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Predicting Success in a Quality Control Course: Does Time Since Taking the Prerequisite Course Matter?

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Predicting Success in a Quality Control Course:
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Abstract

The research objective of this paper is to evaluate predictors of success for a quality control course for undergraduate engineering majors at East Carolina University. The 37 predictors included demographic data (e.g., age, gender, race, academic major), records of success (e.g., incoming GPA, performance in prerequisite courses, time between prerequisite courses and the quality control course), and additional course indicators (e.g., class time of day, student attendance, performance on Test 1 versus overall). This quality control course is evaluated over a three year period with five offerings (sections) by the same instructor for 127 students. The results indicate that the time between the prerequisite course and the quality control course is not statistically significant to success in the quality control course. However, the student's prior semester GPA, incoming cumulative GPA, and performance in the prerequisite course are significant to success in the quality control course.

Background and Motivation

The quality control course at East Carolina University is a graduation requirement for all students majoring in engineering. For the majority of these students it is a terminating course in the area of statistics within their curriculum plan since it is not a prerequisite for any other course. For a small minority, an elective course in lean six sigma is taken that requires quality control as a prerequisite. The quality control course prerequisite is a calculus-based probability and statistics course in the mathematics department, which has calculus II as a prerequisite. This course sequence and prerequisite structure is shown in Figure 1. It should be noted that probability and statistics is a prerequisite for several other engineering courses, not just quality control.

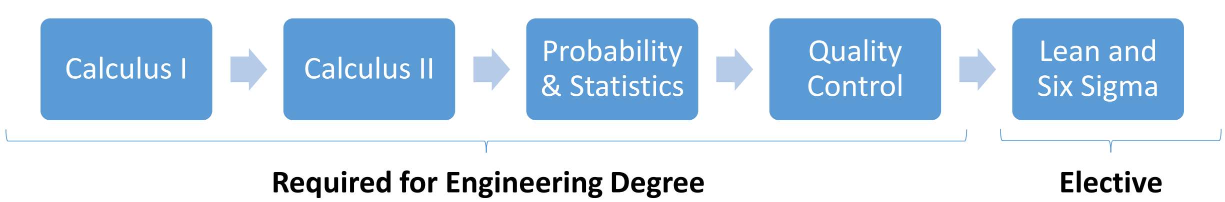

Figure 1: *Prerequisite path for Quality Control at East Carolina University.*

The conundrum that occurs is when should students take quality control? The reason for this issue is that students routinely take it as early as sophomore year to as late as their culminating semester. Furthermore, since the course can be slotted during any of those semesters, it is often shuffled around courses which are more difficult to schedule (e.g., major courses, special electives); thus, at East Carolina University a variety of students, from second semester sophomores to last semester seniors, are enrolled in the course during any given semester.

The motivation for this research was initially to answer the question, "Does the time since taking the probability and statistics prerequisite matter in the subsequent quality control course?" Answering this question would be useful for the engineering department at East Carolina University since the different engineering concentrations (majors) have different projected curriculum plans (paths) which impact when the students take quality control.

However, to analyze a broader set of potential influences, the scope of this paper was expanded to include other factors that may or may not impact success in quality control at East Carolina University. Those factors included demographic data (e.g., age, gender, race, academic major), records of success (e.g., incoming GPA, performance in prerequisite courses, time between prerequisite courses and the quality control course), and additional course indicators (e.g., class time of day, student attendance, performance on Test 1 versus overall).

The paper is formatted as follows: a literature review is provided in the next section; then methodology is presented; results are provided; a discussion is given; and finally conclusions and future work are offered.

Literature Review

There have been a number of engineering education studies that sought to understand the dynamic between prerequisite timing and linking of courses in a sequence with respect to student success. One of the larger longitudinal studies, headed by Dr. Nathan Klingbeil of Wright State University, looked at just-in-time engineering mathematics education and how it impacted student success, student retention, and student motivation. The main change was adding a course to the freshman year entitled *Introductory Mathematics for Engineering Applications* that provided all the prerequisite mathematics needed for students to advance to early core engineering courses (i.e., physics, mechanics, circuits, and computer programming). Thus, students did not get behind on their engineering courses if they were not enrolled in calculus at the beginning of their freshman year. The results of this work have shown that this approach mitigated the impact of varying incoming mathematics preparation and performance of students, and led to better retention, motivation, and higher GPAs for students. These results were positive and even more statistically significant for students from underrepresented groups[1-3].

