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Understanding Student Attitudes in a Freshman Design Sequence*

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Research has shown that students' initial attitudes are key to understanding attrition in engineering programs. The College of Engineering at Michigan State University introduced a cornerstone design sequence in fall 2008 that provided an opportunity to study freshman attitudes towards engineering. We tested whether the new design sequence (DS) was more effective than the older traditional sequence (TS) at positively influencing freshman attitudes over the course of one semester. We collected attitude data twice, i.e., in the beginning and towards the end of fall 2008 semester, using the Pittsburgh Freshman Engineering Attitude Survey, and examined changes in attitude in the two groups with repeated analysis of covariance models. In fall 2008, 722 freshmen entered the College of Engineering. The analyses reported here include data from 389 of those students. We found that freshmen join the program with positive or strongly positive attitudes towards engineering. Those strong attitudes are durable and resistant to change. Students in the DS group had higher ACT scores, enjoyed math and science the most, and did not believe engineering to be an exact science. The DS and TS groups had similar longitudinal trajectories so there was no evidence for differential influence on student attitudes. Strongly positive initial attitudes coupled with insignificant changes in these attitudes could mean that one semester is insufficient to effect a measureable change. This quantitative study is a subset to the longitudinal study based on explanatory mixed methods design. The qualitative data collected in a follow up study (one-on-one interviews) may shed more light on the numerical results to further investigate the effectiveness of the freshman curriculum.

Keywords: freshman design sequence; freshman engineering; freshman attitudes; repeated measures analysis of covariance

1. INTRODUCTION

CHALLENGING ENGINEERING EDUCATION has been a commonplace occurrence over the past two decades. Major concerns about recruitment and retention in science, technology, engineering, and mathematics (STEM) education surfaced in the mid-1980s. Decreasing retention of freshmen in STEM majors was identified by some research studies of large national samples at two– and four-year institutions [1–3]. Approximately 34–40% of high school graduates who abandoned their intentions of entering STEM majors did so at or before college enrollment [4]. During college, 53% of the freshmen who started their academic program in engineering did not graduate with an engineering degree, and at least 50% of this attrition took place during the freshman year [5]. Clearly, the freshman year is critical for student success and retention in engineering programs [6]. The losses due to rising attrition rates are key issues for engineering educators. Considerable effort has been directed to examining the high attrition rates at engineering institutions in order to develop timely interventions [7].

Research suggests that both cognitive and affective issues contribute to attrition among engineering students. While cognitive issues in engineering education involve student knowledge and skills, affective issues relate to their attitudes toward engineering and confidence in their abilities to succeed. The initial attitudes and changes that take place in these attitudes during the freshman year affect student motivation, performance, and retention in engineering programs [8]. Studies have indicated that student attitudes are strongly correlated with their retention in the engineering programs [9]. For instance, a longitudinal study based on a large multi-institutional sample of freshmen found that the students who were most likely to choose engineering majors and complete degree requirements were those who held positive perceptions of engineering and had a measurable interest in science and technology [10]. The same study found that students who avoided engineering majors or dropped out of engineering were those who generally had a negative impression of engineering, lacked confidence in their abilities to complete the engineering program, and had little or no motivation to study science and mathe-

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matics. The study further found that students who left engineering in good academic standing had significantly different attitudes about engineering and themselves than those who stayed in engineering and those who left engineering in poor academic standing. Students who left engineering in good standing liked engineering less when they began their program and had a lower appreciation of the engineering profession than the other students. This category of students also liked math and science less and had lower confidence in their ability to succeed in engineering [9].

Another longitudinal study conducted at seven major four-year institutions that contribute most to the national supply of STEM majors found that students who left engineering were not academically different from those who stayed in engineering and that retention was better correlated with their attitudes than with academic factors. They also found that switchers (those who changed to non-engineering majors) and non-switchers had similar educational experiences but the non-switchers made more effective use of the resources and strategies that enabled them to tolerate and overcome their difficulties [2].

These studies substantiate the argument that students' initial attitudes toward engineering are key to understanding attrition in engineering programs. Accurately measuring students' attitudes and changes in these attitudes over the course of the freshman year allows us to develop effective means to evaluate the engineering programs, to reduce attrition, and improve academic success [11]. Attitude strength may be an important element in this context. Social psychologists have identified several aspects of attitude strength, ranging from the depth of knowledge possessed about an issue, to the extremity of personal attitude about the issue [12]. Despite so much variability in the conceptualization of this construct, researchers do agree that strong attitudes are "resistant to change, persistent over time, and predictive of behavior" [13].

Our literature review indicates that several engineering institutions in the US and abroad have conducted attitude related studies to better understand their students, to develop timely interventions, and to examine to what degree these interventions are meeting their desired goals and objectives [8, 10, 14, 15]. To effect a positive change in the students' initial attitudes, one common and the most talked about intervention that many institutions have adopted is the introduction of design–oriented courses—also called cornerstone or freshman design sequence—in the freshman year. An early introduction of engineering as a design–oriented discipline is hypothesized to significantly enhance student interest and motivation toward engineering [16]. Sheppard and Jenison provide a framework for exposing freshmen to key design qualities and give specific examples of how engineering programs around the US revised their freshman curricula to include engineering design [17, 18]. A number of NSF Coalitions have developed valuable information on teaching freshman design courses to improve the undergraduate engineering curriculum [19]. Research shows that these courses significantly contribute to the progress in academic achievement, create a stimulating environment for advanced cognitive development, and offer diverse experiential backgrounds and perspectives [20]. Based on the success of this type of intervention, some of the institutions have developed regression models to predict attrition and student success even before the students begin their programs. These models allow academic advisors to better inform students, especially those at high risk of attrition, of the opportunities that engineering offers, to develop tailor-made programs to suit varied student interests and to set more realistic retention goals for the institutions [21].

1.1 Context for the study

In line with current trends, the College of Engineering at Michigan State University introduced a cornerstone design sequence in fall 2008. The course sequence was designed to provide freshmen with a broad introduction to the concepts of engineering design, the engineering profession, engineering ethics, engineering problem-solving skills, and teamwork skills. The new sequence comprised two freshman courses: EGR 100 (Introduction to Engineering Design); and EGR 102 (Introduction to Engineering Modeling). EGR 100 was an addition to the existing core course requirement for admission to an engineering major and was also a prerequisite for EGR 102.

The broad goals of the new initiative were:

(1) to attract top students to engineering programs and retain them;
(2) to better prepare graduates to adapt to a quickly and constantly changing global engineering workforce by appreciating the importance of teamwork, project management, innovation, hands-on experience, ethics, career preparation, and professionalism;
(3) to see engineering as a broad field with many opportunities;
(4) to position engineering as a favored choice for prospective students and parents;
(5) to provide an opportunity for an early connection with the college of engineering and its faculty;
(6) and most importantly, to effect an appreciable and positive change in freshman attitudes about engineering.

