APPLICATION OF INDUSTRIAL ENGINEERING METHODS TO THE ANALYSIS OF ENGINEERING STUDENT RETENTION AT A CASE STUDY UNIVERSITY

A Dissertation by

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The following faculty members have examined the final copy of this dissertation for form and content, and recommend that it be accepted in partial fulfillment of the requirement for the degree of Doctor of Philosophy with a major in Industrial Engineering.

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ABSTRACT

The issue of engineering student attrition may be perceived as a daunting and overwhelming obstacle to overcome. Hundreds of studies have been conducted in an attempt to better understand the various aspects of the engineering student attrition, including reasons for leaving, identification of attrition prediction factors, prediction modeling, retention programs and strategies, and assessment of those programs and strategies. This dissertation takes a case study approach to consider each of these factors, while utilizing a variety of industrial engineering methods for modeling and analysis. The dissertation contributed to the current literature in three major aspects. First, it introduced the application of the probabilistic neural network (PNN) to predicting student attrition, which had not been previously been done in the published literature, and compared the results to two other prediction models commonly used for attrition prediction. The PNN proved to have greater sensitivity (probability of correctly predicting a non-retained student) than the other two models. Second, in response to calls from the current literature to publish more qualitative data-driven analysis of the effectiveness of engineering summer bridge programs, this work took an objective mixed model approach to quantitatively evaluate the case study university's past engineering summer bridge program. Results were supported through bivariate correlation analysis of the qualitative data captured through a college-wide student survey. Third, this study modeled a DMAIC approach to addressing engineering student attrition, which has rarely been applied to the field of academia. A report on best practices in engineering student retention was used as a benchmarking tool, and a standard student persistence survey was used to capture student perceptions and guide recommendations for improvements.

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CHAPTER 1

INTRODUCTION AND BACKGROUND

1.1 Research Motivation and Objectives

Engineering is a high-impact occupation with high demand, but not enough qualified individuals to meet that demand [1,2]. Although much effort has been placed on recruiting students to major in engineering, and numerous retention programs have been implemented in various higher education institutions across the nation, we lose on average half of our engineering students to attrition [3]. This is not only a loss of future engineers, but it is a cost of time and money for students as well as universities [4]. Research efforts have been dedicated to this topic of engineering student attrition, ranging from determination of reasons for leaving, to identifying student attributes related to attrition, to developing attrition prediction models, to implementation and assessment of retention programs. This dissertation considers each of these factors through three separate studies at a public, urban, Midwest U.S.A. case study state university. Toward this goal, a variety of industrial engineering tools and methods are used including logistic regression, artificial neural networks, estimation of difference in population proportions using stratified random sampling, bivariate correlation analysis, frequency tables and charts, and a variety of Six Sigma tools including DMAIC (Define, Measure, Analyze, Improve, and Control), SIPOC (Suppliers-Inputs-Process-Outputs-Customers), Cause and Effect Diagram, and Pareto Chart.

This study aims to add to the current literature through three separate studies focused on engineering student retention. Figure 1.1 shows the flow of the research activities and three individual papers to ultimately derive some overall results and conclusions. The following section describes the major contributions of each of the three studies, which are Chapters 2 through 4 of this dissertation. Each chapter includes its own introduction, background, and literature review for the individual study. Likewise, the derived analysis and results of each study is discussed in the individual chapters, but some overall results and conclusions will be discussed at the end of this dissertation.

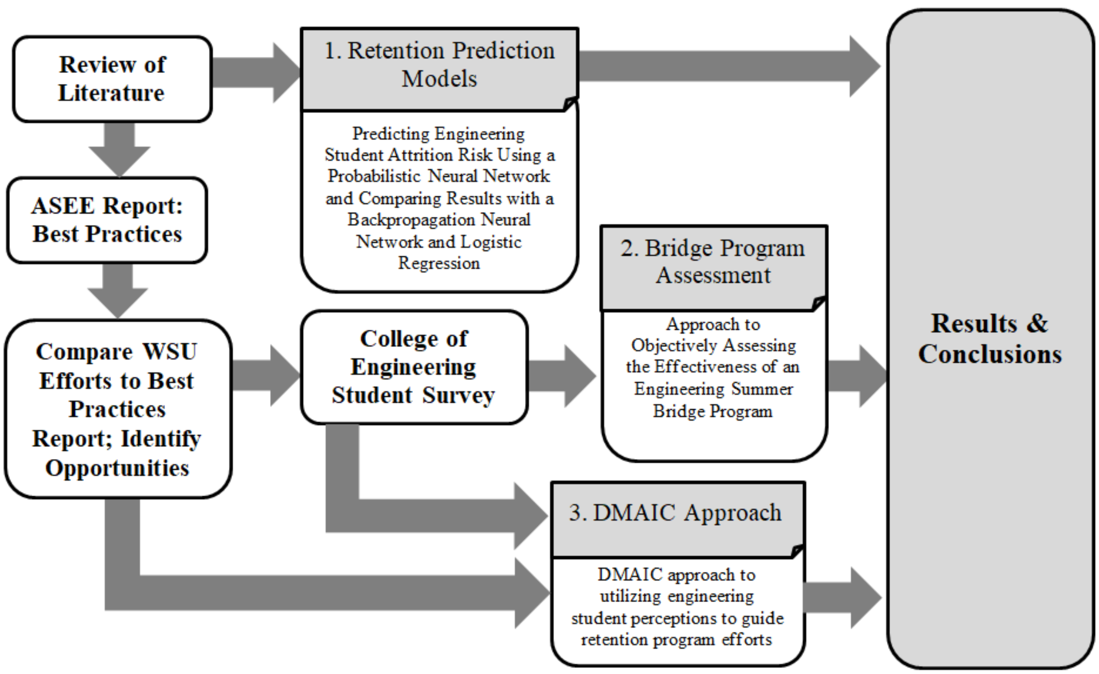

Figure 1.1. Flow of research activities and outcomes.

1.2 Organization of PhD Dissertation

Chapter 2: Predicting Engineering Student Attrition Risk Using a Probabilistic Neural Network and Comparing Results with a Backpropagation Neural Network and Logistic Regression.

In this study, three models were developed based on student data from the College of Engineering of a case study university, and those three models were compared in terms of prediction accuracy, specificity (probability of predicting a retained student), and sensitivity (probability of predicting a non-retained student). For the Chapter 2 study, a retained student was defined as a first-year freshman student retained into the third semester of enrollment, and a non-retained student was defined as a first-year freshman student who left the College of Engineering before their third semester. The major contribution to research for Chapter 2 is the introduction of the probabilistic neural network to the application of student attrition prediction. The study compares two models more widely used in the field (logistic regression and a multi-layer perceptron neural network) to the probabilistic neural network.

Chapter 3: A Mixed Model Approach to Objectively Assessing the Effectiveness of an Engineering Summer Bridge Program.

Chapter 3 describes a second study centered on retention program assessment. It offers a mixed model approach, using both qualitative and quantitative data, to evaluate a specific engineering summer bridge program at the case study university. A study by the American Society for Engineering Education (ASEE) was used as a benchmark for best practice retention programs. The case study College of Engineering had programs similar to five of the seven best practice retention programs. One of the two programs not in practice at the case study university was a summer bridge program. A bridge program had been in existence from the summers of 2011 to 2015, but was discontinued due to a loss in funding. Therefore, the purpose of Chapter 3 was to objectively assess the previous summer bridge program to determine if it was effective in its purpose of increasing retention. Bivariate correlation analysis, as well as longitudinal year-over-year retention data for bridge program participants versus non-participants, served as the quantitative analysis of the bridge program.

