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A Quantitative Analysis of the Effects of a Multidisciplinary Engineering Capstone Design Course

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Background
Capstone design courses seek to prepare engineering students for industry by challenging student teams to solve real-world problems. To improve this preparation, university programs have recently focused on creating multidisciplinary teams. However, there is limited quantitative evidence showing that multidisciplinary student engineering teams develop higher quality projects or are better prepared for the work force.

Hypothesis
Students who take a multidisciplinary capstone design (MCD) course have better outcomes than monodisciplinary capstone students as measured by job placement and/or independent evaluation by industrial professionals of students' products.

Methodology
A single treatment was administered to Georgia Tech capstone design students for one semester with three course conditions: (1) monodisciplinary biomedical, (2) monodisciplinary mechanical, or (3) multidisciplinary biomedical and mechanical engineering. After course completion, students' cumulative GPA, job placement, and design exposition score were obtained and analyzed. This analysis used a generalized linear model for the exposition score and a logistic model for job placement outcomes.

Results
A general linear model showed that all students who took the MCD course, regardless of major, produced an engineering solution that was better than that of their monodisciplinary contemporaries as measured by external industry professionals. Logistic and multinomial regressions showed that the MCD course increased the odds of employment significantly for biomedical engineering students.

Conclusions
In this preliminary investigation, the MCD teams' holistic performance in innovation, utility, analysis, proof of concept, and communication skills was superior to that of their monodisciplinary counterparts, and, on average, they were hired more frequently.

Keywords
interdisciplinary, multidisciplinary, capstone design course, senior design, undergraduate education

Introduction

Across the United States, undergraduate engineering university programs commonly culminate in a capstone design course, an integrative course in which student teams synthesize solutions to open-ended, real-world problems (Dym, Agogino, Eris, Frey, & Leifer, 2005). Typically, in one or two semesters of the course, teams define a problem, plan their approach, propose creative solutions, analyze the solutions, produce or implement the solutions, and communicate them internally and externally.

Traditionally, at the Georgia Institute of Technology, where this study was conducted, capstone design is monodisciplinary with teams averaging five students from the same engineering discipline on a team (e.g., mechanical, electrical, biomedical, industrial, or aerospace). A set of teams, typically subdivided into course sections to accommodate large enrollments, is administered solely within these disciplines – from problem definition to an adjudicated exposition of design solutions at the course climax: the Capstone Design Expo.

The course participants (students, faculty, problem sponsors) could benefit from a more multidisciplinary capstone design (MCD) experience, with team members representing more than one discipline working on problems similarly posed (National Academies Press, 2001). Most compellingly, since these engineering students will need to survive and thrive in these multidisciplinary professional environments after graduation, the university environment should seek to inculcate as many lessons as possible about their inherent challenges and opportunities beforehand. As of 2005, approximately 35% of engineering capstone design courses included interdepartmental or multidisciplinary teams, an increase from 21% in a 1994 survey of 1724 programs at 350 institutions (Howe & Willbarger, 2006). Therefore, as more engineering schools consider a scale-up of MCD initiatives, systematic quantitative and qualitative studies of viable structures, resources, incentives, effects, and perceptions should be undertaken.

This preliminary investigation was conducted in collaboration with faculty and students at the Georgia Institute of Technology Coulter Department of Biomedical Engineering and the Woodruff School of Mechanical Engineering. Two models of product-driven design were examined, sequestered (monodisciplinary) and integrative (multidisciplinary), by analyzing the effects of three versions of senior capstone design coursework implemented concurrently: two monodisciplinary sections (mechanical engineering and biomedical engineering) and one multidisciplinary. This experiment was driven by the following hypothesis: Students who take an MCD course have better outcomes than monodisciplinary capstone design students as measured by job placement and independent evaluation from industrial professionals at the design exposition. Due to the preliminary nature of the investigation, we had to balance the difficulty in getting quantitative data for a large percentage of graduated seniors with the relevance and likely significance of the parameters. Ideally, student performance would be assessed on the job (in graduate school or industry), in multidisciplinary teams, and evaluated to determine if MCD students do better on multi-industry teams than monodisciplinary students in addition to assessing job placement. Such surveys are exceedingly difficult to design, administer, and obtain with statistical value; hence, they were not included in this initial investigation.

The analysis was done over the course of a single semester of capstone design at Georgia Tech. All projects were self-selected by students, and team formation was done organically by the students. Teams ranged from three to eight members with MCD biased toward large teams. The vast majority of students take this class in their final year after completing most of their coursework. Teams were supported either by department funds or industry sponsors. Departmental teams received a maximum of $500 dollars while industry groups had no funding cap. No MCD teams had industrial sponsors. All teams were provided with an expert advisor in their project's field to facilitate design and provide analysis expertise. The instructors carefully monitored the MCD teams to ensure a truly integrative team experience, as opposed to one in which the team divided into two groups of specialists, each performing a single task. This monitoring was done to overcome integrative problems that other multidisciplinary programs have reported (Leonard, Schmidt, Schmidt, & Smith, 2006).

In this paper, the structure of the course will be described in more detail, examples of student teams will be provided, and the metrics by which they were measured quantitatively will be introduced. Next, a statistical analysis of the effect of enrolling in the MCD section relative to the monodisciplinary sections, controlling for confounding factors, will be presented. This analysis is performed using a generalized linear model (GLM) for the continuous variables and a logistic regression to explore the effects of binomial variables. Finally, the results, their limitations, and a summary of the key findings are discussed. We note that this is purely an assessment of outcomes, not an assessment of the learning of the design process.

Background

Capstone Design

Capstone design courses (also referred to as *senior design*) were developed in response to industry experts' observations that graduating engineers were underprepared for real-world applications of their skills and knowledge (Dym et al., 2005). According to Bordogna, Fromm, and Edwards (1993), the primary goals of engineering education should be to develop the students' capabilities to integrate, analyze, innovate, synthesize, and understand contextually. The object of capstone design is to infuse a practical experience into a theory-based undergraduate engineering curriculum.

Participation in capstone design supports students in making the transition from student communities of practice to professional communities of practices – that is, from classroom to real world (Lave, 1988). Working with a client-advisor from the field (professional engineers, start-up companies, corporate representatives, physicians, technicians, hospitals, laboratories) in a type of apprenticeship, similar to what Lave and Wenger (1991) call legitimate peripheral participation, students are challenged with a real-world need. While capstone students are not full members with complete immersion in the professional community (Lave, 1988), contextualizing the problem, need, or service within the field's practices provides students the opportunity for situated learning (Lave & Wenger, 1991) and affords them the opportunity to apply their skills and knowledge toward developing a robust understanding of what it means to be an engineer. This facilitates an identity shift from student to professional engineer (Johri & Olds, 2011).

Typically, capstone design courses employ a product-based learning (Prod-BL) pedagogical approach, which is defined by Leifer as a "problem oriented, project organized learning activity that produces a product for an outsider . . . beyond a 'training exercise'" (Brown & Seidner, 1997, p. 300). Many of the products developed in capstone design are under the advisement or sponsorship of an outside client. For this study, the Capstone Design Expo (hereafter, *design expo*) judges serve as an outside client. These professionals evaluate the products for the quality of the innovation, utility of the device, engineering analysis of the device and its properties, how well the proof of concept was constructed, and the ability of the team to communicate the purpose and use of their device.

