0.155	0.138	0.120	0.102	0.084
6	0.223	0.205	0.188	0.170	0.152	0.134	0.117
7	0.255	0.238	0.220	0.202	0.184	0.167	0.149

Table 5: Marginal effect of F given various values of MA and E, with the remaining factors fixed at their average values.

A closer look at the marginal effects of a specific factor may be found by fixing all but one or two factor scores. In Table 5, the marginal effect of F on *P* is given for different values of MA and E, while the remaining factors are fixed at their means.

For example, student with a high mastery approach goal orientation with improving perceptions of their future careers in engineering has a greater impact on the probability the student will remain an engineering major than when the student's mastery approach goal orientation score is lower. That the MA score has such an impact on the effect F has on *P* should be expected given the significant parameter estimate $\hat{\beta}_{MA*F}$=0.20. The marginal effect of F on *P* is greater when the E score is low than when the E score is high. The impact the E score has on the marginal effect of F on *P*, however, is not significant (z=-1.32, p=0.189).

IV. Conclusions

While each of the statistical methods discussed exposes meaningful attributes of the data, the multiple logistic regression model with pairwise interactions is the method most pertinent to the goals of the study. With this model, we are able to simultaneously consider the relationship between student motivations and their persistence in an engineering degree program.

Such a model provides us with a better picture of how various aspects of student motivation relate to their choice to continue in their major. Even though the two-sample t-tests and the simple logistic regression models each highlighted trends between a factor and a student's major, the multiple logistic regression models provide us with a way to view the effects of a factor given the presence of the other factors. We can use this model to describe how combinations of factor scores relate to the likelihood a student will persist in an engineering major.

The results related to expectancy and perceptions of the future as significant predictors of persistence in engineering have implications for instructional practice. For example, providing students with experiences that build their expectations for successfully completing coursework, especially early on in their engineering programs, may increase the probability that students will persist in an engineering major. Additionally, students' positive perceptions of their future in engineering increase the probability of their persistence in an engineering major. These positive perceptions could be developed by providing students with explicit messages about what their future in engineering might look like.

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