In the process of writing Chapter 3, an engineering student persistence survey was distributed to all undergraduate students in the College of Engineering. Survey results provided qualitative data to serve as further evidence of the effectiveness of a summer bridge program. This chapter contributes to the current literature with the development of a model of inputs and outputs of perceived unpreparedness resulting from the survey. Additionally, the study is a response to the call for more research on bridge program assessment using empirical data.

Chapter 4: DMAIC approach to utilizing engineering student perceptions to guide retention program efforts.

Chapter 4 applies the DMAIC (Define, Measure, Analyze, Improve, and Control) approach to address the subject of engineering student attrition. DMAIC has been widely used in the manufacturing industry and has more recently been applied in the service industry, but its application to academia is sparse. In addition to utilizing DMAIC, the study also serves as a model application of the use of an American Society of Engineering Education (ASEE) report on best practices in engineering, along with a standard Assessing Women and Men in Engineering (AWE) "Persisting in Engineering" survey, as tools for the Measure, Analyze, Improve, and Control phases. The study applies a variety of industrial engineering and Six Sigma tools including Cause and Effect Diagram, SIPOC (Suppliers-Inputs-Process-Outputs-Customers), frequency tables, Pareto chart,

CHAPTER 2

PREDICTING ENGINEERING STUDENT ATTRITION RISK USING A PROBABILISTIC NEURAL NETWORK AND COMPARING RESULTS WITH A BACKPROPAGATION NEURAL NETWORK AND LOGISTIC REGRESSION

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2.1 Abstract

As the need for engineers continues to increase, a growing focus has been placed on recruiting students into the field of engineering and retaining the students who select engineering as their field of study. As a result of this concentration on student retention, numerous studies have been conducted to identify, understand, and confirm relationships between student attributes and attrition. Methods of prediction have also been evaluated and compared. Utilizing the attributes found in previous studies to have correlation with student attrition, this study considers the results of three different prediction methods—logistic regression, a multi-layer perceptron (MLP) artificial neural network, and a probabilistic neural network (PNN)—to predict engineering student retention. The purpose of this study was to introduce the probabilistic neural network to the study of engineering student retention prediction and compare the results of the PNN to other commonly used methods in this field of study. The advantages, disadvantages, accuracy, and overall results for each method are provided as the major contribution of this paper.

2.2 Introduction

It can justifiably be stated that close to half of the students who begin their education in engineering do not follow through to the completion of an engineering degree [5,6]. This topic of student attrition in higher education has been one of increased interest over the past couple of decades. Engineering student retention, specifically, has not been neglected in the search for data on retention, reasons for attrition, and plans for intervention. Although strides have been taken to both recruit and retain engineering students, there is still much room for improvement.

Having the ability to identify students at risk of attrition in order to take preventative measures is one way to address this issue. The effort to correctly identify students at-risk has been taken on with many different models including logistic regression and artificial neural networks. The probabilistic neural network, however, has had little to no exposure in the literature on student retention prediction but may be an appropriate model for the subject because the output of a probabilistic neural network can be set to a probability, which approaches Bayes' optimal solution and could be converted to an attrition risk factor.

2.2.1 Literature Review

The topic of college student retention grew in interest during the 1990's. Early studies considered the effects of singular characteristics such as student age [7], academic advising and counseling [8–10], financial aid [11], campus housing [12], ethnicity [13], student personality type [14], student gender [15], and faculty gender [16]. Research has since expanded to evaluate multiple factors and their effect on retention [5,6,17–22].

As statistically significant relationships were identified, prediction models were developed. Various prediction models have been used and their results have been compared in an effort to identify the best method for identifying students at risk of attrition. One of the longest used and most common methods for predicting student retention is logistic regression. It has faced comparative studies with neural networks on several occasions [20,22,23].

Logistic regression is a common method for student retention prediction. It has proven to give decent results and is one of the models considered in this study. Herzog [19] utilized multinomial logistic regression for analyzing students' first to second year behaviors and also in a comparative study of decision trees, neural networks, and logistic regression and their ability to predict time to degree completion as well as student retention [20]. Jaeger and Hinz [24] used logistic regression to predict first-time freshmen retention relative to student exposure to part-time faculty. Similarly Allen et al. [25] utilized a multinomial logistic regression model to predict the impact of social integration, motivation, and academic performance on third year retention.

In recent years, neural networks have played an important role in classifying and making predictions in various fields of study, including the study of student attrition. A number of articles have been written, offering neural networks as a means of predicting student GPA [5,21], years to degree [20], and retention [22,23,26]. Vandamme et al. [26] compared neural networks to discriminant analysis and decision trees in their ability to predict high, medium, or low risk of student failure or drop out. Though none of the results were promising, due to the categorical rather than dichotomous predictive approach, the neural network accuracies were comparable to the other models [26]. The authors reiterated the desire to classify students by risk rather than just predict success or failure, claiming that they could have achieved over 80% accuracy of dichotomous success/failure prediction with these same models [26].

A study by Lin et al. [23] aimed to compare discriminant analysis, logistic regression, structural equation modeling, and neural networks in terms of engineering student retention prediction accuracy. They found that discriminant analysis had the highest overall prediction accuracy, but it performed the worst of all models in predicting non-retained students, which negates its overall accuracy because the purpose of the model is to identify students at risk or, in other words, to predict non-retained students [23]. Of the remaining models, neural networks had the highest overall prediction accuracy, probability of detecting retained students, and probability of detecting non-retained students [23].

In yet another comparative study, Schumacher et al. [22] considered the prediction accuracy of logistic regression from a previous study [27] in comparison to the accuracy of neural networks and classification trees for the same data set. The purpose of the models was to predict student continuation with an actuarial major at a single eastern U.S. university, with a dichotomous dependent variable classified as “0” for not completing an actuarial degree or “1” for completing an actuarial degree [22]. Results showed that the neural network was more accurate than logistic regression in predicting student retention into the actuarial program through degree completion, and it was also better equipped to handle missing data [22].

Lin et al. [23], Vandamme et al. [26], and Schumacher et al. [22] all proved through the aforementioned studies that neural networks performed as well as (if not better than) logistic regression for predicting student retention [22,23,26]. Lin et al. [23] showed that a neural network was not only appropriate but also more accurate than logistic regression for predicting engineering student retention. Vandamme et al. [26] studied the same topic but focused on student *risk* for passing or failing, so by nature of this non-dichotomous dependent variable output, logistic regression was not even an optional model. Yet the neural network still offered accuracies comparable to the other prediction models [26].

Not only did neural networks outperform in terms of accuracies, but they also have advantages over logistic regression in application. Schumacher et al. [22] highlighted logistic regression’s inability to handle missing data, and showed that neural networks handled the missing data and outperformed logistic regression in terms of prediction accuracy whether missing data was excluded, included, or imputed [22]. Neural networks proved to be more appropriate and provide better results than logistic regression for predicting student retention in each of these three studies [22,23,26].