Multidisciplinary Capstone Design

According to Leifer, "there is an increasing need for organizations to form joint design development teams that collaborate for the life of a project and then disperse. These teams need to quickly locate, evaluate and make effective use of the best resources available (tools, facilities, people)" (Brown & Seidner, 1997, p. 298). However, the general practice is to stratify senior design courses by discipline, which prevents a collaborative exchange of expertise, knowledge, and experience across domains. An MCD experience supports this sharing by placing students from different majors together in the problem-solving space – in this case, mechanical engineers (MEs) and biomedical engineers (BMEs). As in the field, the MCD design-and-build context occurs within a defined time frame and requires that experts from diverse fields communicate effectively across expert domains, engage in quick action, and efficiently allocate resources.

Bordogna, Fromm, and Edward (1993) suggest that the intellectual components of engineering should be connected holistically to avoid what they call "fractionated knowledge" that is not relevant in the real world. Multidisciplinary capstone design addresses this by providing students with an opportunity to integrate theory with practice within their knowledge domain and that of a teammate from another field. This is further articulated by ABET's recommendations to the engineering and engineering education community. ABET states that "As we move into the 21st century, the need to cross and mesh disciplinary boundaries is increasingly evident because new knowledge is increasingly created at disciplinary interfaces" (ABET, 2001). The MCD model implemented in this project was designed to mesh these boundaries while satisfying eight of ABET's eleven student outcomes. Working toward a collaboratively constructed design project, students are afforded the opportunity to experience and demonstrate ABET's criteria that engineering graduates can function on multidisciplinary teams; apply knowledge of mathematics, science, and engineering; design and conduct experiments; analyze and interpret data; design systems, components, or processes to meet needs; identify, formulate, and solve engineering problems; understand professional and ethical responsibility; communicate effectively; and use the techniques, skills, and modern engineering tools necessary for engineering practice (ABET, 2011; Felder & Brent, 2003).

In a 2005 replication of a previous large-scale capstone design survey (see Todd, Magleby, Sorensen, Swan, & Anthony, 1995), Howe and Willbarger determined that "as was true in 1994, the vast majority of departments in 2005 still organized students around departmental teams" (Howe & Willbarger, 2006, p. 4). However, they interpreted the positive trend in interdepartmental teams, from 21% to 35%, as a positive sign that interest was growing. One of the key findings in the first National Capstone Design Conference, the impetus behind the featured papers on capstone design in a special issue of *Advances in Engineering Education*, was that although "there is a movement toward greater use of multi-disciplined teams," they are difficult to establish without "an overarching college wide structure in place to make it happen" (Zable, 2010, p. 3).

The goal of this paper is to advance the current MCD literature, which tends to rely heavily on course evaluations and descriptions of implementations substantiated by student satisfaction self-report surveys. Representative qualitative reports of MCD innovations include those at Brigham Young University (Todd et al., 1993), Colorado School of Mines (Miller & Olds, 1994), Behrend College at Penn State University (Ford, Goodrich, & Weissbach, 2004), Howard University (Thigpen, Glakpe, Gomes, & McCloud, 2004), University of Missouri-Rolla (Stone & Hubing, 2002), Harvey Mudd College (Bright & Philips, 1999), and Santa Clara University (Kitts & Quinn, 2004). Reviewing the literature of capstone design courses, Dutson, Todd, Magleby, & Sorensen (1997) state that “the literature is filled with positive comments from students, instructors, and industrial sponsors who have participated in capstone design courses,” with most participants reporting that they benefitted from it. They suggest that a good indicator of a successful capstone design course is industry’s interest in graduates who have been through the course. Hence, we used job placement as an indicator of success for the MCD course reported here.

Motivation

This experiment was motivated by observations of the quality of some capstone design products, independent of student effort, commitment, and engagement. We suspected that naïvely articulated products reflected the students’ limited exposure to theory and applied skills outside of their own field of study. Specifically in the case of this study, medical devices were primitively constructed due to the limits of BME students’ mechanical, materials, and manufacturing experience. Similarly, the MEs failed to acknowledge physiology and necessary government regulation in the development of their medical devices. For example, a BME team, sponsored and advised by a major trucking company, developed a headset for drivers that could monitor the brain’s beta-wave activity through a type of electroencephalogram, sounding an alarm to alert the driver to impending sleep. However, the BME team’s limited experience with materials and fabrication techniques resulted in a flimsy, primitive structural frame without the elaboration that would have been possible had they had access to the experience and skills of ME majors. At the same time, it is highly unlikely that the sponsor would have sought an ME team for the same project given the specialized knowledge of physiology required for success. We speculated that a multidisciplinary capstone course would enrich the experience for both sets of students as evidenced by the products they developed.

Because the primitive devices produced by the students appeared to be representations of the knowledge limitations of the discrete domains, we hypothesized that, by combining knowledge domains in an MCD course, improved student-designed products – as measured by the design expo performance, job placement, and grade point average (GPA) would provide us with evidence of the course’s effectiveness. Using a needs analysis approach (Karwowski, Soares, & Stanton, 2011) to focus on the requirements related to the goals and needs of the user, capstone design students work with a client-advisor to develop a product with real-world application. We, in turn, used that same needs analysis approach in designing this experiment: the user needs were defined as the experiences and skills students require to be successful collaborators and innovators in an increasingly multidisciplinary world.

Methods

Design

For this comparative study, a single treatment was administered (an undergraduate capstone design course within the College of Engineering at Georgia Tech) with three conditions (BME only, ME only, and MCD) to address the research hypothesis that students who take an MCD course have better outcomes than monodisciplinary students, as measured by independent evaluation from industrial professionals and job placement. Job placement and design expo score were used as indicators of success in the quantitative analysis of the effects. This analysis is performed using a generalized linear model (GLM) for the continuous variables (e.g., expo score), and a logistic regression to explore the effects of binomial variables (e.g., job placement).

Subjects

In the Fall 2010 semester, three versions of senior capstone design course were implemented concurrently: a monodisciplinary mechanical engineering course with 114 students (23 teams), a monodisciplinary biomedical engineering course with 23 students (5 teams), and an interdisciplinary biomedical-mechanical engineering course with 31 students (20 BME and 11 ME distributed among 5 multidisciplinary teams).

Student teams were formed by self-selection within sections of the course. For the MCD teams, those BME projects identified by the instructors as requiring ME expertise were chosen for pairing with ME students who had indicated an interest in a medical device project. This was done after the BME students had completed a semester of analyzing their project and solution possibilities in order to identify the utility of a multidisciplinary team. Sections each comprised approximately one-fifth of the course enrollment. Teams and projects were matched by posting all projects at the beginning of the semester and allowing teams to select their top three preferences among the industry sponsored projects. In cases where only one team most preferred one project, the match was made. When multiple teams chose the same project, multiple teams were matched to it if the sponsor agreed. If not, then best effort was made to offer the teams their second choice. Teams that were not interested in the industry projects or that did not get matched to an industry sponsor (rare) were required to conceive their own projects.

BME and ME instructors recruited BME teams for participation in the MCD section based on their project's suitability for the skills of ME experts. MCD teams' projects were chosen based not on the degree of complexity or popularity but on need for mechanical analysis and design. While enrollment in capstone design is mandatory, enrollment in the interdisciplinary course section was voluntary for the ME students. BME MCD teams that had already begun planning their design during the first semester of their two-semester capstone design coursework pitched their proposals to ME students, who then were given the opportunity to choose a project that resonated with their interests. Students in all three conditions signed Institutional Review Board-approved consent forms to voluntarily participate in the research portion of the study.