The cornerstone design sequence aimed to achieve these objectives by raising the sense of community and fostering interaction centered on design projects anticipating the benefits of long, strong, and integrated technical education, paired with social and professional development [22].

This research study sought to examine the effects of the cornerstone design sequence on freshman attitudes about engineering and to establish whether the new sequence produced a significant improvement over the older traditional sequence with respect to student attitudes about engineering. Whether or not this has been successful is an empirical question and one that this study sought to answer. A study of this nature could be best performed if two cohorts were available for a direct comparison. In this respect, fall 2008 was a unique semester in that students in both streams, the traditional sequence (TS) and the design sequence (DS), were available to form a comparison group and a treatment group, respectively. This opportunity set the stage to examine the key research question: Is the DS an improvement over the TS in terms of its effects on freshman attitudes towards engineering?

1.2 Research hypotheses

To answer the research question, we used repeated measures analysis of covariance (ANCOVA) models with *group* (DS vs. TS) as the between-subject factor (BSF) and time (pre- vs. post-) as the within-subject factor (WSF). For this mixed design context, three null hypotheses are of particular interest:

(1) The Flatness hypothesis—freshman attitudes within subjects do not change over time when disregarding group membership;
(2) The Level hypothesis—freshman attitudes between groups are the same, disregarding *time*;
(3) The Parallelism hypothesis—freshman attitudes within each group show similar patterns of change over *time* ($H_{0,b} : \Delta\mu_{TS} = \Delta\mu_{DS}$). In other words, there is no time–group interaction or no treatment effect.

Geometrically, the Parallelism hypothesis states that if we graphically connect the means of the dependent variable group across time, then all resulting group-specific profiles will be parallel. With regard to the main research question, the Parallelism hypothesis is substantively the most interesting one; it asks whether there is differential change over time (i.e. treatment, intervention, etc.) on the response variable for the TS and DS groups, and for this reason it is to be addressed first. If there is no evidence that the groups' trajectories have different slopes over time, then the Level and Flatness hypotheses become more relevant. Hence, the no-interaction hypothesis (Parallelism) was investigated first and only if it was found to be not significant were the Flatness and the Level hypotheses tested.

The objective was to understand initial freshman attitudes as they enrolled in engineering programs and whether those attitudes were affected by the new design sequence. Improved understanding of attitudinal changes could help in the formative evaluation of the new sequence. More importantly, it could help develop better evaluation methods for engineering programs by incorporating and integrating student attitudes as a source to the existing feedback system. Setting up a wider scope with three research hypotheses was therefore a deliberate effort to not only observe the time effects on the attitudes of two student groups but also study the changes in those attitudes due to important demographic factors (e.g. gender, past performance) that could lead to a better understanding of engineering freshmen. In this context, fall 2008 provided an opportunity when both DS and TS groups were available for direct comparison.

2. METHOD

2.1 General model

The General Linear Model (GLM) provides a flexible framework for the present analyses. We conducted repeated measures ANCOVA models to test the three hypotheses. This model allows comparison of the two groups on measurements made at the beginning and toward the end of the semester while controlling for one or more continuous and/or categorical covariates (e.g. ACT and gender). The mixed design allows testing hypotheses about the effects of both the BSFs (e.g. group and gender) and the WSFs (i.e. time). More importantly, we can investigate interactions between factors as well as the effects of individual factors, including covariates, to answer the research question (Parallelism hypothesis). Estimated marginal means (EMMs) are the predicted mean values for the cells in the model, after controlling other variables. They permit us to interpret the main effects for categorical predictors such as group and gender, while profile plots (interaction plots) of these means illustrate the nature of interaction effects.

The general linear model can be represented in vector notation as:

$$Y = X\beta + \varepsilon \tag{1}$$

Where; Y is the dependent variables' vector, β is the unknown coefficients vector, X is the design matrix comprising independent variables, and ε is the error vector.

For repeated measures, this model is augmented with the number of levels or WSFs. For a pre-, post- design (two time points), the general model can be represented as:

$$\begin{bmatrix} Pre_i \\ Post_i \end{bmatrix} = \begin{bmatrix} X_i & 0 \\ 0 & X_i \end{bmatrix} \begin{bmatrix} \beta_i & 0 \\ 0 & \gamma_i \end{bmatrix} + \begin{bmatrix} \varepsilon_i \\ \varepsilon_i' \end{bmatrix} \tag{2}$$

Where; Pre_i is the pre-test dependent variables vector, $Post_i$ is the post-test dependent variables vector, β_i is the unknown coefficients matrix for pre-test, γ_i is the unknown coefficients matrix for post-test, X_i is the design matrix for independent variables (same for pre- and post-), ε_i is the errors vector for pre-test, and, ε_i' is the errors vector for post-test.

These models inherently incorporate time interactions, *i.e*., pre-, post- or WSFs. Inter-independent variables interactions (or BSFs) can be appropriately added to these models, if needed.

The pre-, post- models, in generic form, are:

$$Pre_i = \beta_0 + x_1\beta_1 + x_2\beta_2 + \cdots + x_k\beta_k + \varepsilon_i \quad (3)$$

$$Post_i = \gamma_0 + x_1\gamma_1 + x_2\gamma_2 + \cdots + x_k\gamma_k + \varepsilon_i' \quad (4)$$

2.2 Survey instrument

As a first step, we needed to identify and/or develop valid and reliable measures that could be used to evaluate student learning, attitudes, and experiences within an engineering program and whether the new freshman engineering experiences were actually reflecting the program's stated goals. Given that we had both cohorts available for research, the study involved comparing attitudes (the outcomes) in the DS group to attitudes in the TS group. For this study, a closed form questionnaire was selected because:

(1) it provides a reliable assessment of student attitudes;
(2) it is commonly used to measure impressions of engineering, enjoyment of working in groups, and self-assessed competencies [23];
(3) it is easier to administer than other alternatives;
(4) it can be given to a large number of subjects with minimal cost;
(5) the responses to the questionnaire can be given with a check list, rating, Likert scale or semantic differentials;
(6) repeated use of the instrument can measure changes in attitudes over time or the effect of a particular intervention.

Experts strongly recommend the use of available instruments since development and validation of a closed form questionnaire is a tedious and time consuming process [24]. A literature search was undertaken to identify a valid and reliable survey instrument that could measure attitudes among student cohorts and, particularly, how they were impacted by the cornerstone design sequence [16, 25–27]. We selected the pre- version of the Pittsburgh Freshman Engineering Attitude Survey (PFEAS) for this study because:

(1) it was the most relevant since it was originally developed for a similar study;
(2) it had been extensively used by various institutions and cited in a number of refereed publications [28–31];
(3) it had an established high degree of validity and reliability [9, 15].

Recent work has raised some concerns about the original instrument [32] and a revised version has been developed [33]. This revised version was not yet available when we started this study.