Probabilistic neural networks have successfully been used in a variety of fields for numerous purposes such as prediction of the state of health of a battery [28], prediction of the carcinogenicity of chemicals [29], plant classification [30], and earthquake magnitude detection [31]. Possibly the most common application of the probabilistic neural network is within the medical field where the prediction model is used for purposes such as classification of Alzheimer's Disease [32], breast cancer classification [33], electrocardiogram (ECG) classification [34,35], MRI classification [36,37], lameness detection [38], detection of sleep apnea hypopnoea syndrome (SAHS) [39], and brain tumor detection [40].

The neural networks most commonly used for student retention prediction are multi-layer perceptron neural networks. The probabilistic neural network, which has been successfully used for other subjects of interest, has not been publicized in literature regarding student retention. Most generally, models offer a binary classification of students—the retained and non-retained, or the stayers and the leavers. The problem with this approach is that if we use such a model to identify students "at-risk", students just below the threshold may fall outside of our target because they have just a slightly higher probability of staying than of leaving, assuming that a 0.5 threshold is used. With its unique ability to provide an output in the form of a probability approaching Bayes' optimal solution [41], the probabilistic neural network should be considered as a contender against logistic regression to predict a student attrition risk factor.

2.2.2 Organization of this chapter

This study focuses on retention prediction models, specifically concentrating on three separate prediction models and their results. In Section 2.3, these methods will each be discussed generally, followed by a description of the data collection and data processing. Section 2.4 summarizes the results for each of the three models, followed by analysis of the output data in Section 2.5. A comprehensive discussion of the outcomes for all three models is given in Section 2.6. Section 2.7 describes the limitations of the study, and Section 8 finalizes the paper with the summary and conclusions.

2.3 Methods

The three models used in this study are logistic regression, a multi-layer perceptron neural network, and a probabilistic neural network. The first two are familiar methods for the given topic. They have been used on numerous sets of data, varying by study, attributes used, and parameters. They have been used individually and collectively, compared and contrasted. The probabilistic neural network, however, has had little to no exposure in the study of student retention prediction. This section will briefly describe each of the three models used in this study.

Logistic Regression. Logistic regression is a common model used to make dichotomous predictions of a dependent variable based on independent variable values, when the relationship is nonlinear. Given a set of sample data, the relationship between the independent variables and the dependent variable can be estimated using the logistic or sigmoid function. It is appropriate and commonly used for student retention prediction since there are multiple student attributes that can be used as the independent variables, and the dependent variable—whether the student stayed or left—is dichotomous. SPSS® was the statistical software used to create the logistic regression model for this study.

A number of studies have been conducted using logistic regression as a model to predict student behavior. For example, Herzog [19] used logistic regression in his study measuring determinants of student retention and again as the baseline model in a comparative study of prediction models for retention and degree completion time [20]. Logistic regression was used to predict community college student retention past the first year in a couple of different studies [42,43] and to predict university student retention past the first year [44]. Another study used logistic regression to evaluate the effects of part-time faculty on freshman student retention [24]. Litzer and Young [45] used a multinomial logistic regression model to classify students into categorical risk levels. Tyson used multinomial logistic regression to evaluate the effects of high school and college physics and calculus courses on engineering degree completion [46].

Multi-layer Perceptron Neural Network. One of the most commonly used artificial neural networks is the multi-layer perceptron (MLP), using the backpropagation learning algorithm. These neural networks are also appropriate due to their ability to handle nonlinear relationships, using student attributes as input to the model and train the model to predict the output of retention or attrition. Although it is used to predict a dichotomous output for this scenario, it is also capable of handling and predicting multiple class outputs. The software used to create and analyze the multi-layer perceptron neural network in this study was NeuralWorks Professional II/PLUS®.

The Multi-layer Perceptron Neural Network has been used for predicting student behaviors through a variety of studies. For example, Herzog [19] used a multi-layer perceptron to estimate student retention and degree completion time. An MLP was later used in a study to predict engineering student retention and GPA [21]. The multi-layer perceptron has been used in several studies to classify student risk of attrition. It was the model used to classify students as "at-risk" or not "at-risk" in a study from the University of Oklahoma [47]. Similarly, a comparative study of prediction models utilized an MLP to classify students into one of three categories: (1) low-risk, (2) medium-risk, and (3) high-risk [6]. Another study used an MLP to classify incoming freshman students into one of three groups: (1) at-risk, (2) intermediate, or (3) advanced, and also to predict retention [17]. A back-propagation neural network was used to predict degree program completion, earned hours, and GPA for students at Middle Tennessee State University [5].

Probabilistic Neural Network. The probabilistic neural network (PNN) is the model introduced to the topic of engineering student retention through this paper. The PNN approaches the Bayes' optimal classifier as the training set increases [41]. Another unique feature of the PNN is that the training and testing output may be provided as a probability for each class. For example, if there are three different classes, the output may be [0.02, 0.15, 0.83], which can be translated as a 2% probability of Class 1, a 15% probability of Class 2, and an 83% probability of Class 3. In the case of student retention, the output would be of the form [retained, not retained], such that an output of [0.17, 0.83] could be interpreted as an 83% risk of attrition. Therefore, a student can be identified on a *scale* of risk, rather than just "at-risk" or "not at-risk". It could be argued that students below a certain probability of retention—say 20%, should not necessarily be the target group; this group may be the students for whom engineering is not an appropriately matched career. Arguably the students hovering around the 50/50 chance of retention are really the students who should be targeted for intervention. Debatably it's the 25% to 75% probability of attrition that should be the main target, or possibly 30% to 70%. The output for the logistic regression model and the MLP will range from 0 to 1 for a dichotomous output, but given a binary classification outcome as offered by the logistic regression or a multi-layer perceptron, these probabilities are not visible. Even if the format of the output is selected to be a value, which would range between 0 and 1, this resulting classification value cannot be interpreted as a probability [48]. However, the probabilistic neural network results do represent a probability based on the training data, and that probability approaches Bayes' optimal solution. The software used to create and analyze the PNN in this study was NeuralWorks Professional II/PLUS®.

2.3.1 Data Collection & Demographics

In order to run the three mentioned prediction models, data was collected for 682 first-year freshman Wichita State University (WSU) students. The dataset included 323 students for the 2006-2007 year and 359 students from the 2010-2011 academic year. This data originally consisted of 58 student attributes related to demographics and academic background, which have been connected with engineering student attrition. The two cohorts of students were combined into one dataset of 682 students and then randomly ordered. Sixty percent of the data was used for training, and 40% was used for testing the model. Therefore, the first 410 of the randomly ordered students were used for training, and the last 272 were used for testing the model.

The primary goal of predicting student attrition is to intervene before the student actually leaves. Studies have shown that most students who leave do so within the first year [49]. Therefore, the input data ultimately included only those attributes which were available within the students' first year, and the output for the models was retention into the third semester.

2.3.2 Data Preparation

The raw data had to be prepared for input to the prediction models. All binary attributes such as male/female, were converted to 0 and 1. Other than GPA values, continuous values were centered and scaled using the equation $(x - \mu)/\sigma$. The output or dependent variable was retention into the third semester. This timeframe was selected since the majority of attrition occurs between the first and second year [49], and it minimizes the possibility of complex scenarios such as transferring students or extended time to degree completion. An output of 0 signifies that the student did not return the third semester, and an output of 1 signifies the student did return the third semester. As mentioned in the previous section, the output of a probabilistic neural network varies in format; it has an output for each class. Therefore, a returning third semester student would have an output of [1 0], and a non-returning student would have an output of [0 1].