Dr. Ziliang Zhou, of California Baptist University, headed a study that coordinated communication between instructors of the prerequisite course and the next course in the sequence. This feedback system was initially implemented with the introductory engineering mathematics courses which feed core engineering, science, and mathematics classes[4-5]. Final results have not been published, only preliminary results; thus, no formal conclusions[4-5].

Another interesting research exploration is evaluating a professor based on his or her students' success in future courses. This concept was discussed by Dr. Scott Carrell and Dr. James West using data from the United States Air Force Academy. What makes their work unique is that the amount of data that was available, the fact that all students (regardless of major) take a common core of mathematics, science, and engineering, and that students do not get to select their instructor (i.e., the student has no choice of instructor and no choice regarding which semester they take a particular course). Their broad results (data included 12,568 students over a 10 year period), showed that a professor's academic rank, teaching experience, and terminal degree status was negatively correlated with student evaluations of a professor; however, a professor's rank, experience, and degree was positively correlated with follow-on course achievement. Likewise, student evaluations of professors were positive predictors of course achievement, but are poor predictors of follow-on course achievement[6]. Unfortunately, since most schools do not have similar data and core course sequences, this study cannot easily be replicated at other schools[6-7].

Additional research includes Clemson University's evaluation of a calculus prerequisite as a bottleneck to its general engineering core. The result of this work included removing the bottleneck and having students begin the calculus sequence during the second semester of their freshman year. The longitudinal results indicate that there is a statistically significant improvement in student retention[8]. There have been other studies that looked at just-in-time delivery of prerequisites and the coordination of course topics to improve student retention, satisfaction, and/or success[9-10].

Research conducted by physics professors for multiple semesters across many instructors for a path of physics courses indicated that the students who performed better in prerequisite courses sustained that advantage in subsequent courses over students who had poorer performance in requisite courses[11].

The work presented in this paper is different than the above cited work for a number of reasons. First, a curriculum change is not being proposed nor studied. Second, neither student satisfaction nor instructor effectiveness is being studied. Third, it is reasonable to assume that students will take quality control at different times in their curriculum plan based on their engineering concentration (major) and their personal interest (i.e., if they plan to take lean six sigma as an elective). Thus, the goal of the research presented here is to evaluate predictors of success for a quality control class, including time since taking the prerequisite course. As noted above, other demographic influences are also examined so that as broad a perspective as possible is considered.

Methodology

Data Overview

The data was collected by the instructor for the quality control course at East Carolina University during the spring semesters in 2013-2015; one section in 2013 and two sections each in 2014 and 2015. In all cases the course was offered two days a week for 75 minutes each lesson. The quality control course is offered throughout the year (fall, spring, and summer), but the majority of students take the course in the spring semester. Also, the instructor of record for this research study only teaches the course in the spring semester, so the data represents five spring semester sections. In total, 127 students attempted the course. As noted this course is required for all engineering students at East Carolina University. The specific degree is a BS in engineering and students can choose to concentrate (major) in biomedical, bioprocess, electrical, industrial and systems, and/or mechanical engineering. It should be noted that electrical was not a concentration at East Carolina University in spring 2013, but was available in fall 2013; with the first graduates in fall 2014. The software used to complete the preliminary data analysis included SAS, R, Weka, and Microsoft Excel; though, SAS and Excel were used for the bulk of the analysis presented herein.

Data Preparation

The transcripts for each student were evaluated to determine factors such as GPA and success in prior courses. If a student transferred a course (e.g., community college or Advanced Placement (AP) credit), then that missing datum was estimated using the student's GPA average for similar courses and a flag variable was created. For example, if a student transferred Calculus I, then the student's GPA average for Calculus II and Calculus III was used to compute the student's Calculus I grade. Furthermore, a flag variable was created to denote whether or not a student transferred a particular course. A number of students were community college transfers; thus, those individual students were also flagged as a community college transfer and their GPA for calculus and other mathematics courses was estimated as previously described. If a student took a course more than once, then only the most recent grade was used.

For students who had not graduated by the time of publication, an estimated graduation time was computed. This estimate was based on their individual course curriculum plan. For example, if a student had satisfactorily completed the first senior design capstone course in fall 2015, then it was assumed that the student would graduate in spring 2016 (upon completion of their second and final semester in senior design).

Included with the transcript data was information collected by the instructor during the course. The course structure and topics did not change during the study period (2013-2015). For example, Test 1 coverage was the same from year to year. The instructor also collected information such as number of absences, assignment averages, etc. Finally, demographic data was collected for each individual student based on department and university surveys.