The PFEAS was developed in 1993 by Besterfield-Sacre et al. for a similar study at the University of Pittsburgh [16]. Since then, it has been adopted by several institutions to evaluate their freshman programs, study attrition and probation issues related to freshmen, and to measure ABET's EC 2000 outcome issues [28–30, 34]. Survey elements are rated on either a five point Likert scale or an ordinal-based self-assessed confidence scale. As part of the development process, the PFEAS underwent rigorous pilot testing and improvement by means of item analysis, verbal protocol elicitation, and factor analysis [29]. The fifty items in the scale cluster into thirteen attitude measures or subscales, as listed in Table 1 [35].

These subscales define the domain of the instrument's main construct, i.e. freshman attitudes about engineering. Three of the subscales, namely Jobs—financial influences for studying engineering, Family—family influence to studying engineering, and Study— confidence about study habits, were not relevant to our study. Any likely differences between the DS and the TS on any of these three subscales would not reflect a treatment effect because the curriculum does not address these topics. To ensure scale reliability, we employed the original instrument but considered ten of the thirteen subscales for data analysis.

The literature shows that the subscales have

Table 1. Thirteen subscales of PFEAS. The name and a brief conceptual definition of each subscale are listed along with the item numbers for the specific questions used to measure the subscale.

No.	Name	Items	Definition
1	Career	1–3, 4*, 5, 6*, 7, 8*, 9*	General impression of engineering.
2	Jobs@	10, 14, 21, 23	Financial influences for studying engineering.
3	Society	11, 20	How engineers contribute to society.
4	Perception	12, 17, 18, 22, 25, 27, 28	Work engineers do & engineering profession.
5	Math	13, 19*	Enjoyment of math & science.
6	Exact	15, 26	Engineering perceived as exact science.
7	Family@	16, 24	Family influence to studying engineering.
8	Basic	29, 30, 31, 32, 35	Confidence in basic engineering knowledge & skills.
9	Communication	33, 34, 35	Confidence in communication & computer skills.
10	Study@	39*, 46	Adequate study habits.
11	Groups	37, 43*, 45*	Working in groups.
12	Ability	38, 40, 42, 49, 50	Problem solving abilities.
13	Compatibility	36, 44, 47, 48	Engineering abilities.

* Reverse scored; @ not considered.

shown little variation in their structure and have, over the years, standardized to one common set of values or loadings. Our independent item analysis supports using the original thirteen subscales as described in previous studies [9, 10]. We used a principle component analysis with Varimax rotation to extract the factors in SPSS 16.0. We found a close match with the original factor loadings of the scale. For standardization and ease of reference, the original loadings were mapped on to the study data to develop normalized mathematical expressions for pre- and post- subscales. The mapped scales vary between 1 and 5 (with finer step variations) and are treated as continuous outcomes.

2.3 Data collection

After receiving approval from the Institutional Review Board, the data were collected twice: at the beginning (pre-test) and towards the end of the fall semester (post-test). The aim was to capture the WSFs (time changes) for the Flatness and Parallelism hypotheses and the BSFs for the Level hypothesis. Two factors that could affect the sample size are the time the survey was administered and the mode of its administration. To ensure maximum participation, the survey for the DS group was conducted during laboratory sessions. Students were provided a link to the survey and were encouraged to take the survey in-class. Out of 495 students registered in the DS courses (450 in EGR 100 and 45 in EGR 102), 82% (406) participated in both pre- and post-surveys. Freshmen in the TS group were comprised of 227 students spread over the campus with no single class in common; hence, an on-line survey was the best option. TS students were approached via the university's secure web mail and urged to respond. The post-participation rate for the TS group was 20% (46).

An overview of the sample shows a large difference between the two sample sizes: 406 in the post-DS group vs. 46 in the post-TS group. Large differences in the two sample sizes could affect the robustness of the model [36]. To reduce the absolute difference in the two sample sizes and to simplify the DS group dynamics, we removed the data for EGR 102 thus decreasing its size to 368 (EGR 100 only). After accounting for cases dropped due to missing data on selected covariates, and dropping participants under the age of 18, a total of 389 (*351 vs. 38*) freshmen were included in the analyses reported here. The sample included 83% males and 17% females; gender was, however, uniformly distributed between the two groups (χ^2 (1) = 1.399, $df = 1$, $p = 0.226$). An independent samples t-test showed that the DS group had higher ACT scores than the TS group ($M = 26.27$ *vs.* M = 20.71; $t = -9.395$, $df = 387$, $p < 0.001$). The ethnic distribution was 80% White-Caucasian, 5% Asian/Pacific Islander, 8% African-American, and 7% Other that included 4% not reported.

2.4 Selection of variables

(1) Dependent Variables (DVs):
PFEAS subscales formed the outcomes or DVs for the statistical model. Two sets of DVs, pre-test DVs (*Pre1-Pre13*) and, post-test DVs (*Post1-Post13*), were examined for treatment effects while controlling the confounding effects of carefully selected independent variables. As mentioned before, three subscales, namely Jobs, Family, and Study, were excluded from the analysis because they were not relevant to our research study.

(2) Independent Variables (IVs):
Ideally, the IVs (also called predictors, covariates or explanatory variables) in a statistical model: should have high correlations with the outcome(s); and should be independent of each other or have low correlations with each other. It was therefore necessary to search for a parsimonious set of IVs that could explain the maximum amount of variance in the outcome(s) thus minimizing the error term (Equation 2). Out of the set of sixteen IVs, we selected three variables: *group*, *gender*, and *ACT composite*. *Group*, a dichotomous variable (DS vs. TS), was the most important predictor since it reflected the effect of primary interest in the research question. *Gender* was the most interesting demographic variable and has typically been of interest in similar studies. *ACT composite*, hereafter simply called *ACT*, was a continuous covariate representing the composite score from the *ACT* exam many students take when applying for admission to universities. It was found to be mildly positively correlated with most of the ten outcomes ($0.015 < r < 0.276$).

2.5 The model

The specific pre-, post- models with the three selected variables could be represented as:

$$Pre_i = \beta_0 + x_{group}\beta_1 + x_{gender}\beta_2 + x_{ACT}\beta_3 + \varepsilon \quad (4)$$

$$Post_i = \gamma_0 + x_{group}\gamma_1 + x_{gender}\gamma_2 + x_{ACT}\gamma_3 + \varepsilon' \quad (5)$$

2.6 Test assumptions and data transformation

Parametric ANCOVA is a powerful tool for analyzing data, especially if the underlying assumptions of linearity, normality, and homoscedasticity are not violated [36, 37]. Moreover, outliers and influential data points sometimes distort the results and may have to be dealt with [38]. To ensure that a repeated measures ANCOVA could accurately summarize the relationship between the predictors and the outcomes, we applied SPSS diagnostic tools to check the validity of each assumption [38]. A summary is presented below.