It is important to note that for the logistic regression model, categorical data is given its own vector value using dummy variables, also known as the "one hot" method. For example, the residency variable has five possible categories: (1) Kansas-resident; (2) resident of a bordering state; (3) resident of a non-bordering state; (4) foreign address; and (5) no address. Therefore, a Kansas resident would have a vector value of [1 0 0 0 0], whereas a resident of a non-bordering state would have a vector value of [0 0 1 0 0]. One major drawback to this format is that it increases the number of variables per attribute. In the residency example, the residency attribute increased from one variable to five variables by changing it to vector form. As a rule of thumb, the maximum number of attributes used in a regression model should be n/15. Since the training sample size is 410, the number of attributes should not exceed 27. The original dataset had 58 attributes, which actually extended to an even greater number of variables due to dummy variables.

Several steps were taken to remove variables from the model. First, all of the attributes that had a high amount of missing data were removed. For example, one original attribute of interest was student grade in the course "ENGR101: Intro to Engineering". Not all students take this course the first year, so many students had a null value for this attribute; therefore it was removed. Next, redundant attributes were removed. For example, "Math GPA" is a numeric value for "Math Grade"; therefore, Math Grade can be removed from the input dataset. Because the data was pulled for two past cohorts, any data corresponding to current standing should not be used for the purpose of a prediction of third semester status. All variables that would not be available at the end of the second semester were therefore removed. For example, the current cumulative GPA includes the coursework taken beyond the third semester and would thus have to be removed from the prediction model.

After this initial elimination of variables, the next step was to check for collinearity and analyze the variables that were high in similarity. For example, in addition to the residency attribute discussed previously, another feature was pulled into the original dataset for Kansas region. The Kansas feature had thirteen different options. The student location, therefore, had a total of 18 variables. Using the correlation tables in SPSS®, Pearson's correlation and significance levels were compared for each of the similar features and their relationship with the output variable of retention into the third semester. Based on this analysis, the feature with the weaker relationship with retention, in comparison to the similar feature, was removed from the model.

After removing variables as described here, the total number of predictor variables was decreased to 20 (see Table 2.1). The variables were evaluated and reduced one step further, taking only the attributes with a significance level of $\alpha \leq 0.05$. This final reduction step removed the last six variables from Table 2.1, resulting in a final list of 14 attributes. Interestingly, the six attributes eliminated at this step were gender, residency, and the binary codes for first generation college student, minority, poverty, and housing (on or off campus). Results are reported for each of the three models using this final set of 14 statistically significant attributes. It is important to note, however, that comparative models were built for both the logistic regression model and MLP, which included the additional six attributes. The models with only the final 14 attributes proved to be slightly more accurate than the models including gender, minority, residency, first generation college student, poverty, and housing.

2.4 Results

Each of the three models was used to predict student retention using the final set of 14 attributes listed in Table 2.1. The models predict whether each student (vector) in the test set will return after the first year (output = 1) or not (output = 0). The model output is compared against the actual results for each student. The performance measures used to compare the three models are the overall accuracy, sensitivity, and specificity. The overall *accuracy* is simply a calculation of the percentage of the test data which was accurately predicted by the model. The *sensitivity* measurement refers to the *probability of the model detecting a non-retained student*, so it is equivalent to the percentage of those students who were correctly predicted as non-retained students out of the total number of students non-retained. The *specificity* measurement refers to the *probability of the model detecting a retained student*, so it is equivalent to the percentage of students correctly predicted retained out of the total number of students retained.

The resulting performance measures are shown in Table 2.2. In addition to the accuracy, sensitivity, and specificity, the models were also compared by constructing the individual confusion matrices of each model. The confusion matrices are shown in Table 2.3.

TABLE 2.1. VARIABLES, SIGNIFICANCE LEVELS, AND PEARSON CORRELATION VALUES

Variable	Variable Type	Sig. 2-tailed	Pearson Correl.
Cumulative GPA at the end of 1st term	Continuous	0.000	.572**
Math GPA at the end of 1st term	Continuous	0.000	.463**
Cumulative earned hours at the end of 1st term	Continuous	0.000	.367**
Calculated summation score	Continuous	0.000	.306**
ACT math imputed	Continuous	0.000	.242**
Freshmen enroll hours by end of 1st term	Continuous	0.000	.161**
Total credits to student end of 1st term	Continuous	0.000	.152**
Highest math course in first year	Scale	0.000	.146**
Age at time of 20th day	Continuous	0.000	-.143**
Student net cost 1st term	Continuous	0.001	-.131**
Financial aid semester award amount	Continuous	0.004	.111**
Financial aid offer accepted (yes/no)	Binary	0.021	.089*
Income levels	Scale	0.025	.086*
College division of major	Categorical	0.050	.075*
Poverty income (yes/no) FASFA based	Binary	0.063	0.071
Female or Male student	Binary	0.080	0.067
Kansas resident (yes/no)	Binary	0.106	0.062
Minority/Non-minority	Binary	0.132	-0.058
First generation student (yes/no)	Binary	0.274	-0.042
Housing flag (on/off campus)	Binary	0.696	0.015

TABLE 2.2. PREDICTION MODEL CLASSIFICATION RESULTS

Model	Accuracy	Sensitivity	Specificity
Logistic Regression	87.5%	65.4%	92.7%
Multi-Layer Perceptron	90.1%	71.2%	94.5%
Probabilistic Neural Network	78.7%	76.9%	79.1%

TABLE 2.3. CONFUSION MATRICES

	Logistic Regression		Backpropagation		PNN	
Predicted	Stayed	Left	Stayed	Left	Stayed	Left
Stayed	204	18	208	15	174	12
Left	16	34	12	37	46	40

Logistic Regression: The logistic regression model was created using only the first 410 of the randomly ordered 682 students. The remaining 272 students were then used to test the model using the resulting regression equation ($\log (p/(1-p)) = \beta_0 + \beta_1 x_1 + \ldots + \beta_n x_n$). The coefficients and variable codes are listed in Table A.1, in Appendix A. The overall prediction accuracy of the logistic regression model was 87.5%. The sensitivity, which measures the ability of the model to identify a non-retained student, was 65.4%. The specificity, which measures the ability of the model to identify a retained student, was 92.7%.

Multi-layer Perceptron Neural Network: The multi-layer perceptron neural network using the backpropagation learning algorithm resulted in an overall accuracy of 90.1% for the test data with a sensitivity of 71.2% and a specificity of 94.5%. The final model used the QuickProp learning rule with a sigmoid transfer function with one hidden layer and a 40-7-1 network structure.

Probabilistic Neural Network: For the probabilistic neural network, the output format can be selected as binary, normalized, or probability. Selecting the normalized output format provides results in a probabilistic format with a probability for each class; the probability for an output of "retained" plus the probability of an output of "non-retained" for each student, therefore, totals one or 100%. Through numerous trials and model optimization, the model parameters were set with a radius of influence of 0.200, sigma scale of 0.850, and sigma exponent (Parzen window width) of 0.450. The final model was able to accurately predict the outcome for 78.7% of the students with a sensitivity of 76.9% and a specificity of 79.1%.