We surveyed the literature to assess other measurements of the quantitative effect of group diversity (e.g., gender, ethnicity, age, major, year, personality, GPA) on group performance to help elucidate valid variables for modeling. Group diversity has varying effects on a group performance, including innovation, quality of ideas, and productivity. In a thorough review of the effects of diversity on performance, Carrillo and Leifer (2003) concluded that the literature produced mixed results. For example, group diversity can result in more creative solutions (Bantel & Jackson, 1989), increased performance, and higher quality ideas in creative tasks, such as product development (McLeod & Lobel, 1992; Neale, Northcraft, & Jehn, 1999). However, the overall effect on performance was found to be negative (Ancona & Caldwell, 1992; Williams & O'Reilly, 1998). Although the creativity of the problem solutions appears to be improved, the end result of those solutions does not directly result in an overall positive performance. Ancona and Caldwell (1992) found scant evidence of a relationship between cohesiveness and performance within diverse groups. In contrast, Chatman, Polzer, Barsade, and Neale (1998) discovered that increased diversity resulted in improved productivity. One study found that overall, group diversity does not positively affect performance (Williams & O'Reilly, 1998). Carrillo's and Leifer's (2003) experiments at Stanford showed that in short projects (e.g., two weeks) high-diversity teams had the lowest average scores and were especially weak in design implementation, while in longer project (e.g., 30 weeks), the high-diversity teams improved markedly, yielded the highest average performance in four of five design assignments, and had the least variation in category performance. Other studies specific to engineering capstone curricula have yielded more anecdotal and qualitative results, primarily describing the challenges and team dynamics associated with diverse team composition (Amon, Finger, Siewiorek, & Smailagic, 1995; Davis & Masten, 1996). These studies indicate that the team experience better prepared the students for professional practice (Neeley, Elzey, Bauer, & Marshall, 2004) because it taught them to work together to overcome conflict and integrate opposing views (Amon et al., 1995; Davis & Masten, 1996). In view of the mixed results from the literature, this 16-week study – with its quantitative significance and its independent variable being diversity of student major – seems timely and useful.

We also reviewed the literature to determine what factors (e.g., gender, ethnicity, age, major, co-op participation, personality, and GPA) had the greatest influence on job placement to help elucidate valid variables for modeling. Relevant factors to this study were GPA and major. Studies have consistently found that GPA is the strongest predictor of job placement and persistence in engineering (Albrecht, 1994; Jackson, Gardner, & Sullivan, 1993). To prevent GPA from being a confounding factor in this study, it was controlled for when analyzing the effect of course version. According to the U.S. Bureau of Labor Statistics *Occupational Outlook Handbook*, 2011 job placement rates also vary significantly between engineering majors, which could also be a confounding factor for analysis. Thus, when performing the analyses below, major was included as a variable of interest and controlled for in all analyses.

Procedure

Teams were presented with a problem from an external sponsor or advisor, such as a medical professional or an engineering company, or devised their own problem. Approximately one-third of the course projects were identified from the instructor's correspondence with industry sponsors prior to the semester, although students did not have access to that information. These projects were posed as challenges faced by the sponsor that required the effort of a team of engineers over the course of a semester to produce a working physical prototype and report. The remaining projects were student teams' own conception through observation or conversation with faculty, family, or coworkers. In the span of one 15-week semester, all teams developed creative solutions to the problems, analyzed them, and physically fabricated prototype solutions given a $500 reimbursable budget, under the advisement of six faculty and three graduate teaching assistants. In the case of the BME and multidisciplinary medical device designs, the Food and Drug Administration's 510k regulatory report was also filed. At the end of the semester, several expositions featuring all 33 teams were held. The teams were judged at the expositions by faculty and external professionals to yield a single quantitative score from the following criteria: (1) innovation, (2) utility, (3) analysis, (4) proof of concept, and (5) communication skills. Each team was evaluated by five or six judges who gave scores of 1, 2, or 3 (best) in each of the five categories listed above. Students also received individual course grades for their written and oral reports, meeting contributions, and peer evaluations.

To further explicate the types of problems, inventions, and teams comprising the capstone design course, two team projects are described: one monodisciplinary and one MCD. A monodisciplinary team of five MEs invented an automobile-powered water pump for a market in sub-Saharan Africa, where 41% of people lack easy access to water for farming and drinking (Figure 1). It works with any car and sets up in 90 seconds. An MCD team of four BMEs and two MEs invented a medical device for cataract surgery, the second most common surgery in the U.S. (Figure 2). Their simple, handheld device performs a technique called capsulorhexis, removing the lens of the eye much more effectively than the average surgeon. Both teams demonstrated

FIGURE 1. A five-student monodisciplinary team designed, analyzed, and fabricated an automobile-powered water pump.

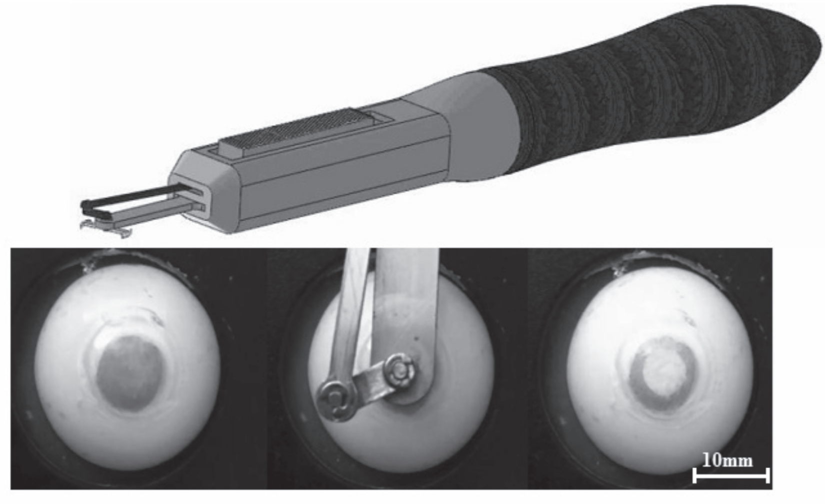

FIGURE 2. A six-student multidisciplinary team designed, analyzed, and fabricated a device to improve safety and quality of cataract surgery, performing a technique called capsulothexis. Their project won top honors at the design expo.
Top: schematic; bottom: in operation on an eyeball model.

creativity in their solutions, undertook numerous design and analysis cycles, considered parameters such as power, weight, cost, mechanical loading, and deformation, and produced fully functional prototypes. Both teams earned high grades in the course consistent with their GPAs, performed very well in the design expo (top 3 out of 33 teams), and continued working on the projects after the course ended.