(1) Linearity: Linearity of the relationship between variables was examined with two kinds of scatter plots: scatter plots of raw residuals vs. predicted values superimposed with lowess smoothing lines; and scatter plots of covariate

ACT vs. outcomes. No evidence of gross non-linearity was found between the pre-, post-measures and the predictors.

(2) Normality: To test normality, histograms and Quantile-Quantile (Q–Q) plots of studentized residuals were examined. Our models generally met the normality assumption except for a few outliers in the data. The Central Limit Theorem also supported the normality assumption because the sample size was larger than the typical figure of 30.

(3) *Homoscedastic*ity: The pattern of data spread was examined with scatter plots of studentized residuals vs. predicted values. The data were found to be homogeneous except for six out of twenty measures (including pre- and post-) where evidence of heteroscedasticity was found. Box's tests of equality of covariance matrices supported this pattern (Table 2).

(4) Influential Data: Highly influential data points can change the fit of the model. On examination of bubble plots of studentized [39] residuals, we found four data points highly influential in most of the outcomes (seventeen out of twenty measures including pre- and post-). The data points were highly influential due to the large Cook's distance paired with large residuals and large leverage values.

Removal of influential data points was neither justified nor recommended for a relatively smaller TS group. Although parametric ANCOVA is generally robust to violations of assumptions, we rank-transformed the data because rank transformation removes the effects of influential data, reduces the importance of normality or homoscedasticity assumptions and promotes robustness and power in the analysis of covariance [36, 37, 40]. Rank transforming the outcome variable effectively converts the ANCOVA into a non-parametric procedure that no longer assumes normality or homoscedasticity (although it has little effect on the linearity assumption). Bubble plots of the rank-transformed data showed no influential observations. Box's tests also confirmed equality of covariance matrices for all the ten rank-transformed outcomes (Table 2).

3. RESULTS

Based on Equations 4 and 5, we developed ten models, one for each subscale. The models were examined with and without rank transformation. Similar results were obtained with both the approaches thus supporting our earlier statement about parametric ANCOVA being robust to violations of normality or homoscedasticity. Our analyses are generally based on raw (i.e., untransformed) data, except for the outcomes that showed marginal differences and were treated with rank-transformed data as well. Table 3 shows the ANCOVA results of ten models in SPSS 16.0 with raw and rank transformed data. Perception and Basic were the only two models that had shown significant time–group interaction (parallelism) because of a few highly influential data points and were also treated with rank transformed data. Before summarizing the overall results we present detailed analysis of one of these models, namely Perception.

3.1 Data analysis

3.1.1 Perception (Pre4-Post4)

This subscale measures the freshman perception of what engineers do in terms of innovation, creation, problem solving, use of technology, and the professionalism and respect that goes with it. It consists of seven items (Table 1) and is among the strongest of the thirteen subscales. SPSS provides two sets of test results: WSFs and BSFs (see Table 3).

3.1.1.1 Tests of WSFs:

The Parallelism hypothesis was rejected with the raw data, however, the corresponding test on rank data failed to reject the Parallelism hypothesis ($H_{0,b}: p = 0.047$ for raw data, $H_{0,b}: p = 0.081$ for rank data). The difference between the two tests was due to the presence of a few outliers in the raw data, and therefore the rank-transformed results were more credible. The two groups effectively had parallel trajectories in how their perceptions of engineering work, and the engineering profession changed over the span of one semester. In other words, there was no treatment effect on

Table 2. Box's test for homoscedasticity for raw, rank-transformed data. The transformation corrected homoscedasticity problems apparent in the raw data for the Math, Basic, Groups, Ability and Compatibility subscales.

	Raw Data				Rank Transformed Data			
Outcome	**Box M**	**F**	**df1/df2**	**Sig.**	**Box M**	**F**	**df1/df2**	**Sig.**
Career	10.09	1.076	9/7265	0.377	1.162	0.124	9/7265	0.999
Society	3.831	0.408	9/7265	0.932	5.161	0.55	9/7265	0.839
Perception	13.43	1.431	9/7265	0.169	8.465	0.902	9/7265	0.523
Math	20.71	2.207	9/7265	0.019	1.384	0.147	9/7265	0.998
Exact	5.642	0.601	9/7265	0.797	3.83	0.408	9/7265	0.932
Basic	32.32	3.443	9/7265	<0.001	7.847	0.836	9/7265	0.583
Communication	5.764	0.614	9/7265	0.786	3.14	0.334	9/7265	0.964
Groups	19.42	2.069	9/7265	0.029	10.87	1.159	9/7265	0.317
Ability	40.11	4.274	9/7265	<0.001	14.81	1.578	9/7265	0.115
Compatibility	20.79	2.215	9/7265	0.018	14.77	1.574	9/7265	0.117

Table 3: Repeated measures ANCOVA test results for ten PFEAS subscales. Results based on analyzing both raw data and rank-transformed data are presented separately for each subscale. The partial eta squared (η^2) measures the proportion of variance explained by each effect.