Several outliers were evident when the analysis began, showing large error terms for the various prediction models. Upon further inspection, all of these outliers fit into one (or more) of the following categories:

- The student failed or withdrew from the course (i.e., not completing all of the assignments and/or the final exam; thus, having an extremely low course grade on a 0-100% scale),
- The student withdrew from the university after completing the course,
- The student transferred to another major (outside of engineering), and/or the student transferred to another university after completing the course (in each of these cases the student transferred immediately after completing the quality control course).

These issues were not easily corrected with traditional regression techniques related to overcoming missing values; thus, these data points were eliminated from consideration for prediction.

Variables Considered

The response variables considered are provided in Table 1. The three variables of interest are the Test 1 grade (since that material is the material most relevant to the prerequisite course), the Course Grade (as a percentage), and the Course Letter Grade (e.g., 4.0 GPA scale).

Table 1: *Response Variables Considered*

Response Variables	Variable Type
Test 1 Grade	Continuous, 0-100%
Course Grade	Continuous, 0-100%
Course Letter Grade	Discrete, 0-4

Predictive factors included demographic data (e.g., age, gender, race, academic major), records of success (e.g., incoming GPA, performance in prerequisite courses, time between prerequisite courses and the quality control course), and additional course indicators (e.g., class time of day, student attendance, performance on Test 1 versus overall). A complete list is shown in Table 2. The variable type, based on the format of the data is also indicated in the table.

- A variable that is numerical has either continuous (e.g., cumulative GPA) or discrete numerical information (e.g., GPA for a specific course).
- A variable that is categorical has multiple levels (e.g., a student's specific engineering concentration).
- A variable that is binary is a special categorical variable that has only two categories (e.g., a flag variable indicating whether or not a student transferred from a community college).

It should be noted that specific grades for a particular course were known only if the course was taken at East Carolina University. If the course was taken at another university, community college, or transferred by AP credit, then it was considered a transferred course and the GPA was estimated as previously described. Note that some of these variables will have multicollinearity issues with each other (i.e., Calculus I, Calculus II, and Calculus III are averaged to obtain the Calculus Average GPA). Thus, the researchers were cognizant to avoiding overfitting the model with superfluous variables.

Statistical Methods

The statistical methods considered for evaluating the predictive variables with respect to the response variables were exploratory data analysis (including a correlation study) and a predictive regression study. The predictive regression models included Linear, Logistic, Exponential, Normal, Poisson (with a Log link function), Tweedie (with a Log link function), Negative Binomial (with a Log link function), Multinomial (with a Cumulative Logit link function), Inverse Gaussian (with a Power of -2 link function), and Gamma (with a Power of -1 link function). The settings and link functions considered were all default selections of SAS version 9.4 (m3). The various regression model techniques were compared using the Akaike Information Criterion[12] (AIC), AICc, and the Bayesian Information Criterion (BIC). For the purposes of this project, the authors considered statistical significance at the $\alpha = 0.05$ level. AIC, AICc, and BIC were used as the comparisons for goodness of fit between the models created, rather than R^2 and Adjusted R^2, because techniques for calculating R^2 and Adjusted R^2 regarding goodness of fit for some nonlinear models are not universally accepted by the statistics community[13].

Table 2: *Predictive Variables Considered*

Predictive Variables	Variable Type
Age at Start of Course	Numerical
Calculus and Diff. Eq. Average GPA	Numerical
Calculus Average GPA	Numerical
Calculus I Grade	Numerical
Calculus II Grade	Numerical
Calculus III Grade	Numerical
Community College Transfer	Binary
Credits Passed in Semester	Numerical
Credits Transferred	Numerical
Cumulative Credits Passed	Numerical
Incoming Cumulative GPA	Numerical
Differential Equations Grade	Numerical
Double Concentration	Binary
Double Major	Binary
Engineering Concentration	Categorical
Gender	Binary
Honors College (Yes or No)	Binary
Minority (Yes or No)	Binary
Minority Type Code	Categorical
Number of Absences	Numerical
Number of Quality Control Repeats	Numerical
Prerequisite Prob. & Stat. Grade	Numerical
Remedial Algebra Taken	Binary
Remedial Functions Taken	Binary
Remedial Precalculus Taken	Binary
Remedial Trigonometry Taken	Binary
Prior Semester GPA	Numerical
Semester Taken	Categorical
Time Before Graduation (Years)	Numerical
Time Between Prerequisite (Years)	Numerical
Time of Day (Afternoon/Morning)	Binary
Time of Day of Course	Numerical
Transfer Calculus I	Binary
Transfer Calculus II	Binary
Transfer Calculus III	Binary
Transfer Diff. Eq.	Binary
Transfer Prob. and Stat.	Binary