DATA AND ANALYTICAL METHODS

Tables 1a–c list the quantitative parameters that were collected and separates them by variable classification: cumulative GPA at graduation, expo score, major, course version, and job placement status after graduation (unemployed, employed in graduate school or engineering job, or other). Table 1a contains both GPA and expo score (continuous variables) information. The mean GPA was found to be 2.98 ±0.5 with skewness = 0.224 and kurtosis = –0.829, which are consistent with only slightly non-normally distributed data. The mean expo score was found to be 9.94 ±1.09 with skewness = –0.116 and kurtosis = –0.384, which are consistent with slight non-normality. Both fall close enough to a normal distribution that they can be assessed using analyses that assume normal distribution of data. Both variables were also plotted against normal percentiles, and no data outliers were seen (data not shown). Table 1b contains the variables major, course version, and job status. There were 168 total students: 43 BME and 125 ME. The coding of these variables is shown to denote a reference group, always denoted by the coding value of 0. The reference major was BME, and thus its value is shown as 0 in Table 1b. From this group of students, three capstone design course versions were taken: MCD, ME, and BME. The MCD group was analyzed as the reference course version. Finally, job status (JS) was obtained seven months after course completion for 122 of the students. The unemployed

TABLE 1a
Analysis of Continuous
Variables Measured for Regression Analyses

	GPA	Expo score
Mean	2.98	9.94
Std. dev.	0.50	1.09
Min.	2.06	7.17
Max.	4.00	12.10
Skewness	0.22	−0.12
Kurtosis	−0.83	−0.38

TABLE 1b
Analysis of Nominal Variables Measured and Coding
Convention for Regression Analyses

Variable/Category	Coding	Sample size	Percentage
Major			
BME	0	43	25.6
ME	1	125	74.4
Course version			
MCD	0	31	18.5
ME	1	114	67.9
BME	2	23	13.7
Job status			
Unemployed	0	20	16.4
Engineering job	1	65	53.3
Other Job	2	15	12.3
Grad/med school	3	22	18.0

Job status missing = 46

group was analyzed as the reference group. Forty-six students' employment status was lost to follow-up. Table 1c further divides several of the variables defined in Tables 1a,b into binomial variables. In each case, the variables have been divided such that the group that is being analyzed is singled out from the rest of the population. For instance, the course version is divided into two dummy variables CV_{ME} and $CV_{BME.}$ The MCD course version is the reference group, and thus its value is always 0, so that no dummy variable is needed to define this parameter. The variable *GPA* was also divided into three dummy variables GPA_{Low}, GPA_{Med}, and GPA_{High}. The reference group was any GPA <2.5. Again, because this is the reference group, its value is always 0, and thus there is no need to create a variable for it. Finally, the student's job status was redefined as the binomial variable $JS_{BIN.}$ The reference group was defined as the unemployed, and all other employment was condensed into a single value (JS values 1 to 3 from Table 1b).

GPA was chosen as a variable of interest because it not only is a criterion considered by potential employers but also serves as a proxy for the intellectual ability and effort of the student. Thus, by controlling for GPA in the analysis, we tried to assure that the team and

TABLE 1c
Analysis of Binomial Variables Measured and Coding Convention for Regression Analyses

Variable/Sub-class	Category	Coding	Sample size	Percentage
Course version				
ME	Not ME	0	54	32.1
ME	ME	1	114	67.9
BME	Not BME	0	145	86.3
BME	BME	1	23	13.7
GPA				
Low	Not 2.5–3.0	0	110	65.5
Low	2.5–3.0	1	58	34.5
Med.	Not 3.0–3.5	0	120	71.4
Med.	3.0–3.5	1	48	28.6
High	<3.5	0	137	81.6
High	3.5–4.0	1	31	18.5
Job status				
	Unemployed	0	20	16.4
	Employed*	1	102	83.6

Course version, GPA, and job status variables from Table 1b are divided into binomial dummy variables.
Job status missing = 46
* A combined variable of all job statuses given the values 1–3 in Table 1b

project selection process did not predetermine or highly influence the values of the dependent variables. While not a perfect measure of a student's drive to succeed in academia, controlling for GPA serves to mitigate the effect of student differences in ability and effort. Thus, all analyses that are performed control for the GPA of the student so that only students of approximately equal GPA are compared.

To interpret the data in the analysis, a generalized linear model (GLM) and logistic regression were used. Briefly, a GLM is a form of linear regression that uses the linear model to relate to the response variable by a distribution function (a normal distribution in this study); it allows the magnitude of the variance of each measurement to be a function of its predicted value. This model also assumes homoscedasticity of the data and that sampling was done independently. To confirm homoscedasticity of the data, the residuals of each variable were plotted against the predicted value, and no trend was seen in the data (not shown). All of the information collected was done in a blind fashion by a third party (see Acknowledgements), and no value depended on any other. In the model, parameter coefficients were determined using a least squares regression algorithm. In order to assess the effect of single variables, our modeling efforts followed standard practice to create a reference group that has a value of 0 for all parameters.

The logistic function is used to transform any binomial (0-1) variable that varies across a parameter(s) to a linear distribution that can vary from $-\infty$ to $+\infty$. The resulting transformed model looks similar to a simple linear regression model; however, the underlying distribution is binomial, and the parameter coefficients must be calculated using maximum likelihood estimates (MLE) instead of least squares regression. Logistic regression assumes that all variables are independent and that they are not collinear, as they were thought to be in this study. Logistic regression has the added benefit of assessing odds of a given piece of data given the parameter value (i.e., the odds of a student who has a 3.5 GPA having a job versus a student who has a GPA of <2.5). The odds can be obtained by exponentiating the parameter value multiplied by its MLE. For this model, the reference group was a BME student who took the MCD course version, had a GPA of <2.5, and an expo score of 0. The expo score was normalized and then analyzed in several ways. First, each judge's scores were normalized to the mean. The normalization was done by taking the total points for all teams that an individual judge evaluated and summing to obtain the total number of points given by the judge. This sum was then normalized by dividing by a factor, which is a total score of ten points per team (two points in each of the five categories) multiplied by the number of teams seen by the judge. The result of this calculation (the normalization factor) was then used to normalize each judge's score, which was done by multiplying the judge's original score for the team by the calculated normalization factor. This procedure was performed for each judge.

The validity of this normalization was then tested by an ANOVA with Dunnett's post test using the overall expo score mean and standard deviation as the control group with an $\alpha = 0.05$. The results showed that the normalization was successful and that no judge's score fell outside the 95% confidence interval.

The expo scores for the previous two semesters were compared to the semester analyzed in this paper in order to provide some measure of external validity and thereby ensure that the score of all expo judges was not skewed toward any particular factor or set of teams in the semester analyzed. This comparison was done using an ANOVA with Tukey's post test. The mean and standard deviation of the score in each of the five categories assessed by the judges was determined for each of the semesters. An ANOVA was then performed, which showed that the scores were not significantly different between semesters in the innovation, utility, analysis, and communication skills categories. The proof-of-concept category was found to be significantly lower between the fall and spring semesters; however, the overall ANOVA for the proof-of-concept category was not significant, which indicates that variability was high for this category and that with such a small sample size (three semesters) it is difficult to draw concrete significant association. A graph of these results and their standard deviations is given in Figure A1 (Appendix A), with further breakdown by team and overall score in Figure A2.