Source			Raw Data					Rank Transformed Data				
Outcome	**Hypotheses**		**SS**	**df**	**F**	**Sig.**	η^2	**SS**	**df**	**F**	**Sig.**	η^2
Pre1-Post1 Career	WSF	time	0.25	1	1.603	0.206	0.004	22365	1	3.644	0.057	0.009
		time*group	0.072	1	0.462	0.497	0.005	9184	1	1.496	0.222	0.004
		time*gender	0.328	1	2.101	0.148	0.005	12506	1	2.038	0.154	0.005
		time*ACT	0.029	1	0.189	0.664	<0.001	21115	1	3.441	0.064	0.009
		error (time)	60.02	385				2362800	385			
	BSF	Intercept	318.5	1	707.8	<0.001	0.648	8306847				
		group	0.553	1	1.228	0.269	0.003	30431	1	1.41	0.236	0.004
		gender	0.309	1	0.686	0.408	0.002	3774	1	0.175	0.676	<0.001
		ACT	2.518	1	5.594	0.014	0.014	172963	1	8.016	0.005	0.020
		error	173.2	385				8306847	385			
Pre3-Post3 Society	WSF	time	0.064	1	0.231	0.631	0.001	5701	1	0.709	0.4	0.002
		time*group	0.049	1	0.174	0.676	<0.001	186	1	0.023	0.879	<0.001
		time*gender	0.106	1	0.379	0.539	0.001	11036	1	1.372	0.242	0.004
		time*ACT	0.004	1	0.013	0.910	<0.001	1170	1	0.145	0.703	<0.001
		error (time)	107.3	385				3097346	385			
	BSF	Intercept	319.1	1	444.8	<0.001	0.536	7962156	1	425.16	<0.001	0.525
		group	1.905	1	2.655	0.104	0.007	48084	1	2.568	0.110	0.007
		gender	1.069	1	1.490	0.223	0.004	26032	1	1.390	0.239	0.004
		ACT	15.82	1	22.06	<0.001	0.054	327624	1	17.495	<0.001	0.043
		error	276.2	385				7209957	385			
Pre4-Post4 Perception	WSF	time	0.119	1	1.579	0.21	0.004	19692	1	3.036	0.082	0.008
		time*group	0.299	1	3.961	0.047	0.010	19811	1	3.054	0.081	0.008
		time*gender	0.02	1	0.262	0.609	0.001	19.73	1	0.003	0.956	<0.001
		time*ACT	0.082	1	1.091	0.297	0.003	3897	1	0.601	0.439	0.002
		error (time)	29.06	385				2497511	385			
	BSF	Intercept	328.7	1	1234	<0.001	0.762	7423036	1	341.66	<0.001	0.470
		group	0.216	1	0.810	0.369	0.002	11432	1	0.526	0.469	0.001
		gender	<0.001	1	<0.001	0.982	<0.001	4229	1	0.195	0.659	0.001
		ACT	2.045	1	7.681	0.006	0.020	120823	1	5.561	0.019	0.014
		error	102.5	385				8364547	385			
Pre5-Post5 Math	WSF	time	0.495	1	2.29	0.131	0.006	5688	1	1.208	0.273	0.003
		time*group	0.163	1	0.752	0.386	0.002	521.183	1	0.111	0.740	<0.001
		time*gender	0.052	1	0.242	0.623	0.001	1111.6	1	0.236	0.627	0.001
		time*ACT	0.188	1	0.870	0.351	0.002	8592	1	1.824	0.178	0.005
		error (time)	83.3	385				1813843	385			
	BSF	Intercept	217.9	1	217.9	<0.001	0.361	5371666	1	239.45	<0.001	0.383
		group	12.25	1	12.25	0.001	0.031	258674	1	11.531	0.001	0.029
		gender	0.037	1	0.037	0.848	<0.001	8911	1	0.397	0.529	0.001
		ACT	0.007	1	0.007	0.932	<0.001	22066	1	0.984	0.322	0.003
		error	385	385				8636665	385			
Pre6-Post6 Exact	WSF	time	0.474	1	1.693	0.194	0.004	4819	1	0.765	0.382	0.002
		time*group	0.585	1	2.089	0.149	0.005	11592	1	1.84	0.176	0.005
		time*gender	0.751	1	2.683	0.102	0.007	11616	1	1.843	0.175	0.005
		time*ACT	0.958	1	3.422	0.065	0.009	2899	1	0.460	0.498	0.001
		error (time)	107.8	385				2426157	385			
	BSF	Intercept	268.4	1	308.3	<0.001	0.445	9050516	1	456.4	<0.001	0.542
		group	4.801	1	5.515	0.019	0.014	99915	1	5.039	0.025	0.013
		gender	4.482	1	5.148	0.024	0.013	87800	1	4.428	0.036	0.011
		ACT	12.79	1	14.69	<0.001	0.037	265448	1	13.387	<0.001	0.034
		error	335.1	385				7634199	385			
Pre8-Post8 Basic	WSF	time	0.107	1	1.058	0.304	0.003	813	1	0.162	0.687	<0.001
		time*group	0.630	1	6.228	0.013	0.016	18143	1	3.615	0.058	0.009
		time*gender	0.045	1	0.442	0.506	0.001	483.94	1	0.096	0.756	<0.001
		time*ACT	0.165	1	1.628	0.203	0.004	7529.95	1	1.501	0.221	0.004
		error (time)	38.96	385				1932003	385			
	BSF	Intercept	132.8	1	285	0	0.425	2800195	1	134.1	<0.001	0.258
		group	1.12	1	2.403	0.122	0.006	40685	1	1.95	0.163	0.005
		gender	7.34	1	15.74	<0.001	0.039	334881	1	16.04	<0.001	0.040
		ACT	8.558	1	18.36	<0.001	0.046	398137	1	19.08	<0.001	0.047
		error	179.4	385				8033828	385			
Pre9-Post9 Communication	WSF	time	0.152	1	0.999	0.318	0.003	1165	1	0.305	0.581	0.001
		time*group	0.044	1	0.287	0.593	0.001	67	1	0.018	0.895	<0.001
		time*gender	0.168	1	1.104	0.294	0.003	2132	1	0.305	0.581	0.001
		time*ACT	0.013	1	0.088	0.767	<0.001	32.277	1	0.008	0.927	<0.001
		error (time)	58.75	385				1472696	385			
	BSF	Intercept	208	1	209.6	<0.001	0.353	6303939	1	255.1	<0.001	0.399
		group	0.546	1	0.55	0.459	0.001	21523	1	0.871	0.351	0.002
		gender	0.585	1	0.589	0.443	0.002	14458	1	0.585	0.445	0.002
		ACT	0.002	1	0.002	0.966	<0.001	25928	1	1.049	0.306	0.003
		error	382.1	385				9512110	385			

Table 3. (*cont.*)

Source			Raw Data					Rank Transformed Data				
Outcome	Hypotheses		SS	df	F	Sig.	η^2	SS	df	F	Sig.	η^2
Pre11-Post11 Groups	WSF	time	<0.001	1	<0.001	0.992	<0.001	6579	1	1.150	0.284	0.003
		time*group	0.374	1	1.661	0.198	0.004	8944	1	1.563	0.212	0.004
		time*gender	0.063	1	0.282	0.596	0.001	453.7	1	0.079	0.778	<0.001
		time*ACT	0.081	1	0.359	0.549	0.001	1460	1	0.255	0.614	0.001
		error (time)	86.61	385				2202786	385			
	BSF	Intercept	291.7	1	318.4	<0.001	0.453	8593608	1	398	<0.001	0.508
		group	2.067	1	2.255	0.134	0.006	48962	1	2.268	0.133	0.006
		gender	0.826	1	0.901	0.343	0.002	21179	1	0.981	0.323	0.003
		ACT	19.92	1	21.74	<0.001	0.053	548878	1	25.42	<0.001	0.062
		error	352.7	385				8312692	385			
Pre12-Post12 Ability	WSF	time	0.233	1	2.497	0.115	0.006	797	1	0.159	0.690	<0.001
		time*group	0.043	1	0.463	0.497	0.001	3552	1	0.710	0.400	0.002
		time*gender	0.020	1	0.219	0.640	0.001	3381	1	0.676	0.412	0.002
		time*ACT	0.082	1	0.881	0.349	0.002	302	1	0.060	0.806	<0.001
		error (time)	35.85	385				1926581	385			
	BSF	Intercept	214.2	1	459.3	<0.001	0.544	5307254	1	230.8	<0.001	0.375
		group	0.238	1	0.511	0.475	0.001	348	1	0.015	0.902	<0.001
		gender	1.783	1	3.822	0.051	0.010	128247	1	5.579	0.019	0.014
		ACT	0.356	1	0.764	0.383	0.002	8859	1	0.385	0.535	0.001
		error	179.5	385				8850298	385			
Pre13-Post13 Compatibility	WSF	time	0.071	1	0.535	0.465	0.001	3776	1	0.686	0.408	0.002
		time*group	0.412	1	3.116	0.078	0.008	12911	1	2.345	0.127	0.006
		time*gender	0.066	1	0.497	0.481	0.001	4673	1	0.849	0.357	0.002
		time*ACT	0.324	1	2.449	0.118	0.006	2693	1	0.489	0.485	0.001
		error (time)	50.93	385				2120033	385			
	BSF	Intercept	216.5	1	387.9	<0.001	0.502	5254910	1	240.1	<0.001	0.384
		group	0.823	1	1.474	0.225	0.004	35587	1	1.627	0.203	0.004
		gender	10.17	1	18.22	<0.001	0.045	360574	1	16.48	<0.001	0.041
		ACT	0.404	1	0.723	0.396	0.002	21772	1	0.995	0.319	0.003
		error	214.9	385				8423482	385			