Although the accuracy levels were relatively high for all three models, the measurement that is arguably of highest interest is the sensitivity. The purpose of the model would be to accurately target the students who, without intervention, will leave the College of Engineering. Furthermore, there are students who were correctly predicted to continue into the third semester, but may still be at risk of leaving after the one-year milestone. As mentioned in Section 2.3, there are students who will have a very high probability of staying with engineering, and there are students who have a very low probability of staying with engineering. Could it then be said that the students with a very high probability of staying are truly a good fit for engineering and more likely to succeed, while those students with a very low probability of staying with engineering are possibly better fit for another degree? Should all students predicted to leave the College of Engineering be targeted for intervention? Should all students predicted to stay in the College of Engineering be considered "safe"? Would it be more appropriate to target the students who are in the mid-probability ranges as the students "at-risk"? With these questions in mind, the next section analyzes the data at the at-risk level.

2.5 Analysis

It is important to calculate accuracy, sensitivity, and specificity at the model level in order to validate the usability of the models. However, it is necessary to then consider how the models would be used to target students for intervention. Clearly, targeting all of the students predicted to leave is not the optimal solution. Looking at the predicted value for each individual student as a percentage rather than the predicted class can provide greater insight into the risk level of each student. The question then becomes "What are the upper and lower thresholds for the 'at-risk' category?" A first step would be to graph the data to get a visual representation of the probability of retention. Scatter plots were created for the logistic regression model output data, the MLP output data, and the PNN output data in Appendix A, Figures A.1 through A.3. The scatterplots show the students who did, in fact, stay as the first series and the students who did, in fact, leave after the second semester as the second series, plotted in their random order across the x-axis at their predicted percentage output. The hope was to see three horizontal segments— the top segment having few to no actual non-retained students, the bottom having few to no retained students, and then a middle band mixed with retained and non-retained. The upper and lower limits of the middle band would represent the upper and lower thresholds at which to set the "at-risk" levels.

Unfortunately, based on these scatterplots, there is not a clearly defined "at-risk" section. It may then be useful to consider the number of students that each probability range represents. The probability range can take on a countless amount of options and may be quite subjective (e.g., 20% to 80%, 25% to 75%, 25% to 80%, etc.). For the purpose of this study, three different "at-risk" ranges were evaluated: 20% to 80%, 25% to 75%, and 30% to 70%. Analyses of these three settings are shown below by model.

Logistic Regression: Using the sigmoidal function to convert the logistic regression model's output into percentages provides a value that we can estimate as a probability for retention. Setting the "at-risk" range to the students falling within 30% to 70% probability of retention, the logistic regression model has 28 out of 272 students (10%) who fall into this range. Calculations of accuracy, sensitivity, and specificity of the remaining 90% of the students are then 91.0%, 71.1%, and 95.5%, respectively. Increasing the "at-risk" range to include all students whose probability of retention fall between 25% and 75% results in a total of 42 out of 272 students (15%) being identified as "at-risk". The accuracy, sensitivity, and specificity of the model based on the remaining 85% of students are then 92.2%, 74.4%, and 96.3%, respectively. When the "at-risk" range is increased to include all students within the 20% to 80% probability of retention, there are a total of 62 out of 272 students (23%) that are identified as "at-risk". Accuracy, sensitivity, and specificity based on the remaining 77% of students are then 93.3%, 75.0%, and 97.1%. These results are summarized in Table 2.4.

TABLE 2.4. LOGISTIC REGRESSION "AT-RISK" ANALYSIS

"At-risk" Range	**% of students at-risk**	**Accuracy**	**Sensitivity**	**Specificity**
30% - 70%	10%	91.0%	71.1%	95.5%
25% - 75%	15%	92.2%	74.4%	96.3%
20% - 80%	23%	93.3%	75.0%	97.1%

Multi-layer Perceptron Neural Network: Using these same ranges for the results from the MLP neural network provides a different set of results. Using the narrower range of 30% to 70%, 35 of the 272 students (13%) are identified as "at-risk", and the accuracy, sensitivity, and specificity based on the remaining 237 students are 91.6%, 69.8%, and 96.4%, respectively. Widening the range to 25% to 75%, 53 of the 272 students (19%) are identified as "at-risk". The resulting accuracy, sensitivity, and specificity are then 93.2%, 72.2%, and 97.3%. If the risk range is widened to 20% to 80%, 76 of the 272 students (28%) fall within the “at-risk” range, and the accuracy, sensitivity, and specificity are 93.9%, 69.0%, and 98.2%. These results are summarized in Table 2.5.

Table 2.5. BACKPROPAGATION “AT-RISK” ANALYSIS

“At-risk” Range	**% of students at-risk**	**Accuracy**	**Sensitivity**	**Specificity**
30% - 70%	13%	91.6%	69.8%	96.4%
25% - 75%	19%	93.2%	72.2%	97.3%
20% - 80%	28%	93.9%	69.0%	98.2%

Probabilistic Neural Network: Since the probabilistic neural network has more spread in the output percentages, more students fall within the mid-range of probability. Therefore a higher percentage of students fall into the “at-risk” range at the pre-determined bandwidths than do in the logistic regression and MLP models. A total of 84 of the 272 students (31%) fall within the 30% to 70% range of probability of retention. For the remaining 69% of the students, the model prediction accuracy is 89.4%, sensitivity is 82.9%, and specificity is 91.2%. Widening the “at-risk” range to 25% to 75% probability of retention increases the number of at-risk students to 121 of 272 (44%) and increases model accuracy for the “non-risk” students to 92.1%; sensitivity calculates to 79.4%, and specificity increases to 95.7%. Further widening the “at-risk” threshold values to 20% and 80% results in a total of 158 of the 272 students (58%) labeled “at-risk”. The accuracy for the remaining students is then calculated at 94.7% with a sensitivity of 87.0% and specificity of 96.7%. Results are summarized in Table 2.6.

Table 2.6. PNN “AT-RISK” ANALYSIS

“At-risk” Range	**% of students at-risk**	**Accuracy**	**Sensitivity**	**Specificity**
30% - 70%	31%	89.4%	82.9%	91.2%
25% - 75%	44%	92.1%	79.4%	95.7%
20% - 80%	58%	94.7%	87.0%	96.7%

Consideration must be made to the percent of students that fall into the “at-risk” range in order to make a decision on the range to be used. Time, effort, and resources are required for intervention actions taken toward the students identified as “at-risk”, so the institution or organization responsible for these costs must decide what range results in a reasonable scope.

2.6 Discussion

The purpose of these prediction models is to predict student attrition with the goal of targeting students at risk of attrition. Considering this ultimate purpose of the models, it could be argued that accuracy is not necessarily the measurement of priority. The “cost” of predicting a student will leave when the student actually stays is not as high as the “cost” of predicting a student will stay when the student actually leaves. It would be preferable for unnecessary intervention actions to be taken on a student who would ultimately stay anyway, than to allow a student to slip through the cracks because the prediction model did not predict them as being at risk. Therefore, sensitivity is a valuable measurement of focus.

Although the PNN did not outperform logistic regression or the backpropagation neural network in terms of overall accuracy or specificity, it did offer comparable results of those measures while outperforming in terms of sensitivity. It also provides the additional benefit of offering an output in the form of a probability approaching Bayes’ optimal solution, which can be translated as an attrition risk factor. This ability allows for greater precision in targeting students for intervention.

2.7 Limitations of Study

One of the greatest limitations of this study is that our actual data is dichotomous—the student *leaves* after the second semester or the student *stays* after the second semester. The goal is to predict students at-risk, which would logically be students from both outcomes. It is therefore difficult to measure the accuracy of an "at-risk" prediction because there is no actual classification of "at-risk".