Results

General Linear Modeling

A GLM analysis was performed to determine if expo score could be predicted by major, course version, and GPA. To do this, course version was divided into two dummy variables, as given in Table 1c, with the MCD group as the reference group. GPA was modeled as a continuous variable, and major was coded as seen in Table 1a with BME as the reference group. Equation 1 shows the full model with expo score as a function of major, course version, and GPA.

$$\textit{Expo score} = \beta_0 + \beta_1(\textit{Major}) + \beta_2(CV_{\mathrm{ME}}) + \beta_3(CV_{\mathrm{BME}}) + \beta_4(GPA) \tag{1}$$

An overall analysis of variance (ANOVA) was performed on the model to determine its stability and to show significance of this model in interpreting the data. The model converged and had an F value of 8.64 corresponding to $p < 0.0001$. The data was then fit using least squares regression and the best-fit beta values as seen in Equation 2, where statistically significant variables and their coefficients are bolded.

$$\begin{aligned} \textit{Expo score} = {} & 10.25 - 0.041\,(\textit{Major}) - \mathbf{1.182\,(\boldsymbol{CV}_{ME})} - \mathbf{1.574\,(\boldsymbol{CV}_{BME})} \\ & + 0.246\,(\textit{GPA}) \end{aligned} \tag{2}$$

The parameter estimate, standard error, 95% confidence interval, chi-square value, and probability for each parameter estimate are given in Table B1 (Appendix B). The reference group for this model was a hypothetical BME student who took the MCD course version and had a GPA of 0.0. A negative parameter estimate means that a variable has a negative association with the outcome when compared to the reference group. Equation 2 shows that major and both course versions correspond negatively to expo score while GPA had a positive association with expo score. However, the magnitude of the association between the parameters and expo score is only statistically significant for the course version variables (bolded, $\alpha < 0.05$). In other words, ME majors and GPA did not have a statistically increased or decreased association with expo scores (over BME majors), but the course version the students took did have a statistically significant association with expo score. Because the association between course version and expo score is negative and is statistically significant, both monodisciplinary course versions cause a statistically significant decrease in expo score relative to the multidisciplinary group, even when comparing students who had the same GPA and major. The magnitude of this difference is larger for BME students than ME students in monodisciplinary course versions, though not to a statistically greater amount.

To assess whether the measured factors were valid for prediction of the expo score, an adjusted R^2 value was calculated to be 0.2105. Discussion of this R^2 and its relatively low value can be found in Appendix B and a more in-depth analysis of the coefficients seen in Equation 1 is given in Table B1. For this GLM model, GPA and major have no significant association with expo score, which indicates that there was no significant bias in expo score toward students with higher or lower GPAs or from different majors. Because scoring was done on a team basis and not by individual, the lack of significant GPA indicates that no significant bias in team composition, in terms of GPA, was present. To further confirm this association, Pearson correlation coefficients were calculated between all predictors, and no significant correlation between GPA and team or course version was found. This correlation analysis and its implications are further discussed in Appendix B and Table B2.

Logistic Regression

The logistic regression model attempts to determine if there was an association between the binomial job status (employed or not employed) and the predictor variables: major, course version of capstone design taken, GPA, and expo score. This modeling was performed in order to tease out factors important to job status regardless of what kind of job was obtained (engineering, non-engineering, or graduate/medical school). Using the coding shown in Table 1c, course version was divided into two dummy variables with the multidisciplinary group as the reference group. Expo score was modeled as a continuous variable, and major was coded as seen in Table 1b with BME as the reference group. For this regression, GPA was divided into three dummy variables (shown in Table 1c) with a GPA of <2.5 as the reference group. GPA was made into a hierarchical variable to determine what level of GPA was necessary to increase the odds of employment; the new model is given in Equation 3, where the base individual is a BME major on a multidisciplinary team with a GPA of <2.5 and an expo score of 0.

$$\text{Logit}(JS_{\text{BIN}}) = \beta_0 + \beta_1(Major) + \beta_2(CV_{\text{ME}}) + \beta_3(CV_{\text{BME}}) + \beta_4(GPA_{\text{Low}}) + \beta_5(GPA_{\text{Med}}) + \beta_6(GPA_{\text{High}}) + \beta_7(Expo\ score) \quad (3)$$

A likelihood ratio (LRT) and Wald χ^2 test were performed to confirm that the global null hypothesis could be rejected. The LRT χ^2 value was 25.863 with a $p = 0.0005$ while the Wald χ^2 value was 17.506 with a $p = 0.0144$. Again, $\alpha = 0.05$ was the threshold for significance, and thus the null hypothesis (that none of the parameters were able to predict job status) was rejected, and the model was further analyzed using maximum likelihood estimates. The results of this analysis are given in Table 2.

The BME course version had a significant negative association with having a job as compared with the MCD course version when controlling for all other parameters in the model. In other words, BME students who took the MCD course version had statistically higher odds of having a job than did those BME students who did not take the MCD course version when comparing students of identical major, GPA, and expo score. The odds ratio for a BME student to have a job who did not take the MCD course version versus a BME student who did was 0.050, or roughly 20 times lower than that of the MCD group.

The GPA_{Med} parameter was positively associated with having a job, controlling for course version, major, and expo score. In other words, students with a GPA from 3.0 to 3.5 had statistically higher odds of having a job than did those with a GPA of <2.5. The odds ratios for having a job at either the medium or high GPA level were 11.85 and 7.8 times higher, respectively, than for the reference group (GPA of <2.5), controlling for all other parameters in the model.

TABLE 2
Maximum Likelihood Parameter Estimates of the Logistic Regression Model Proposed in Equation 3

Parameter	Est.	Stand. error	Wald 95% CL	Wald χ^2	Prob. $> \chi^2$	Odds Ratio	Odds ratio 95% Wald CI
Intercept (ß0)	0.03	2.98	[−5.8,5.87]	0	0.99	–	–
β1 (*Major*)	−1.14	1.54	[−4.17, 1.88]	0.55	0.46	0.32	[0.02, 6.57]
β2 (CV_{ME})	0.1	1.22	[−2.28, 2.48]	0.01	0.93	1.11	[0.10, 11.98]
β3 (CV_{BME})**	**−2.99**	**1.31**	**[−5.55, −0.44]**	**5.26**	**0.02**	**0.05**	**[0.004, 0.65]**
β4 (GPA_{Low})	0.38	0.71	[−1.01, 1.76]	0.28	0.59	1.46	[0.37, 5.80]
β5 (GPA_{Med})**	**2.47**	**1.02**	**[0.48, 4.46]**	**5.92**	**0.02**	**11.85**	**[1.62, 86.77]**
β6 (GPA_{High})*	2.06	1.17	[−0.24, 4.35]	3.07	0.08	7.81	[0.78, 77.71]
β7 (*Expo score*)	0.2	0.26	[−0.31, 0.72]	0.6	0.44	1.23	[0.73, 2.05]

** Bold fields represent parameter estimates with statistically significant values ($\alpha < 0.05$)
* Parameter estimates with statistically significant values ($\alpha < 0.1$)

Because the BME course version was significant, the question of which type of employment the students had higher odds of obtaining was of interest. To explore the effect of which type of employment were more likely, we constructed a multinomial logistic regression:

$$\text{Logit}\ (JS_{\text{Eng}}),\ \text{Logit}\ (JS_{\text{Other}}),\ or\ \text{Logit}\ (JS_{\text{Grad}}) = \beta_0 + \beta_1\,(Major) + \beta_2\,(CV_{\text{ME}}) + \beta_3\,(CV_{\text{BME}}) + \beta_4\,(GPA_{\text{Low}}) + \beta_5\,(GPA_{\text{Med}}) + \beta_6\,(GPA_{\text{High}}) + \beta_7\,(Expo\ score) \quad (4)$$

For this model, the job status data were divided into the four strata seen in Table 1b. The base group for each stratum was considered the unemployed group. A logistic model was then designed for each of the employment strata (engineering job, non-engineering job, and graduate/medical school), and the subsequent maximum likelihood estimates calculated for each of the betas (see Table 3). For this multinomial regression, the reference group for each stratum was a BME major who took the MCD course version, had a GPA of $<$2.5, and had an expo score of 0.