this subscale. The tests also failed to reject the Flatness hypothesis for both data sets implying there was no time effect—the trajectories were not only parallel, they were also flat. Additionally, gender and ACT did not significantly interact with time in both the data sets. The partial eta squared (η^2) values, which measure the proportion of variance explained by an effect, show that these WSF effects explain very little ($\leq 1\%$) of the variance in this subscale.

3.1.1.2 Tests of BSFs

These tests failed to reject the Level hypothesis in both data sets; *group* had no influence on the subscale when disregarding *time* effects. In addition, *gender* did not influence it, whereas *ACT* significantly influenced the subscale in both the data sets ($\beta_{pre} = -0.012$, $\beta_{post} = -0.018$, $p = 0.006$ for raw data and $\beta_{pre} = -0.099$, $\beta_{post} = -0.142$, $p = 0.019$ for rank data). In other words students with higher *ACT* scores had lower perception about this outcome when controlling for gender and group affiliations and disregarding the time effects.

3.1.1.3 Estimated Marginal Means (EMMs)

The profile plots for time–group interaction indicate that while the interaction was insignificant, the overall means for both groups remained above 4.00 on the scale of 1–5. Figure 1 displays the profile plot for Perception subscale. The flat, nearly overlapping lines indicate that the groups start out with very similar means at pre-test, and that neither group's mean changes much over time. Because the scores could range from 1 to 5, these means are all quite high thus indicating that students' general impression of engineering starts and remains high in both the groups. Table 4 gives the EMM values for the raw data for ten subscales.

This model (Fig. 1) shows three results:

- freshmen had strongly positive initial perceptions of what engineers do in terms of innovation, creation, problem solving, use of technology, professionalism and respect that goes with being an engineer, irrespective of their gender or group affiliation;
- these strong initial perceptions did not change over the course of one semester;
- freshmen with higher *ACT* scores had signifi-

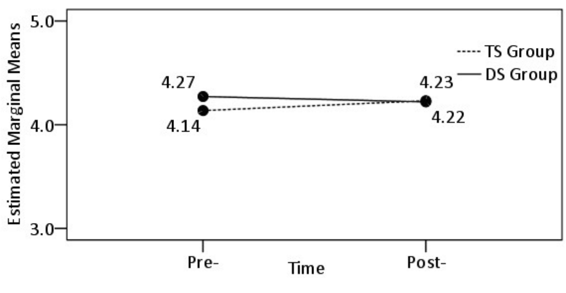

Fig. 1. Profile plot of the *time*group* effect on the Perception subscale. The longitudinal trajectories from pre-test to post-test for the two groups are nearly identical, which is why the interaction effect is not significant.

Table 4. Mean scores for ten PFEAS subscales from the ANCOVA analyses, broken down to illustrate the *time*group* and *gender* effects.

	Group*Time Effect					
	DS		TS		Gender Effect	
Outcome	Pre-test	Post-test	Pre-test	Post-test	Males	Females
Career	4.11	3.99	4.25	4.05	4.07	4.13
Society	3.49	3.62	3.28	3.47	3.51	3.42
Perception	4.27	4.22	4.14	4.23	4.21	4.21
Math	4.09	3.91	3.57	3.49	3.77	3.77
Exact	3.19	2.91	3.38	3.31	3.30	3.10
Basic	3.80	3.75	3.55	3.71	3.83	3.57
Communication	3.50	3.73	3.57	3.86	3.63	3.70
Groups	3.35	3.12	3.08	3.01	3.18	3.10
Ability	3.93	3.87	3.90	3.78	3.93	3.81
Compatibility	3.58	3.66	3.37	3.63	3.71	3.41

cantly lower perception for this subscale—a somewhat unexpected result.

3.2 Summary of results

A summary of the analyses on ten repeated measures ANCOVA models is presented below.

- The Parallelism hypothesis was not rejected in any of the ten outcomes; the *time*group* interactions were not statistically significant for any of the subscales. The significance noted in the raw data for two of the subscales—Perception ($p = 0.047$) and Basic ($p = 0.013$)—was due to four highly influential data points and therefore disregarded in favor of the rank-transformed results. There was no treatment effect of the DS in terms of its effects on freshman attitudes about engineering relative to the TS.
- The Flatness hypothesis also was not rejected in any of the ten outcomes. The partial eta squared (η^2) measures show that the WSF effects explain very little ($\leq 2\%$) of the variance in all the models. There was no time effect on student attitudes for any of the subscales when disregarding the *group* membership.
- The EMMs for all of the ten outcomes were positive on a raw scale of 1–5 (with scores of 1–2 meaning negative perceptions, 3 meaning neutral perceptions, and scores of 4–5 meaning positive perceptions). The subscales Career and Perception were strongly positive (*EMMs > 4.0*) meaning that these subscales could be more resistant to change than the other subscales. The interpretation of this is that engineering freshmen joined the program with positive initial attitudes towards engineering, and these initial attitudes did not change during the course of one semester (Table 4).
- The Level hypothesis was rejected in two subscales: Math ($p = 0.001$ for both data sets) and Exact ($p = 0.0019$ for raw data and $p = 0.025$ for rank data) as shown in Table 3. The EMMs values in Table 4 (averaging over pre- and post-) indicate that the DS group had higher means for Math ($M = 4.00$ *vs.* $M = 3.53$) and lower means for Exact ($M = 3.05$ *vs.* $M = 3.35$), meaning that DS group enjoyed math and science subjects more and was less likely to believe that engineering was an exact science. The significantly more positive attitudes in the DS group could be due to their stronger background in math and science (the DS group must meet the higher math requirement), higher *ACT* scores, and better understanding that engineering was not an exact science.