Additionally, this study was specific for two cohorts of students at Wichita State University, so results may not be generalized for all engineering students. Although a fairly large sample of data was used and the attributes used have been identified through various studies as discussed in the literature review, each university is unique in class format, faculty, advising, tutoring, etc. All of which could impact the outcome of student retention. Likewise for the "at-risk" analysis, the relatively small test dataset of 272 students becomes even smaller when making calculations of accuracy, sensitivity, and specificity of the non-risk students. These calculations and the percentage of students falling into the risk categories are only rough estimates based on specific examples and would not be expected to translate precisely across alternative sets of data.

Although specifically stated as the definition of "retained" for the purpose of this study, it is important to note that this paper only addresses retention into the third semester. A possibility for future study would be to consider attributes and/or model accuracies past the first year. An additional option for future study is further analysis of the 14 attributes which held a significant relationship with retention since this paper focused on the prediction models rather than the predictor variables.

2.8 Summary and Conclusions

Logistic regression and multi-layer perceptron neural networks have been used in numerous studies to predict student retention and even engineering student retention specifically. They have proven to be effective models for this application, and this specific study reiterates their capabilities. The major contribution of this study, however, was the introduction of the probabilistic neural network to the application of engineering student retention prediction. Although the logistic regression model and the MLP resulted in higher overall prediction accuracy, their ability to detect non-retained students was lacking in comparison to the newly applied probabilistic neural network. It can quite defensibly be stated that for the purpose of preventing student attrition, the most important capability of a prediction model is its ability to detect a student that will, without intervention, eventually leave engineering. If this statement is true, then a model's sensitivity is of, at least equal if not more, importance than the model's accuracy. For this specific study and set of data, the sensitivity for the logistic regression model was only 65.4%; the sensitivity for the MLP was 71.2%, but the sensitivity for the PNN was significantly higher at 76.9%.

CHAPTER 3

A MIXED MODEL APPROACH TO OBJECTIVELY ASSESSING THE EFFECTIVENESS OF AN ENGINEERING SUMMER BRIDGE PROGRAM

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3.1 Abstract

This study applies a mixed model approach to assess a specific engineering summer bridge program in terms of its effect on student retention. The program is assessed quantitatively by reviewing the year-by-year retention of program participants versus non-participants over four years and considering the statistical significance of the difference between the percentage of program participants retained and non-participants retained. Qualitative data and demographic information were collected through a college-wide student survey, and bivariate correlation data is analyzed to determine statistically significant relationships among variables. The quantitative analysis shows that program participants were retained at a higher rate than non-participants with a p-value of 0.006. The qualitative study provides evidence of the impact perceived preparedness has on self-efficacy, course work confidence, college involvement, and satisfaction with grades and student and faculty interactions. This finding offers evidence that a summer bridge program aimed to better prepare incoming freshman for the engineering curriculum could have a high impact on academic and social integration, and therefore increase student retention.

3.2 Introduction

3.2.1 Purpose

The case study university, and its College of Engineering in particular, has made great strides toward increasing student retention. However, the 6-year graduation rate for this university's College of Engineering was 35% [50], indicating a need for improvement. It is a process of continuous improvement to develop, implement, and assess retention efforts. As an initial broad benchmarking effort to evaluate the retention programs at the case study university, a side-by-side comparison was made between an American Society of Engineering Education (ASEE) report on best practices in engineering student retention [51] and the retention practices within the case study College of Engineering. The full side-by-side comparison can be found in Mason et al. [52]. As a result of that benchmarking process, it was found that the case study university had retention programs similar to five of the seven reported best practice programs. One of the two missing programs was a summer bridge program. The college had a summer bridge program for four consecutive summers (2012-2015), but had recently been discontinued due to a loss in funding. This observation, along with the ongoing efforts to increase student retention, raised the question of whether the bridge program had been effective in its purpose of increasing retention. If evidence of its effectiveness could be shown, it may be worth the effort to seek future funding to reinstate the program. Therefore, the purpose of this study was to evaluate the effectiveness of the previously existing engineering summer bridge program. Cabrera et al. [53] challenged scholars to "conduct robust, empirical analyses of [bridge] programs to justify their existence and to inform and improve practice". This paper takes an objective, systematic approach to evaluate the effectiveness of a specific engineering summer bridge program at the case study university. The objective is accomplished in a four-step process:

1. Utilize the results of a national best-practice study as a benchmark
2. Review existing literature on engineering summer bridge programs and their corresponding assessments

3. Use statistical methods to determine whether or not the past engineering summer bridge program was effective in the purpose of retaining engineering students
4. Utilize results of a student survey to analyze significant correlations between student perception of preparedness and other student outcomes

3.2.2 Background

Wichita State University is a public, urban Midwest university, and it had a summer bridge program called Bridge for Engineering and Engineering Technology Students (BEETS) for the summers preceding the fall semesters of 2012 to 2015. The program was open to all incoming freshmen engineering or engineering technology students, but outreach and recruitment targeted underrepresented students, and preference was given to underrepresented students (female, Hispanic, African American, or Native American), students majoring in Engineering Technology, first generation students, transfer students, students living on campus, and veterans. All other applications were taken on a first-come, first-served basis, and only 50 spots were available. The goal of the program was to provide incoming freshmen with an opportunity to become familiar with the campus resources and to "jump-start" their education. It was a one-week project-based program focused on academic enrichment and hands-on activities to promote academic and social integration from the very beginning of the college experience. Participants were also given the opportunity to move onto campus before the students not participating in the bridge program. The BEETS program was primarily funded by a federal grant to support student success and retention, which covered most of the program's expenses. Students only had to pay a $50 application fee, and they were eligible for $500 retention scholarships for each of the second and third semesters continuing in the College of Engineering.

The intent of spreading the scholarship through to the second and third semesters was to promote retention through the third semester. One of the unique features of the BEETS program was the commitment extended beyond the one-week session. The program director took on a mentorship role and kept in close contact with each of the program participants. In order for the students to receive their $500 scholarship the second and third semesters, they had to remain enrolled in the College of Engineering and fulfill certain requirements including maintaining a minimum GPA and checking in with the program director at various times throughout the semester. The BEETS program served a total of 181 participants over the course of its four year existence.

The bridge program selected as a best practice by ASEE and used as the benchmark for this study was the Minority Engineering Program Academic Boot Camp (ABC) from Purdue University. The program served as a 5-week simulation of the academic demands of the first semester of the engineering program. Participants stayed on campus for the duration of the camp and were exposed to the first-semester experience of taking Chemistry, Calculus, MATLAB, Physics, and English, but in a 5-week, non-credit bearing simulation of the workload. The camp included an engineering design project and offered unique opportunities such as company tours, professional mentoring, and exposure to campus resources, social activities, and team-building experiences. The goal of the program was to expose students to the demanding climate of the engineering program, while integrating them into the college by introducing them to faculty, campus resources, and other students. In the first five years of program existence, the first year retention rates for ABC participants were on average 7.5% higher than non-ABC participant retention rates [51].

The following literature review discusses the importance of engineering student retention and seeks to consider the format, assessment methods, and outcomes of summer bridge programs at other universities to serve as a guide to the current work. Through this review process, gaps in the current literature are then identified and addressed through this study.