The GPA_{Med} parameter again had a statistically significant positive association with having an engineering job and acceptance to graduate/medical school (over the reference group) when comparing students within the same course version, major, and expo score. For employment in fields other than engineering and graduate/medical school (JS_{Other}), GPA played a less significant role in determining employment status, but still the higher GPA strata did have an increased odds of employment over the reference group. Also of interest, is that for graduate/medical school, GPA_{High} showed a statistically significant increase in the odds of employment, though not statistically higher than for the GPA_{Med} group. No inferences about students who went to graduate school and had a GPA from 2.5 to 3.0 were made because all students whose employment status was obtained and who were going to graduate/medical school had a GPA $>$ 3.0.

TABLE 3
Maximum Likelihood Parameter Estimates of the Multinomial Logistic Regression Model Proposed in Equation 4.

	Intercept (β0)	β1 (*Major*)	β2 (CV_{ME})	β3 (CVB_{ME})	β4 (GPA_{Low})	β5 (GPA_{Med})	β6 (GPA_{High})	β7 (*Expo score*)
Engineering job								
Estimate	−1.93	−0.79	0.26	**−2.84**	0.49	**2.13**	1.43	0.33
Prob.	0.55	0.61	0.83	**0.04**	0.50	**0.04**	0.23	0.24
Odds ratio	0.15	0.46	1.30	**0.06**	1.63	**8.42**	4.19	1.40
Other job								
Estimate	2.42	−2.14	−0.27	**−3.06**	−0.40	2.17	1.48	−0.10
Prob.	0.53	0.26	0.87	**0.05**	0.70	0.07	0.32	0.77
Odds ratio	11.24	0.12	0.76	**0.05**	0.67	8.76	4.38	0.90
Grad/medical school								
Estimate	**−9.37**	−1.99	0.22	**−4.19**	na	**11.94**	**12.08**	0.14
Prob.	**0.05**	0.28	0.89	**0.02**	na	**<0.0001**	**<0.0001**	0.74
Odds ratio	**0.0001**	0.14	1.24	**0.02**	na	**153891**	**175606**	1.15

Bold fields represent statistically significant factors ($\alpha < 0.05$).

The BME course version had a significant negative association with having any kind of job as compared to the MCD course version, controlling for all other parameters in the model. Therefore, BME students who took the MCD course version had statistically higher odds of having a job in any field than did those BME students who did not take the MCD course version, comparing students of identical major, GPA, and expo score. The odds ratio for a BME student to have a job who did not take the MCD course version versus a BME student who did was between 0.019 and 0.046, averaging 30 times lower than that of the MCD group. To evaluate the goodness-of-fit of the logistic models, Hosmer and Lemeshow's goodness-of-fit test and Nagelkerke's pseudo R^2 values were used. The results and description are given in Appendix C. In summary, the logistic regression accounts for a significant portion of the likelihood of the measurements.

Discussion

Table 4 summarizes the key findings in this analysis of the effects of the multidisciplinary, engineering capstone design course.

General Linear Modeling

The model showed that students who took the MCD course version had a statistically higher expo score than did students who took any other course version even when controlling for major and GPA of the students. Multidisciplinary teams created a product that earned a higher expo score than monodisciplinary teams as judged by industry, medical, and academic professionals with no prior knowledge of their groups' mono- or multidisciplinary composition. The average decrease in score was 10% to 15% for the students who did not take the MCD course version. Due to how the course versions were constructed, several factors that could play a role in this result were not analyzed in the models.

First, the multidisciplinary teams had more students on each team. The MCD teams had six to eight members while typical teams in BME and ME had three to five members. This increase in team members might lead to more person hours spent on the project. Therefore, the MCD teams may have received higher scores because of the increased number of hours possibly committed to the project. Because no teams in the BME or ME course versions had seven or eight members, no clear quantitative comparison controlling for group number could be made between these two groups when modeling. However, interviews and surveys with the students showed that scheduling for such teams was

Table 4
Summarized Outcome of All Modeling

		Employment		
Course version	Expo score	Engineering	Grad/med school	Other
ME	Lower	Equal	Equal	Equal
BME	Lower	Lower	Lower	Lower

"Lower" denotes a statistically significant amount lower than the multidisciplinary students; while "equal" denotes a statistically equal score or odds to a multidisciplinary student.

challenging and led to difficulties in meetings and getting everyone organized and working simultaneously. Furthermore, according to course instructors, teams of three or four members have historically scored higher than teams of five or six members in monodisciplinary capstone design courses. Interview data gathered from these teams in the qualitative component of this study indicate that larger teams had more fragmentation and less clarity on individual assignments. Students perceived that this dissonance contributed to a lower quality product than the students had hoped. Thus, larger teams were not a clear asset to the teams but rather an organization obstacle to overcome. In future studies we hope to make a more direct comparison of multidisciplinary groups with team sizes identical to those of other course versions.

Second, the MCD teams had a phased start as compared with the ME and BME course versions. To make MCD teams, ME students were added to the BME groups after the first semester of the BME course was completed. In contrast, the BME students had a two-semester course while the ME students took a one-semester course. Thus, compared with the other ME groups, the MCD teams had an extra semester to evaluate the problem and conceptualize designs. However, the MCD teams still did statistically better in the design expo than the BME teams who also had two semesters to complete their project. The expo scores were not statistically different between the BME and ME teams. The BME students who took the MCD course version in their second semester were asked to go back to the problem definition and conceptual design phases with their newly expanded team. The new design concepts generated from this redesign phase were fundamentally different from those of the BME teams alone. Most of the relevant background information, design concept analysis, and research of the preliminary work had to be redone in the second semester for these MCD teams on the basis of these new design concepts. Therefore, since BME teams that had two semesters to develop and produce their design received statistically similar scores to those of the single-semester ME teams and since the BME students in MCD teams were asked to redesign their product, the phased start was seen as a negligible advantage to the MCD teams.

Logistic Regression

Possibly, due to the voluntary nature of reporting job outcome, some bias was introduced in the job status data. Though not measurable or quantifiable, we can hypothesize two readily available skews to this information. First, students who were unemployed might be reluctant to report their job status, resulting in an underrepresentation of this cohort. On the other hand, students who had jobs or were in graduate school might be excited to report their success, resulting in a contrasting overrepresentation of this group. In this case, the skew would be toward the null (no difference in job outcome regardless of parameters), and any difference seen in analysis would only be made more significant if all data were reported. Alternatively, students without jobs have more free time to respond to university communication. In this case, the bias would be toward the unemployed group, and any difference seen in analysis would be less significant if all data were reported. Because these are unknowable, for the purposes of this paper, we treated the data as representative of the population.

Both the logistic regression model and the multinomial model showed that GPA and the BME course version were significant factors in having a job. The significant role of GPA in increasing the odds of having a job makes intuitive sense because many recruiters require a minimum GPA (often 3.0) before an interview. Interestingly, students with the highest GPAs did not have statistically significant greater odds of obtaining a job than a person with a GPA of <2.5 in the model shown in Equation 3. According to the model, students with a GPA of 3.0 to 3.5 had higher odds of obtaining a job than did those with a GPA of 3.5 to 4.0. However, the sample size for the high-GPA students was lower than of the medium-GPA students (24 vs. 38), thus suggesting a lack of power in the analysis. Therefore, we performed a power analysis on the data and found that the study was underpowered for the high-GPA group. In order to obtain adequate power for significance, 29 students would need to have had a high GPA. Furthermore, when job status was divided into the four strata seen in Table 1b, the distribution of students in the GPA_{High} stratum was much higher in the graduate/medical school group than in other job categories. This unequal distribution of students could also bias the data toward the null (no difference in GPA).