In addition, we examined the two covariates, *gender* and *ACT*, and compared their response in other similar studies. Some interesting findings are given below:

- Definite gender differences were found in four of the subscales. Females rated lower than males in all the four attitude measures: Basic ($p < 0.001$; $M = 3.57$ *vs.* $M = 3.83$); Ability ($p = 0.051$; $M = 3.81$ *vs.* $M = 3.93$); Compatibility ($p < 0.001$; $M = 3.41$ *vs.* $M = 3.71$); and Exact ($p = 0.024$; $M = 3.10$ *vs.* $M = 3.30$). In other words, females had lower confidence levels in basic engineering knowledge and skills, problem solving abilities, and engineering abilities. They also perceived engineering as being an exact science less than their male counterparts. These findings are consistent with literature in the area [10].
- The covariate, *ACT* significantly affected six of the subscales: Career ($p = 0.014$; $\beta_{pre} = -0.018$, $\beta_{post} = -0.015$ for raw data, $p = 0.005$ for rank data), Society ($p < 0.001$; $\beta_{pre} = -0.042$, $\beta_{post} = -0.041$ for raw data, $p < 0.001$ for rank data), Perception ($p = 0.006$; $\beta_{pre} = -0.012$, $\beta_{post} = -0.018$ for raw data, $p = 0.019$ for rank data), Exact ($p < 0.001$; $\beta_{pre} = -0.027$, $\beta_{post} = -0.047$ for raw data, $p < 0.001$ for rank data), Basic ($p < 0.001$; $\beta_{pre} = 0.026$, $\beta_{post} = 0.035$ for raw data, $p < 0.001$ for rank data), and Groups ($p < 0.001$; $\beta_{pre} = -0.043$, $\beta_{post} = -0.049$ for raw data, $p < 0.001$ for rank data). *ACT* was also related to the explanatory variable *group*—the DS group had higher *ACT* scores than the TS group—which was why it was important to adjust for this covariate in the models. The

literature also supports the strength of this predictor [9, 41].

4. DISCUSSION

We set out to answer whether the new cornerstone design sequence was more effective than the older traditional sequence at positively influencing freshman attitudes about engineering over the course of one semester. We compared students in the new DS to students in the previous TS by collecting attitude data twice over the course of a semester and examining changes in the two groups' attitudes with repeated measures ANCOVA models. We have found that freshmen join the program with positive (EMMs > 3.00) and strongly positive (EMMs > 4.00) attitudes toward engineering that could be resistant to change. Students in the DS had higher ACT scores, enjoyed math and science more, and did not believe engineering to be an exact science. We found some interesting results in how *gender* and *ACT* performed as covariates in the model. The DS group, however, had a similar longitudinal trajectory to the TS group, so there was no evidence of differential influence on student attitudes. This lack of treatment effect could be because of one or all of the factors given below and could have affected the models' ability (power) to detect differences.

- DS was a set of newly designed courses that would certainly require a break-in period and constant feedback to reach a level of maturity before it could fully meet the course objectives. It may not be realistic to expect a new course to meet all its goals and objectives at the outset. The DS may be more effective after it is refined and operating smoothly.
- The short time between pre- and post- surveys—eleven weeks of experience—may simply not be enough to effect an appreciable change in the two groups' attitudes.
- We only looked at one of the two DS courses that were designed for sequential treatment over the freshman year. The compound effect of taking the two courses in the intended sequence could be significantly larger than that of taking only the first part alone.
- The different data collection methods and their associated incentives for TS and DS groups could have contributed to large differences in participation rates due to selection bias. There may have been a selection bias for higher achieving or more motivated students to complete the online surveys, which may have skewed the data for the TS group.
- The fact that some PFEAS subscales are now known to suffer from poor internal reliability and structural validity [32] could also have affected our model, making it harder to detect intervention effects.

To probe into the above factors and better understand the construct, we are continuing with a second phase of this study that includes further collection of data with a bigger and more homogeneous sample to include both EGR 100 and EGR 102 and to employ the revised version of the scale, if possible. We also want to add a qualitative component (one-on-one interviews) that could help us examine the new sequence with mixed methods design that could broaden our perspective about our students' attitudes and how these could change in a course sequence.

5. CONCLUSIONS

Colleges of engineering across the country are investing in cornerstone design courses to better prepare, motivate, and retain students in engineering programs. The presence of both the design sequence and the traditional sequence students on campus at the same time (which is relatively rare) provided us with a context within which to conduct a "natural" quasi-experiment. This study found that the attitudes of students in a design sequence and students in a traditional sequence were very similar (and strongly positive) early in their first semester and that these attitudes were durable and resistant to change over the course of that semester for both groups of students. The same pattern of results was found for ten different subscales of the PFEAS that measure different dimensions of attitudes about engineering. These strongly positive initial attitudes coupled with insignificant changes in these attitudes could mean that one semester of exposure to the design sequence is insufficient to effect a measurable change. The results of this quantitative study indicate that we need to develop a better understanding of the fine-grained details of the actual implementation of such cornerstone engineering courses. Such research is critical for the formative evaluation of these programs in order to improve curriculum development efforts. Clearly, tight and focused quantitative studies such as this one need to be complemented with more longitudinal studies and with more qualitative data. We are currently engaged in a broader research program (of which this study is a part) where we seek to gain more insight into the learning that take place in freshman courses. This larger research program includes a qualitative component (i.e. one-on-one interviews with randomly selected students) as well as classroom observations. We believe that such a mixed methods approach is essential for developing a better understanding of students' real life experiences with freshman courses.