3.3 Literature Review

3.3.1 Student Retention

Student persistence proves to be an area of high opportunity in the realm of higher education. According to the U.S. Department of Education [54], the national average 6-year graduation rate in 2017 for public universities was 59%. For 4-year institutions with open admissions, the average 6-year graduation rate was only 39% [54]. Although great strides have been made to increase student retention, the struggle of attrition still exists, and it is of increased concern for fields of study representing high impact and high demand positions in the workforce. Science, Technology, Engineering, and Math (STEM) majors in particular were addressed by the President's Council of Advisors on Science and Technology a few years ago. The report stated that "…the effectiveness of STEM education in the country will determine whether we are able to find solutions to many challenges, such as energy and health, and will ensure a better understanding of ourselves, our planet, and the universe" [2]. Falling into the category of STEM and high-impact majors is the high-demand field of engineering. Engineering has appeared on Manpower Group's list of most difficult positions to fill in the U.S. for the past consecutive 9 years [1]. Yet, inspite of the known importance of opportunities for engineering and the efforts to recruit and retain engineering students to meet engineering demand, engineering student attrition is still a major concern for the United States. The American Society for Engineering Education (ASEE) recently provided aggregate results for engineering college graduation rates, reporting an average national 5-year graduation rate of 49.7% [3].

The problem is continuing to be addressed from multiple angles—identification of at-risk students, intervention programs, and a variety of retention programs [17,22–24,55,56]. The American Society for Engineering Education (ASEE) led a project in 2012 to gather information from universities nation-wide to determine best practices for engineering student retention programs [51]. One of the results was the selection of seven programs at seven different universities that demonstrated the best practices toward the goal of increasing engineering student retention. The report serves as an excellent benchmarking source for universities seeking opportunities to improve engineering student retention. Ideally, there would be no limit on time, money, or resources and an institution could utilize a study such as this report by ASEE to develop retention programs reflective of all seven best practices. Unfortunately, there *are* limits to the time, money and resources that a university can invest into such programs. Prior to making a decision to continue or discontinue an existing retention program or to adopt a new retention program, the effectiveness of the program of interest should be investigated and evaluated.

3.3.2 Summer Bridge Programs

The overarching objective of most summer bridge programs is to increase the probability of student success and retention by preparing students for the transition from high school to the rigorous requirements of college [53,57–60]. Although there are numerous summer bridge programs in existence across the nation at various universities, the programs themselves are highly variable across institutions. Some summer bridge programs are developed to reach the STEM student population, focused broadly on science, technology, engineering, and math [60], while other bridge programs specifically target science students or engineering students [57,58].

Some programs narrow their focus even further to target minority or underrepresented students [53,57,59,60], while others target those students who are underprepared in their mathematical skillset [58].

Programs vary, not only by their targeted participants, but also by the format, structure, and length of time. For example, some bridge programs last only a few days where students may stay on-campus or select to stay off-campus at a lower cost [57]. However, it was found through the review of programs and literature that most bridge programs last four to six weeks and the students stay on-campus to promote integration to the university [51,53,58–61]. Often, a high priority of the bridge program is providing the students with a sense of belonging by connecting them with the campus, faculty, and students to build an internal support group before the semester begins [53,57]. Program content may focus on preparing students for the engineering program by brushing up on physics and math [53,58,60]. Another focus may be on increasing the probability of success in the engineering program through training on learning strategies or making students aware of the campus resources that can assist them through their education [53,60]. A highly successful program is one that can effectively target all of these needs and objectives.

3.3.3 Program Assessment

Through the review of literature, a few bridge program assessment studies were identified, and their assessment methods are discussed here. Tomasko et al. [61] utilized a pre-program and post-program survey to assess students' perception of preparedness and sense of belonging to determine whether Ohio's Science and Engineering Talent Expansion Program (OSTEP) had a positive impact on each of these factors. The surveys ask questions related to motivation for pursuing a STEM degree and STEM career, as well as feelings and attitudes about major, school, and studying, and perceived impact of the summer bridge program. Preparedness was measured on five elements: study skills, social interactions, comfort with content, expectation of classes, and general college preparation. Their results showed that students felt better prepared and more comfortable with the university after the program [61].

Gleason et al. [58] evaluated The University of Alabama's Engineering Math Advancement Program (E-MAP) by comparing mathematic placement exam scores before the program to scores 2 and 3 years later. Additionally, they compared the E-MAP participant first semester math course success rate with non-participant success rate. Retention rate was compared for E-MAP participants and non E-MAP students using three different statuses: (1) students remaining in engineering, (2) students leaving STEM altogether, and (3) students leaving engineering but staying in a STEM field. The study tracked three cohorts of students to make these comparisons. Overall, E-MAP improved STEM student retention by approximately 12%, but there were not a statistically significant higher percentage of participants than non-participants remaining in engineering [58].

To assess the University of Arizona's New Start Summer Program (NSSP), Cabrera et al. [53] utilized two main sources—data from their Office of Institutional Research Planning and Support (OIRPS) and results from a longitudinal survey. The study utilized the OLS regression method to predict GPA and logistic regression to predict retention. The results showed that NSSP participation was a significant predictor for first-year GPA, and NSSP participants were more likely to be retained into the third semester than non-participants with an odds ratio of 1.52 (statistically significant) [53].

Strayhorn [59] utilized descriptive and multivariate statistics to analyze longitudinal survey data and consequently assess a summer bridge program. Data was collected at three points: (1) summer prior to entering college, (2) beginning of first fall term, and (3) end of first fall term. The survey aimed to measure academic self-efficacy, sense of belonging, academic skills, and social skills. Results showed that student academic self-efficacy and academic skills were statistically significantly higher at the end of the program than at the beginning of the program; student sense of belonging and social skills were slightly higher, although not at a statistically significant level, at the end of the program than at the beginning of the program [59].

Cabrera et al. [53] and Strayhorn [59] point out the need for empirical study of bridge program effectiveness as many studies rely on descriptive measurements through program participant surveys rather than concrete measurements of outcomes such as retention and GPA. As noted by Bogue [62], student surveys are often included as part of the outreach program itself, and they are taken at the end of the program when students are "revved up". Therefore, the results are more of a measurement of their satisfaction or enjoyment from the program rather than a measurement of whether or not the program achieved its outcome goals. Tinto [63] points out that there is value in waiting a period to measure the outcomes of a program since some effects will accumulate over time. Additionally, while survey information may help guide program improvement initiatives, program assessment must be scientifically- and statistically-based rather than perception-based. Although Cabrera et al. [53] and Strayhorn [59] did contribute their own empirical study of bridge program effectiveness, the fundamental limitation to each of these studies is that the study is based on a single program at a single institution. Therefore, results may not be generalizable across all institutions and across all bridge programs. Similar assessments must be made for other bridge programs at other institutions in order to observe patterns and make some generalized conclusions. In response to this call to research, the following section explains the unbiased data analytical approach to evaluate the effectiveness of the BEETS program in its purpose of increasing student success as measured by student retention.

3.4 Methods

3.4.1 Quantitative: Retention Percentage

This study took a mixed model approach to analysis. The first phase looks at the data in terms of comparing BEETS participants to non-participants. This method takes a statistical approach to analyze the relationship between bridge program participation and retention. The goal is to distinguish the differences between BEETS participants and non-BEETS participants in relationship to retention into the third semester. The analysis considers a comparison of the percentage of students retained each year for participants and non-participants. Percentages and significance levels are calculated and reported using SPSS.