Results

Exploratory Data Analysis

Using all 127 data points and 37 predictor variables, exploratory data analysis was completed to evaluate the predictive capabilities of the explanatory variables. To provide visual insight, box plots, bubble plots, cluster analysis, decision trees, etc. were created. The majority of these outputs corresponded to the authors' expectations; for example, students with more absences did poorer in the course as shown in Figure 2. Note that the higher letter grades cluster in the upper left of this figure, corresponding to lower absences. In other cases, the model outputs did not confirm nor deny the authors' expectations. For example, the time between taking the prerequisite course and the letter grade is shown in Figure 3 and indicates that there is generally no difference in the letter grade based on the time between the prerequisite mathematical statistics course and the quality control course. Note, a test on the consistency of the variance for this variable was completed, and it was not significant. The two year amount is lower than the other values; however, it is not significant due to differences in sample sizes among the various time between values.

Correlation

Using all 127 data points, the most negatively correlated and most positively correlated variables are presented (variables within a ±0.15 correlation are not presented) in Table 3. Interestingly enough, the *Time Between Prerequisite (Years)* predictive variable is not one of the most negatively nor positively correlated variables as its values ranged from -0.09 to -0.14 for the three response variables. In absolute terms, the five most correlated predictor variables were (in order of most absolute): *Semester GPA*, *Cumulative GPA*, *Credits Passed that Semester*, *Prerequisite Probability and Statistics Grade*, and *Calculus and Differential Equations Average GPA*. The authors acknowledge that the quality control grade is obviously not independent from the semester GPA, cumulative GPA, and credits passed that semester. However, in the interest of exploring potential indicators, they were treated as such.

The other two most correlated predictors (in absolute terms) are both measures of past (or current) student success in mathematics, including the prerequisite grade and the average GPA in calculus and differential equations. Note, while most students completed all three calculus courses prior to taking quality control, the prerequisite structure does not enforce that curricular relationship. Furthermore, differential equations may or may not have been taken in the same semester or prior to quality control.

If the nine outliers are eliminated (as mentioned in data preparation), then the only additional predictive variable that would be included in Table 3 would be *Community College Transfer* with a positive correlation ranging from 0.14 – 0.20. This implies that community college transfers perform better.