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REFERENCES

1. V. Tinto, *Leaving college: rethinking the causes and cures of student attrition*, 2nd ed. Chicago, Ill: University of Chicago Press, 1993.
2. E. Seymour, Tracking the processes of change in US undergraduate education in science, mathematics, engineering, and technology, *Science Education,* **86**, 2001, pp. 79–105.
3. A. W. Astin, K. C. Green, W. S. Korn, M. Schalit, *The American freshman: twenty-year trends, 1966–1985,* Higher Education Research Institute, UCLA., Los Angeles, CA 1987.
4. E. Seymour and N. M. Hewitt, *Talking about leaving: why undergraduates leave the sciences*: Westview Press, 2000.
5. A. W. Astin, What matters in college, *Liberal Education,* **79**, 1993, pp. 4–15.
6. M. Besterfield-Sacre, C. J. Atman, and L. Shuman, How freshman attitudes change in the first year, in *ASEE Annual Conference*, Anaheim, CA, 1995, pp. 157–163.
7. J. E. S. Leonhard E. Bernold, Chris M. Anson, Understanding Our Students: A Longitudinal Study of Success and Failure in Engineering With Implications for Increased Retention, *Journal of Engineering Education,* **96**, 2007, pp. 263–274.
8. Q. Li, D. B. McCoach, H. Swaminathan, and J. Tang, Development of an instrument to measure perspectives of engineering education among college students, *Journal of Engineering Education,* **97**, 2008, pp. 47–56.
9. M. Besterfield-Sacre, C. J. Atman, and L. J. Shuman, Characteristics of freshman engineering students: Models for determining student attrition in engineering, *Journal of Engineering Education,* **86**, 1997, pp. 139–149.
10. M. Besterfield-Sacre, M. Moreno, L. J. Shuman, and C. J. Atman, Gender and ethnicity differences in freshmen engineering student attitudes: A cross-institutional study, *Journal of Engineering Education,* **90**, 2001, pp. 477–489.
11. R. M. Felder, G. N. Felder, M. Mauney, C. E. Hamrin, and Dietz, A longitudinal study of engineering student performance and retention. Part III—gender differences in student performance and attitudes, *Journal of Engineering Education,* **84**, 1995, pp. 151–163.
12. J. A. Krosnick, D. S. Boninger, Y. C. Chuang, M. K. Berent, C. G. Carnot, Attitude strength: one construct or many related constructs?, *Journal of Personality and Social Psychology,* **65**, 1993, pp. 1132–1151.
13. E. M. Pomerantz, S. Chaiken, and R. S. Tordesillas, Attitude strength and resistance processes, *Journal of Personality and Social Psychology,* **69**, 1995, pp. 408–419.
14. M. A. Hutchison-Green, D. K. Follman, and G. M. Bodner, Providing a voice: qualitative investigation of the impact of a first-year engineering experience on students' efficacy beliefs *Journal of Engineering Education,* **97**, 2008, pp. 177–190.
15. J. Burtner, The use of discriminant analysis to investigate the influence of non-cognitive factors on engineering school persistence, *Journal of Engineering Education,* **94**, 2005, pp. 335–338.
16. M. Besterfield-Sacre and C. J. Atman, Survey design methodology: measuring freshman attitudes about engineering, in *ASEE Annual Conference*, Admonton, Canada, 1994, pp. 236–243.
17. S. Sheppard, Jenison, Rollie, Freshmen engineering design experiences and organizational framework, *International Journal of Engineering Education,* **13**, 1997, pp. 190–197.
18. S. Sheppard, Jenison, Rollie, Examples of freshman design education, *International Journal of Engineering Education,* **13**, 1997, pp. 248–261.
19. J. D. Burton, D. M. White, Selecting a model for freshman engineering design, *Journal of Engineering Education,* **87**, 1997, pp. 327–332.
20. J. W. Dally, G. M. Zhang, A freshman engineering design course, *Journal of Engineering Education,* **82**, 1993, pp. 83–91.
21. A. Scalise, Besterfield-Sacre, M., Shuman, L., Wolfe, H., First term probation: models for identifying high risk students, in *30th ASEE/IEEE Frontiers in Education Conference*, Kansas City, MO, 2000, pp. 11–16.
22. T. F. Wolff, Residential initiative / cornerstone engineering program, MSU, East Lansing, Program Overview Nov. 27 2006.
23. M. Besterfield-Sacre, C. J. Atman, and L. J. Shuman, Engineering student attitudes assessment, *Journal of Engineering Education,* **87**, 1998, pp. 133–141.
24. S. Sudman and N. M. Bradburn, *Asking questions: a practical guide to questionnaire design*: Jossey-Bass, 1982.
25. The Cooperative Institutional Research Program (CIRP) freshman survey, 2008, http://www.gseis.ucla.edu/heri/PDFs/surveyAdmin/tfs/tfs08.Instrument.pdf
26. M. R. Anderson-Rowland, A first year engineering student survey to assist recruitment and retention, in *26th ASEE/IEEE Frontiers in Education Conference*, Salt Lake City, Utah, 1996, pp. 372–376.
27. Assessment tools for attitudes and skills, http://www.foundationcoalition.org/publications/brochures/2002-Feb-27_Assessment_Attitudes_and_Skills.pdf
28. L. Lindsley and V. Burrows, A comparison of attitudes about engineering between introductory design students in different programs, in *ASEE Annual Conference* Honolulu, Hawaii, 2007, pp. 1–12.
29. M. Besterfield-Sacre, N. Y. Amaya, L. J. Shuman, C. J. Atman, and R. L. Porter, Understanding student confidence as it relates to first year achievement, in *28th ASEE/IEEE Frontiers in Education Conference*, Tempe, AZ, 1998, pp. 258–263.
30. N. J. Mourtos and B. J. Furman, Assessing the effectiveness of an introductory engineering course for freshmen, in *32nd ASEE/IEEE Frontiers in Education Conference*, Boston, 2002, pp. F3B–12–16.

31. L. E. Bernold, Spurlin, J. E., Anson, C. M., Understanding our students: a longitudinal-study of success and failure in engineering with implications for increased retention, *Journal of Engineering Education,* **96**, 2007, pp. 263–274.
32. J. Hilpert, G. Stump, J. Husman, and W. Kim, An exploratory factor analysis of the Pittsburgh Freshman Engineering Attitudes Survey, in *38th ASEE/IEEE Frontiers in Education Conference*, Saratoga Springs, NY, 2008, pp. 1–6.
33. J. Hilpert, G. Stump, J. Husman, W. Kim, W.-T. Chung, and J. Lee, Steps toward a sound measure of engineering student attitudes: Pittsburgh Engineering Attitudes Scale—Revised, in *39th ASEE/ IEEE Frontiers in Education Conference*, San Antonio, TX, 2009, pp. 1–6.
34. M. Besterfield-Sacre, L. J. Shuman, H. Wolfe, C. J. Atman, J. McGourty, R. L. Miller, B. M. Olds, and G. M. Rogers, Defining the outcomes: a framework for EC-2000, *IEEE Transactions on Education,* **43**, 2000, pp. 100–110.
35. M. Besterfield-Sacre, M. Moreno, L. J. Shuman, and C. J. Atman, Comparing entering freshman engineers: institutional differences in student attitudes, in *ASEE Annual Conference* Charlotte NC, 1999.
36. S. F. Olejnik and J. Algina, Parametric ANCOVA and the rank transform ANCOVA when the data are conditionally non-normal and heteroscedastic, *Journal of Educational Statistics,* **9**, 1984, pp. 129–149.
37. W. J. Conover and R. L. Iman, Analysis of covariance using the rank transformation, *Biometrics,* **38**, 1982, pp. 715–724.
38. C. Collins and S. J. Pierce, Evaluating regression models: understanding and using regression diagnostics to improve your analyses, in *Evaluation 2008: Evaluation Policy and Evaluation Practice, the annual conference of the American Evaluation Association* Denver, CO, 2008.
39. J. Fox, *Applied regression analysis, linear models, and related models*: SAGE Publications, Inc., 1997.
40. S. F. Olejnik and J. Algina, A review of nonparametric alternatives to analysis of covariance, *Evaluation Review,* **9**, 1985, pp. 51–83.
41. M. S. Deberard, G. I. Spielmans, and D. L. Julka, Predictors of academic achievement and retention among college freshmen: a longitudinal study, *College Student Journal,* **38**, 2004, pp. 66–80.

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