The GPA data becomes more interesting when analyzing the results from the model in Equation 4. The highest GPA stratum played a significant role in students getting into graduate/medical school, and only for this group did having the highest GPA give an odds ratio higher than that of having a GPA of 3.0 to 3.5. Furthermore, GPA seemed not to play as significant a role in obtaining employment in fields other than engineering and graduate/medical school. This consequence also seems reasonable as jobs outside of these fields do not always require a GPA disclosure when hiring, which would reduce its importance.

Both the logistic model and multinomial models show much higher odds of employment for BME students in MCD teams than for monodisciplinary teams. BME students who did not take the MCD course version had a 20 to 30 times lower odds of being employed than did BME students who took the MCD course version. This difference cannot be attributed to GPA differences or major because these odds calculations controlled for GPA, expo score, and major. This number seems unreasonably high, and when examining the confidence interval in Table 2, the true value of the odds ratio could be as high as 0.648. However, even at the highest odds estimate, this still gives MCD students an almost 1.55 times higher odds of having a job than do the non-MCD students. Again, this seems unusually high. Because all MCD teams participated in schoolwide invention competitions, the Capstone Design Expo and Georgia Tech's Inventure Prize, we speculated one cause of this high ratio might be publicity exposure afforded the MCD teams. In fact, one of the teams did very well in the competition and received funding to continue development of their product, and a press release was sent out highlighting the team's design. Published in the region's major newspaper (Markiewicz, 2011), the press release was also broadcast across many state television and radio news channels. The competition events also gave MCD teams opportunities to meet industry professionals.

The success of the teams in Georgia Tech's Inventure Prize competition led two of them to form start-up companies with their product, so that of the five MCD teams, approximately 40%, were employed before graduation. The added exposure, networking, press, and jobs were created as a direct result of having an excellent product. Accordingly, we do not consider the factors above as completely independent influences on outcome. In any future studies, we anticipate that as the sampling population grows larger, the 40% employment rate prior to graduation will likely decrease, in which case MCD coursework would show a more moderate effect on employment. However, regardless of the significance of employment outcome, the authors suggest that MCD design coursework is justified by its products being judged better by diverse professionals.

Finally, both the logistic and multinomial models showed that BME students were statistically less likely to have a job, while ME students who did not take a MCD capstone design course were not significantly affected. These different outcomes led us to wonder why there is a disparity in job status between the two majors. Because there were three times as many ME students as BME students, their employment ratios may have been less sensitive to the increase represented by the MCD teams' high employment. Also, most ME jobs are not in the biomedical field, so we speculate that an ME student's showing a biomedical product for a senior design device would have less of an impact on a nonmedical employer than it would on one in a biomedical engineering field. This disparity suggests that these ME students, unless applying for jobs in a biomedical field, would have a minimal increase in job odds over their monodisciplinary counterpart.

Overall Study

The factors that control a student's ability to succeed in capstone design are not strictly quantitative. In that regard this study is limited. Capstone success is likely to be influenced by nonquantitative factors such as a student's drive to create a physical product, off-the-record experience, passion, and communication skills. These factors might lead the student to pick a particular course version biasing team composition and outcomes. Future studies should determine quantitative metrics for these factors by surveying the students before and after capstone design courses and incorporating the results into the models above.

In the future, we recommend larger populations of each course version to get more accurate estimates with smaller confidence intervals than those obtained in this study. Extensions of this study might combine multiple semesters or incorporate students from multiple institutions. Furthermore, identical class structures and team sizes would alleviate potential biases introduced in this study. Finally, factors other than GPA, major, expo score, and course version would make these models more robust and perhaps increase the R^2 value of the linear models. Some relevant factors we did not consider in these models, but which could affect employment or expo score, are the following: number and length of internships students have completed, laboratory or clinical research completed, connection of students to the company or institution that hired them, years in school, and student age. Students who have a confirmed job after graduation prior to the start of capstone design should also be excluded. Finally scaling this course structure to an entire college of engineering will require novel administrative, reward, and incentive structures for faculty, students, and sponsors.

Conclusions

While this initial investigation did not acquire and assess all the possible variables that could influence employment status or expo score, it is an initial step toward showing that MCD coursework is valuable in producing a team product and presentation that external industry professionals judge as having holistically better innovation, utility, analysis, proof of concept, and communication skills than those of their monodisciplinary counterparts. Our study also shows that students in MCD courses have, on average, a higher likelihood of being employed seven months after graduation. Extrapolating the results found here to other majors, we believe that with the incorporation of MCD design across all engineering majors, students will better prepare themselves for the qualities valued in professional practice and be more likely to obtain professional employment. However, we recognize that while GPA and major have no significant associations with expo score (considering first the major as a differentiator), the intellectual distance between the domains of BME and ME may not be far enough to be significant. This separation could become significant when combining more disparate fields, such as business or industrial design; this factor should be analyzed and controlled for in future studies.

A prevailing observation in the BME undergraduate community is that, while future job predictions are positive, current employers are uncertain what to do with BME graduates because the fairly new field is still evolving (Meijer, 2008, 2011). This uncertainty, coupled with the BME students' lack of expertise in any specific engineering field, has led to tepid industrial response to hiring BME undergraduates. It is clear that due to the breadth of fields these students are asked to cover in their coursework and the multidisciplinary nature of the work that occurs in the BME field, an undergraduate cannot build adequate specificity in any particular field to completely address any one of the complex components associated with medical problems. Thus, these students may be best suited to coordinating with engineers who have expertise in more specific areas; yet it is rare that their curriculum supports this type of multidisciplinary coursework.

To our knowledge, this is the first study to show a quantitative benefit to multidisciplinary work, controlling for multiple factors that could have confounded previous studies on similar topics. This benefit is highlighted in Table 4 where MCD students showed distinct improvements over their non-MCD counterparts in at least one outcome and, in the case of BME majors, in every outcome tested. The ability to compare students of equal GPA, major, and course version makes a stronger and more valid argument that favors engineering institutions encouraging MCD course work.

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APPENDIX A: EXPOSITION SCORE ANALYSIS

The average expo score for three consecutive semesters for each category assessed by judges is shown in Figure A1. The averages and distributions of the scores for all teams for the three semesters are shown in Figure A2.

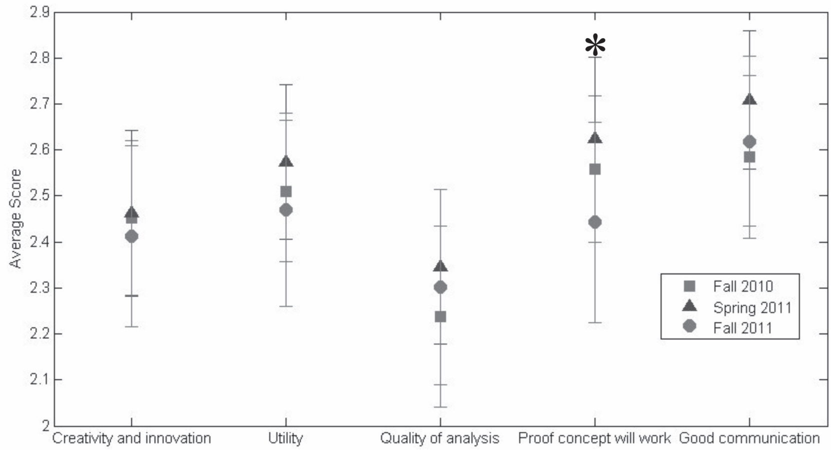

FIGURE A1. Average expo score for three consecutive semesters for each category assessed by judges. Results show that scores from each semester were not statistically different except for between spring and fall of 2011 (under proof of concept) where the fall semester was found to be statistically lower than the spring 2011 score as judged by Tukey's post test $\alpha = 0.01$.