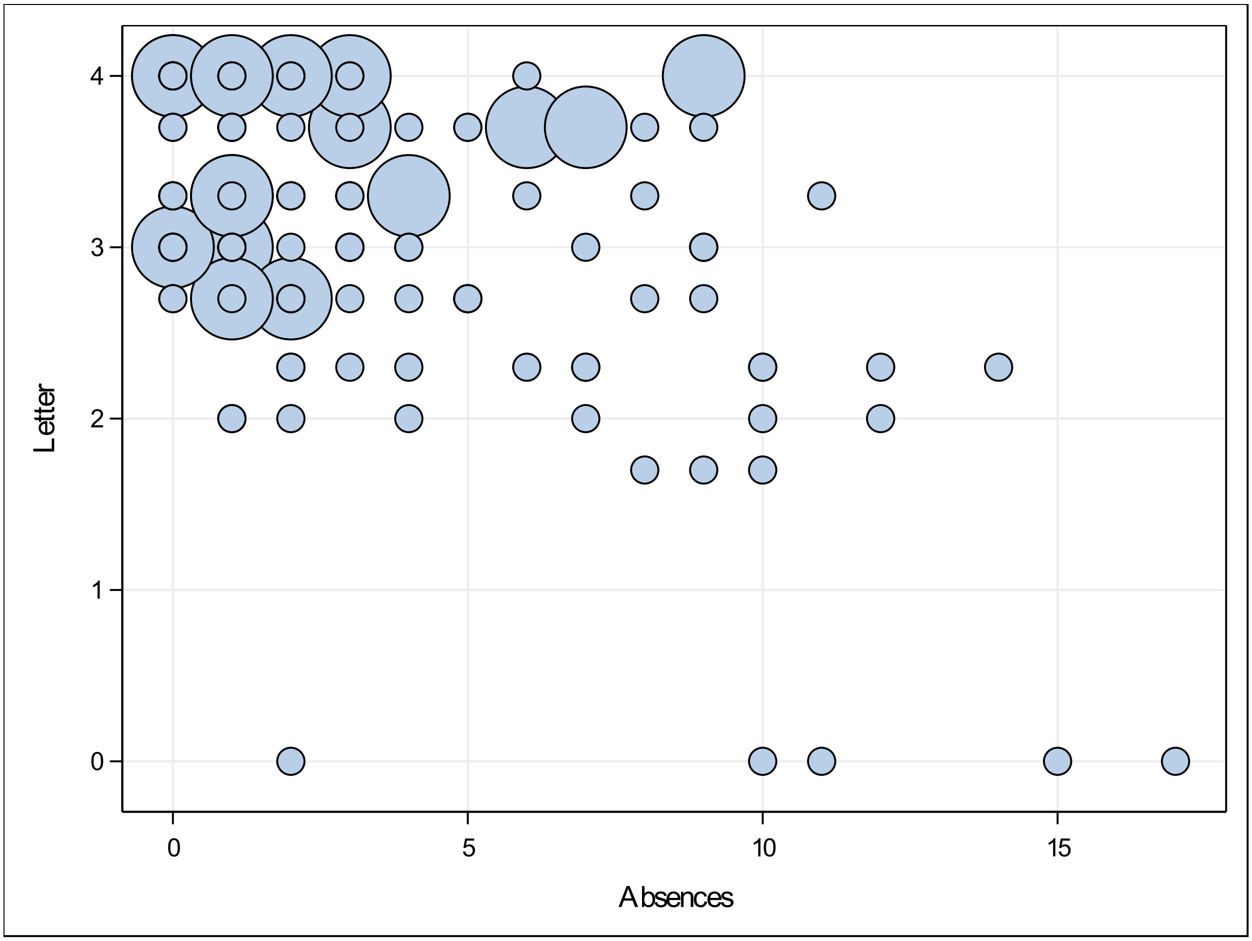

Figure 2: *Bubble Plot of Absences versus Letter Grade.*

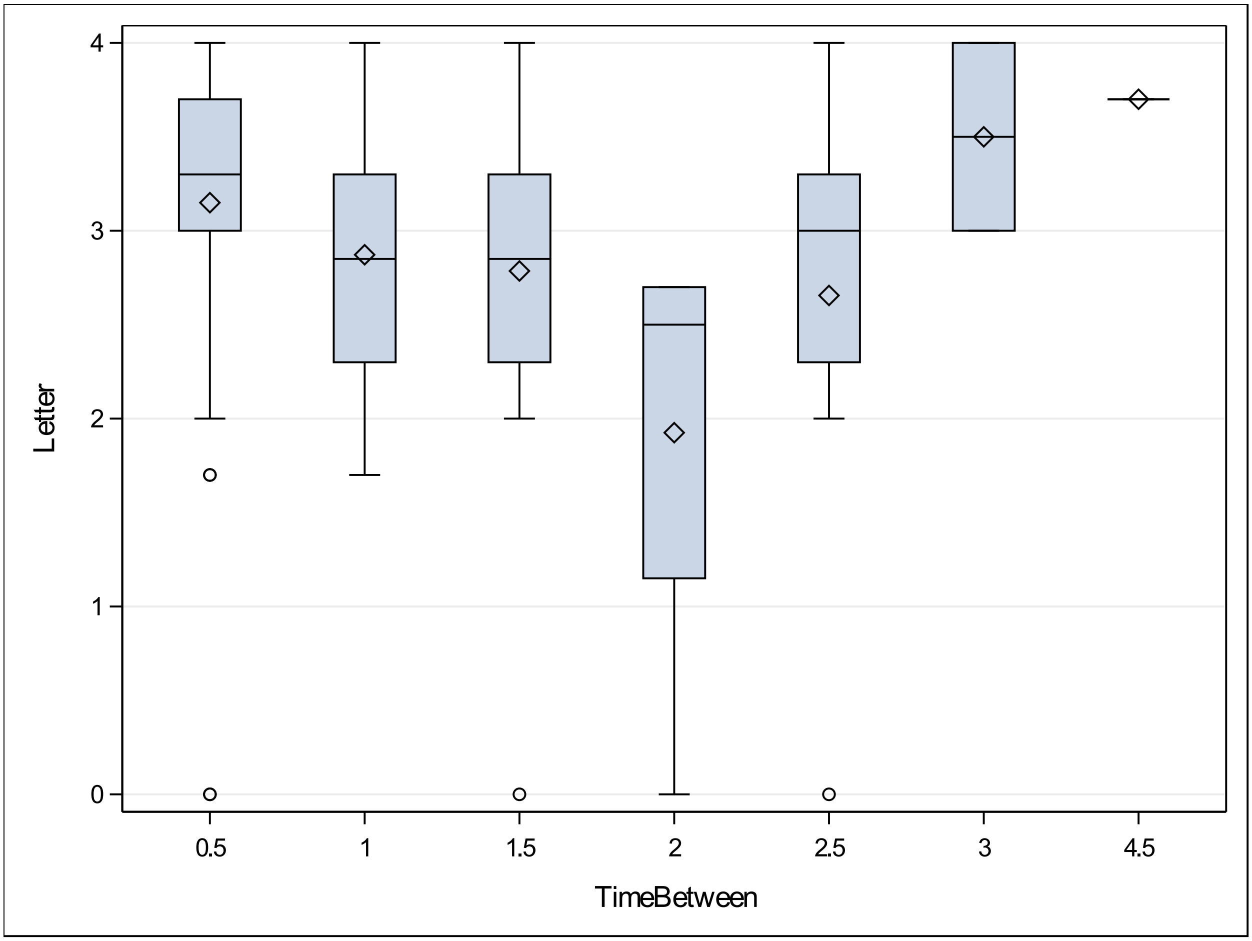

Figure 3: *Box Plot of Time between Prerequisite Course and Quality Control Course (in Years) versus Quality Control Letter Grade. Note, a test on the consistency of the variance for this variable was completed, and it was not significant. As depicted the two year amount is lower than the other values; however, the variable is not significant due to differences in sample sizes across the values.*

Table 3: *Correlation of Predictive Variables and Response Variables that exceed ± 0.15 and implications for full data set.*

Predictive Variables	Response Variables			Implication
	Test 1 Grade	Course Grade	Course Letter Grade	
Number of Absences	-0.20	-0.43	-0.53	Increased student absences implies poorer performance.
Time Before Graduation (Years)	-0.17	-0.24	-0.29	The closer a student is to graduation implies better performance.
Time Between Prerequisite (Years)	-0.09	-0.14	-0.15	The shorter the time between prerequisite implies better performance.
Gender	0.28	0.17	0.23	Female student implies better performance.
Calculus I Grade	0.33	0.22	0.31	A higher Calculus I GPA implies better performance.
Calculus III Grade	0.33	0.18	0.33	A higher Calculus III GPA implies better performance.
Calculus II Grade	0.40	0.22	0.35	A higher Calculus II GPA implies better performance.
Differential Equations Grade	0.36	0.30	0.39	A higher Differential Equations GPA implies better performance.
Calculus Average GPA	0.42	0.24	0.39	A higher average Calculus GPA implies better performance.
Calculus and Diff. Eq. Average GPA	0.43	0.30	0.44	A higher average Calculus and Diff. Eq. GPA implies better performance.
Prerequisite Prob. & Stat. Grade	0.45	0.37	0.50	A higher prerequisite probability and statistics GPA implies better performance.
Credits Passed in Semester	0.17	0.41	0.51	The higher number of credits passed in the current semester implies better performance.
Prior Semester GPA	0.56	0.68	0.65	The higher semester GPA implies better performance.
Incoming Cumulative GPA	0.57	0.67	0.66	The higher cumulative GPA implies better performance.

**Note: Table sorted based on Course Letter Grade.*

Predictive Regression

Using the SAS version 9.4 (m3), an assortment of predictive regression models and transformations (i.e., Linear, Logistic, Exponential, Normal, Poisson, Tweedie, Negative Binomial, Multinomial, and Inverse Gaussian, Gamma) were considered using different selection techniques (e.g., forward, backward, stepwise, and user-directed). The various regression model techniques were compared using the Akaike Information Criterion (AIC), AICc, and the Bayesian Information Criterion (BIC) with an $\alpha = 0.05$ level of significance.

For course letter grade, the best model for AIC, AICc, and BIC was to only include three variables in a linear model: the *Prior Semester GPA*, *Absences*, and the *Prerequisite Probability and Statistics Grade*. For course grade (0-100%) the best model for AIC, AICc, and BIC was to only include four variables in a linear model: the *Incoming Cumulative GPA*, the *Prior Semester GPA*, *Absences*, and the *Prerequisite Probability and Statistics Grade*. For the Test 1 grade (0-100%), the best model for AIC, AICc, and BIC was to only include three variables in a linear model: *Prior Semester GPA*, *Calculus II grade*, and the *Time of Day* binary variable (e.g., morning or afternoon – with morning students performing worse on Test 1). The summary of this information is provided in Tables 4-6. These results were consistent across all demographics (e.g., gender, race, age); however, we cannot report on whether these demographic results were significant for specific demographics due to sample size.