* indicates statistical significance.

APPENDIX B: GENERAL LINEAR MODELING

The parameter estimates and probabilities shown in Table B1 and whose results can be seen in Equation 2 are calculated by keeping all other variables constant and only varying the parameter of interest. In Table B1 and B2 parameter estimates with statistically significant values are bolded and highlighted. To assess whether the measured factors of the general linear model were valid for prediction of the expo score an adjusted R^2 value was calculated. The adjusted R^2 for this model is 0.2105 which means that the model accounts for ~21% of the total variance seen in the data. This is a relatively low amount; however, when other factors that were available such as gender, stratifying the GPA (as seen in Table 1c), and years in college were added to the model the fit improved only slightly (adj. $R^2 = 0.2415$). The increase in variable number (100% increase) relative to gain in R^2 was seen as relatively low and thus these factors were removed from the model. Not stratifying the GPA was further bolstered by GPA having no statistical significance in the model from Equation 1 as seen in Table B1. Several non-linear regression techniques were also attempted and no significant increase in R^2 was seen for these techniques.

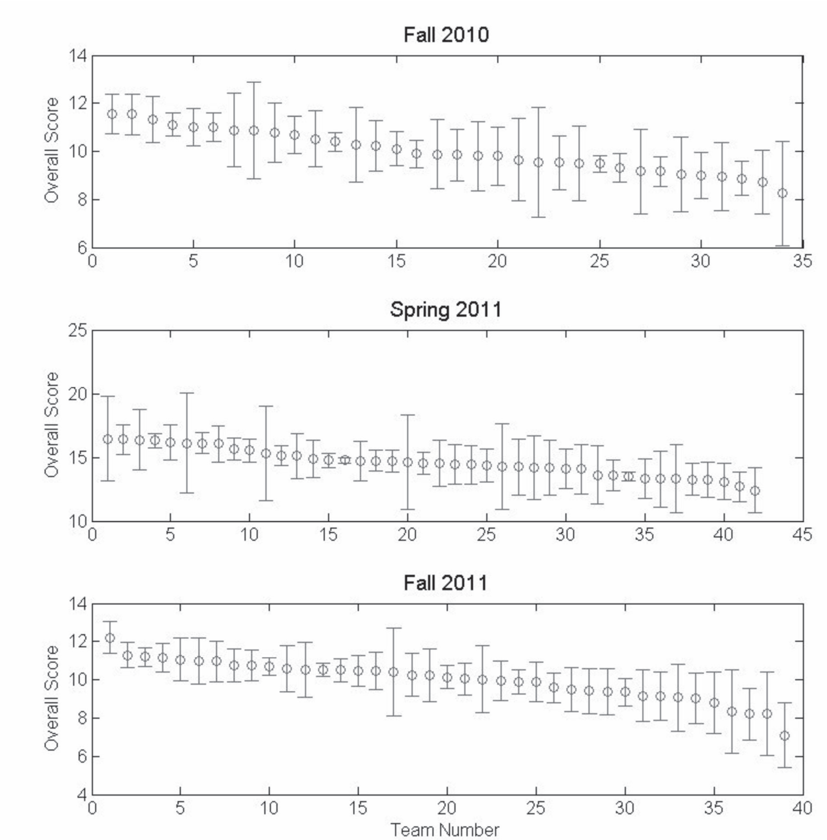

FIGURE A2. Average overall team score (from all five categories) and associated standard deviation for fall 2010, spring 2011, and fall 2011 design expos.

To further confirm this association, Pearson correlation coefficients were calculated between all predictors. A low correlation (< | 0.01 |) was found between GPA and major and GPA and any course version. This indicates that students were not unequally distributed between major or course version in terms of GPA. Additionally, the Pearson correlation coefficient was calculated between all predictors and expo score. Using an $\alpha = 0.05$ for significance, major and GPA were not found to be significantly correlated with expo score; while either the ME or BME course versions were negatively correlated to expo score to a statistically significant level. No correlation between GPA and expo score indicates that teams were evenly distributed in terms of GPA and thus that no bias in team composition due to the project and team selection process was occurring, at least in terms of GPA. Results of this test are given Table B2.

TABLE B1
Regression Results for the Linear Model Proposed in Equation 1

Parameter	Est.	Stand. error	Wald 95% CL	Wald χ^2	Prob. > χ^2
Intercept ($\beta 0$)	10.25	0.50	[9.28, 11.23]	425.35	<0.0001
$\beta 1$ (*Major*)	–0.04	0.37	[–0.76, 0.68]	0.01	0.91
$\beta 2$ (CV_{ME})**	**–1.18**	**0.31**	**[–1.78, –0.58]**	**14.81**	**0.0001**
$\beta 3$ (CV_{BME})**	**–1.57**	**0.30**	**[–2.16, –0.99]**	**28.08**	**<0.0001**
$\beta 4$ (*GPA*)	0.25	0.15	[–0.05, 0.54]	2.65	0.10

** Bold fields represent parameter estimates with statistically significant values ($\alpha < 0.05$)

TABLE B2
Pearson Correlation Coefficients Between All Variables ($N = 168$)

	Major	CV_{ME}	CV_{BME}	*GPA*
Expo score	–0.11	**–0.24**	**–0.19**	0.12
Probability	0.16	**0.002**	**0.01**	0.12

Bold fields represent statistically significant factors ($\alpha < 0.05$)

APPENDIX C: LOGISTIC REGRESSION

When analyzing data with a logistic regression, an equivalent statistic to the R^2 value used in linear modeling does not exist, which means that assessing the validity of the indicator variables to predict the outcome in logistic regressions is not as straightforward as in linear regression. This inclarity is because indicator variable coefficients in logistic regression are maximum likelihood estimates which are arrived at through an iterative computational process. They are not calculated to minimize variance, so correlation to goodness-of-fit does not apply. However, to evaluate the goodness-of-fit of logistic models, several strategies are commonly used. In this paper Hosmer and Lemeshow goodness-of-fit test and Nagelkerke's pseudo R^2 values were chosen. Both of these tests do not provide the precise measurement equivalent of an R^2 but taken together can indicate how good a model's variables are at predicting the outcome.

Hosmer and Lemshow's goodness-of-fit test divides subjects into deciles based on predicted probabilities, then computes a chi-square from the observed versus expected frequencies. It tests the null hypothesis that there is no difference between the observed and predicted values of the response variable. Therefore, when the test is not significant one cannot reject the null hypothesis and thus one is saying that the model fits the data well. An additional parameter is necessary to assess whether the indicator variables tested are important for outcome prediction. To make this assessment, Nagelkerke's R^2 value can be used, which takes the squared ratio of the model with and without the indicator variables and normalizes by the maximum ratio possible. Nagelkerke's R^2 value is considered *pseudo* because it is on a similar scale with traditional R^2s, ranging from 0 to 1 with higher values indicating better model fit; but it cannot be interpreted identically to typical R^2 values because the indicator variables represent likelihood ratio optimizations and not raw data approximation.

The logistic regression from Equation 3 had a Hosmer and Lemeshow goodness-of-fit test χ^2 value of 4.396 with $p = 0.733$. Thus, the null hypothesis cannot be rejected, and the model can be considered to fit the data well. Nagelkerke's R^2 value was 0.317, which is relatively low, but signifies that the logistic regression can account for a significant portion of the likelihood of the measurements.