In each of the Tables 4-6, the results provided include an analysis of variance (ANOVA), values for the performance metrics (s, R^2, Adjusted R^2, AIC, AICc, and BIC), and parameter estimates. Since the resulting models were all linear, the parameter estimates can be applied as a linear equation to predict the response variable. A positive coefficient for the parameter estimate indicates an improved grade or test score; whereas, a negative coefficient indicates a worse grade or test score. For all predictor variables that were included in the final three models, only *Absences* and *Time of Day* (with morning performing worse on Test 1) had a negative impact on the grade. The other predictor variables (*Prior Semester GPA*, *Incoming Cumulative GPA*, and *Calculus II grade*) had positive impact on the grade.

Table 4: *Final Predictive Model for Course Letter Grade; including ANOVA, Performance Metrics, and Parameter Estimates.*

Analysis of Variance				
Source	DF	Sum of Squares	Mean Square	F Value
Model	3	25.089590	8.363200	45.760000
Error	114	20.834140	0.182760	
Total	117	45.923730		

s	0.4275
R-Square	0.5463
Adj R-Sq	0.5344
AIC	-76.6228
AICC	-76.08709
BIC	-185.54007

Parameter Estimates				
Parameter	DF	Estimate	Standard Error	t Value
Intercept	1	1.637239	0.183558	8.92
Prior Semester GPA	1	0.557617	0.056905	9.8
Absences	1	-0.04256	0.01205	-3.53
Prob. & Stat. Grade	1	1.195552	0.313976	3.81

Table 5: *Final Predictive Model for Course Grade (0-100%); including ANOVA, Performance Metrics, and Parameter Estimates.*

Analysis of Variance				
Source	DF	Sum of Squares	Mean Square	F Value
Model	4	0.274390	0.068600	35.010000
Error	113	0.221440	0.001960	
Total	117	0.495830		

s	0.04427
R-Square	0.5534
Adj R-Sq	0.5376
AIC	-610.83881
AICC	-610.08206
BIC	-716.98539

Parameter Estimates				
Parameter	DF	Estimate	Standard Error	t Value
Intercept	1	0.625577	0.030505	20.51
Prior Semester GPA	1	0.036858	0.010041	3.67
Inc. Cuml. GPA	1	0.03885	0.014884	2.61
Absences	1	-0.002967	0.001307	-2.27
Prob. & Stat. Grade	1	0.101412	0.032553	3.12

Table 6: *Final Predictive Model for Test 1 Grade (0-100%); including ANOVA, Performance Metrics, and Parameter Estimates.*

Analysis of Variance				
Source	DF	Sum of Squares	Mean Square	F Value
Model	3	0.777680	0.259230	26.930000
Error	114	1.097300	0.009630	
Total	117	1.874980		

s	0.09811
R-Square	0.4148
Adj R-Sq	0.3994
AIC	-423.98388
AICC	-423.44816
BIC	-532.90114

Parameter Estimates				
Parameter	DF	Estimate	Standard Error	t Value
Intercept	1	0.496178	0.044107	11.25
Prior Semester GPA	1	0.078868	0.013754	5.73
Calc. 2	1	0.029666	0.012161	2.44
Time (Binary)	1	-0.059054	0.018273	-3.23

Tertile Analysis

Additional analysis was conducted to determine if the prediction for the different tertiles (terciles) based on *Incoming Cumulative GPA*. The top tertile had an *Incoming Cumulative GPA* of a 3.3 or better (on a 4.0 scale). The middle tertile had an *Incoming Cumulative GPA* of a 2.9-3.3, and the bottom tertile had an *Incoming Cumulative GPA* of a 1.8-2.9. This analysis was done on the cleaned data set; thus, students who have withdrawn, transferred, or failed the course were not included in this analysis. The downside to this analysis is that we are segmenting the population into groups of approximately 40 observations; thus, sample size is an issue with achieving statistically significant results. These results are provided in Table 7.

Table 7: *Significant Variables (α = 0.05) for Response Variables for the Three Tertiles of Students (based on Incoming Cumulative GPA).*

<table>
<tr><th></th><th></th><th colspan="3">Response</th></tr>
<tr><th></th><th></th><th>Letter</th><th>Course Grade</th><th>Test 1</th></tr>
<tr><td rowspan="3">Tertile</td><td>Top</td><td>Inc. Cuml. GPA
Calc. I Grade
Cumulative Credits</td><td>Inc. Cuml. GPA
Calc. II Grade
Cumulative Credits</td><td>Inc. Cuml. GPA
Time (Binary)
Calc. Ave. (Calc. I, II, & III Grades)</td></tr>
<tr><td>Middle</td><td>Prior Sem. GPA</td><td>Prior Sem. GPA</td><td>Prob. & Stat. Grade</td></tr>
<tr><td>Bottom</td><td>Semesters to Graduation</td><td>Prior Sem. GPA
Prob. & Stat. Grade
Calc. I Grade</td><td>Inc. Cuml. GPA
Time (Binary)
Semesters to Graduation</td></tr>
</table>

The results indicate that the aforementioned results in Tables 4-6 are useful, but some performance indicators within the tertiles are unique. For example, for the top tertile, better performance in calculus (whether it is *Calc. I*, *Calc. II*, or *Calc. Average*) indicates a better performance in quality control. Perhaps this is due to a separation in mathematical ability of the top tier students. In addition, *Cumulative Credits* is significant for *Letter Grade* and *Course Grade*. With the more courses completed, the better the student performed. Perhaps this is an indication of persistence and/or the development of good student habits (since the quality control course being studied is heavily weighted towards tests and exams; rather than routine homework).

In the middle tertile, there were less unique observations. *Prior Semester GPA* is the only significant variable for *Letter Grade* and *Course Grade*, and the *Prerequisite Probability and Statistics Grade* is the only significant variable for Test 1. This indicates that middle tier students perform based on prior performance (i.e., continuing down the path).

In the bottom tertile, the unique observation was the predictor variable: *Semesters to Graduation*. *Semesters to Graduation* was significant for *Letter Grade* and *Test 1*. With the students closer to graduation performing better. This indicates that these students are determined to graduate.

Discussion

The results indicate that the most important and useful predictors of student success for the quality control course at East Carolina University are *Prior Semester GPA*, *Incoming Cumulative GPA*, *Prerequisite Probability and Statistics Grade,* and *Absences*. These predictor variables seem logical because they capture important pieces of information about the student. The first, *Prior Semester GPA*, is a measure of how that student did in the prior semester; which is partially a function of their most recent courses but also their current state (e.g., personal life, time commitments, study habits). The second variable, *Incoming Cumulative GPA*, is a measure of how well a student has done up to that point in all courses. The third variable, *Prerequisite Probability and Statistics Grade*, is a measure of how well they know the foundational mathematical concepts that are emphasized and applied in quality control. The fourth variable, *Absences* is a small part of the course grade (which the authors' acknowledge is a bias); however, it shows how dedicated the student is to learning the material and time commitments.

With respect to *Test 1 Grade*, the best model found included a different makeup of predictor variables than the *Course Grade* and *Course Letter Grade*. Furthermore, the *Test 1 Grade* model is not as good of a fit based on R^2 and Adjusted R^2 than the other two response variables; thus, there is more variation in the prediction. The predictor variables make logical sense for *Test 1 Grade*, which included the *Time of Day* binary variable. The authors suspect that the first test of the quality control course was *literally* a wake-up call for those 8AM students, who were able to make the proper adjustments for the following three tests and final exam over the duration of the class to allow for this variable to be insignificant for the *Course Grade* and *Course Letter Grade*.

Some of the predictor variables were statistically significant at the $\alpha = 0.05$ level with the response variables (without the presence of other variables), but perhaps the information captured by the unused predictor variables was better captured by the variables that were used. For example, the average GPA of the three calculus classes is a good indication of mathematical ability; however, the student's specific comprehension of probability and statistics (as captured by the grade in the prerequisite course) is more pertinent to quality control than the student's collective mathematical ability. These variables were not included to provide the overall best prediction model and limit issues with respect to multicollinearity.

Regarding the *Time Between Prerequisite and Quality Control* course variable, it was not significant in any of the models that were evaluated. The presumption that the time between the prerequisite and the quality control course is clearly refuted by Figure 3 from the exploratory data analysis section of this paper. The more significant issue is how well did the student do in the prerequisite course, which was clearly shown by the results of this work.

Conclusions and Future Work

The overwhelming conclusion of this work is that student success in quality control is primarily a function of the student's prior semester GPA, cumulative GPA, and the student's prior ability in the prerequisite probability and statistics course. Other factors, such as time since taking the prerequisite, are not as important and in some cases are insignificant.

Future work would include attempting to replicate the study with additional instructors and with other universities. Furthermore, the approach could be used for any course that is similar to quality control from a prerequisite structure (i.e., a terminating course in a student's curriculum plan that is routinely taken by sophomores, juniors, and seniors).

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