3.4.2 Qualitative: College-Wide Student Survey

As an alternative to the commonly used pre- and post-survey of program participants, this study utilized results of a college-wide student survey. Since the primary objective of a bridge program is to prepare students for their upcoming college experience, the second method of analysis utilizes the results of this survey to draw some conclusions about relationships between student unpreparedness and other student perceptions and attributes. In the spring of 2017, a survey was created using Qualtrics software and was disseminated via e-mail to all undergraduate students in the College of Engineering at this case study university, approximately

1700 students. Of the surveys dispersed, 344 returned with responses. The student survey was adapted from the Assessing Women and Men in Engineering (AWE) "Persisting in Engineering" survey [64]. The objective of the survey was to gain insight on student perceptions of their experiences in the College of Engineering in order to identify successful programs and features of the college as well as determine opportunities for improvement. Part of the analysis of the survey included evaluation of the correlations among the various student attributes and responses to questions using SPSS. One significant finding was the number of statistically significant relationships among student attributes and perceptions with respect to the students' feelings of preparedness by their high school curriculum. The analysis of these outcomes serves as supporting evidence of the potential impact of a bridge program to help prepare students for the engineering degree program.

3.5 Results

3.5.1 Retention Percentage Results

Since BEETS recruitment was targeted toward specific groups, and those groups were also given selection preference when space was limited, the BEETS percent retained could not simply be compared to the general population of engineering students. To address the issue of selectivity bias and ensure the populations were being compared based on similar samples, a stratified random sample was taken from the population of engineering students who did not participate in the program. The stratified sampling took one similar non-participant for each BEETS participant, matching on cohort and the variables of selection bias. The percentages are shown in Table 3.1.

TABLE 3.1. BEETS POPULATION WITH MATCHING SAMPLE

Variable	BEETS (B)/non-participant (N)	(N = 181) Count	Percent
Female	N	57	31.5%
	B	57	31.5%
Military	N	6	3.3%
	B	6	3.3%
Underrepresented Minority	N	49	27.1%
	B	49	27.1%
First Generation	N	73	40.3%
	B	74	40.9%
Engineering Technology Major	N	1	0.6%
	B	1	0.6%
On-Campus Housing	N	125	69.1%
	B	126	69.6%

Table 3.2 shows the percent of BEETS and non-BEETS students retained into the third semester. A total of 130 (71.8%) of the non-participants from the stratified sample were retained into the third semester, while 150 (82.9%) of the BEETS students were retained into the third semester. This difference in population proportions is statistically significant with a p-value of 0.006.

TABLE 3.2. RETENTION INTO 3RD SEMESTER

	3rd semester		Total
	non-retained	retained	
Non-Participant	51 28.2%	130 71.8%	181
BEETS Participant	31 17.1%	150 82.9%	181

Retention was also tracked by cohort for the group of non-BEETS participants along with the group of BEETS participants. Figure 3.1 shows the third semester retention comparison by student cohort. The bar chart (Figure 3.1) starts with the incoming fall 2012 cohort, showing the percentage of students retained into the third semester (fall 2013) and ends with the cohort of fall 2015 incoming students along with the corresponding percent retained into the third semester (fall 2016). The line represents the difference between the percentages of BEETS students retained and non-BEETS students retained into the third semester by cohort. With only a sample size of 4 cohorts, we don't have a large enough sample to make any statistically sound inferences about the fluctuation in the percentages retained. There were some changes in administration at the college level within this time frame, which could have had an impact on both the BEETS and non-BEETS students. The decline in percentage of students retained over the first three years may also be at least partially attributed to a loss in momentum from the start of the program until the end of the program. Although the hypothesis cannot be proven at a statistically significant level, the numbers suggest that there may be a relationship between the number of participants and program effectiveness. The first cohort was the smallest cohort with 27 participants and also had the highest retention rate, while the 2014 cohort was the largest cohort with 57 participants and also had the lowest retention rate (Table 3.3). Additionally, since administration—and specifically the program director—remained in contact with all bridge program participants, the number of students to track, contact, and uphold relationships with, grew steadily each year.

TABLE 3.3. COHORT SIZE AND RETENTION INTO THIRD SEMESTER

	2012		2013		2014		2015	
	Cohort Size	%Retained	Cohort Size	%Retained	Cohort Size	%Retained	Cohort Size	%Retained
BEETS	27	92.6%	49	85.7%	57	78.9%	48	79.2%
Non-BEETS	28	78.6%	47	80.9%	61	70.5%	45	60.0%

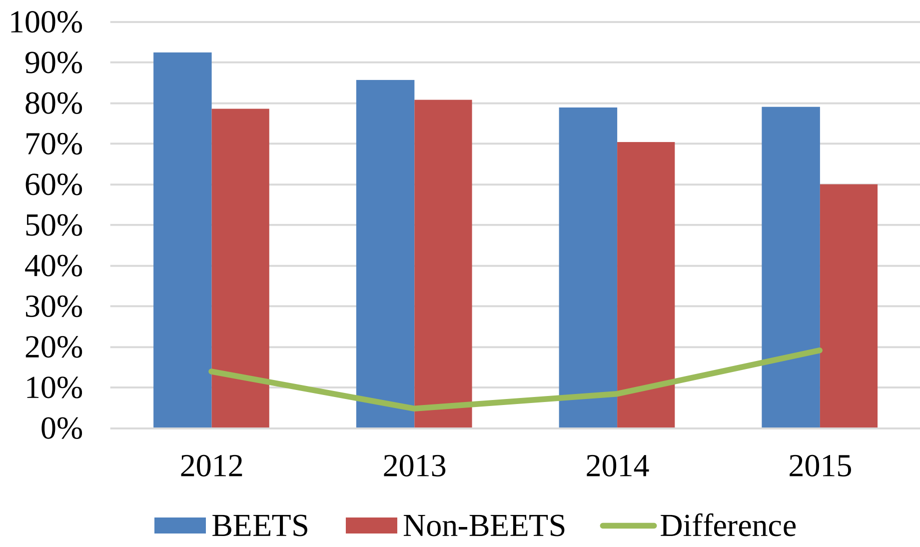

Figure 3.1. Third semester retention by cohort.

3.5.2 Results of Student Survey

The survey captured individual responses for 344 College of Engineering students. The participants were mostly male (78.8%). Over half (53.8%) of the respondents were White, followed by International students (20.3%). Close to one-third of the participants were first generation college students (30.8%). Of the 344 students, 37.2% were seniors, 23.8% were juniors, 20.9% were sophomores, and 18.0% were freshmen. The majority of the participants came to the university immediately following high school (57%). Another 18% came directly from a 2-year college, 9.9% from working, and 8.1% from a 4-year college. The remaining students came from the military, vocational or technical college, or other unlisted location.

Students were asked a variety of questions related to their background, college involvement, perceptions, attitudes, and experiences. When merged with data from student records, the student survey collected 136 data points for each student. Analysis of the survey data provides evidence of the possible impact that an increased perception of preparedness can have on other student perceptions and experiences. The analysis of bivariate correlations found that the variable with the highest number of statistically significant relationships with other variables was the following survey question, which had level of agreement response options: "My high school coursework adequately prepared me to be successful in an engineering curriculum". Appendices B show tables of the student attributes and survey responses having a statistically significant relationship with this question. The relationship model shown in Figure 3.2 summarizes these results based on the analysis of the correlation significance and consideration of the sequence of events.

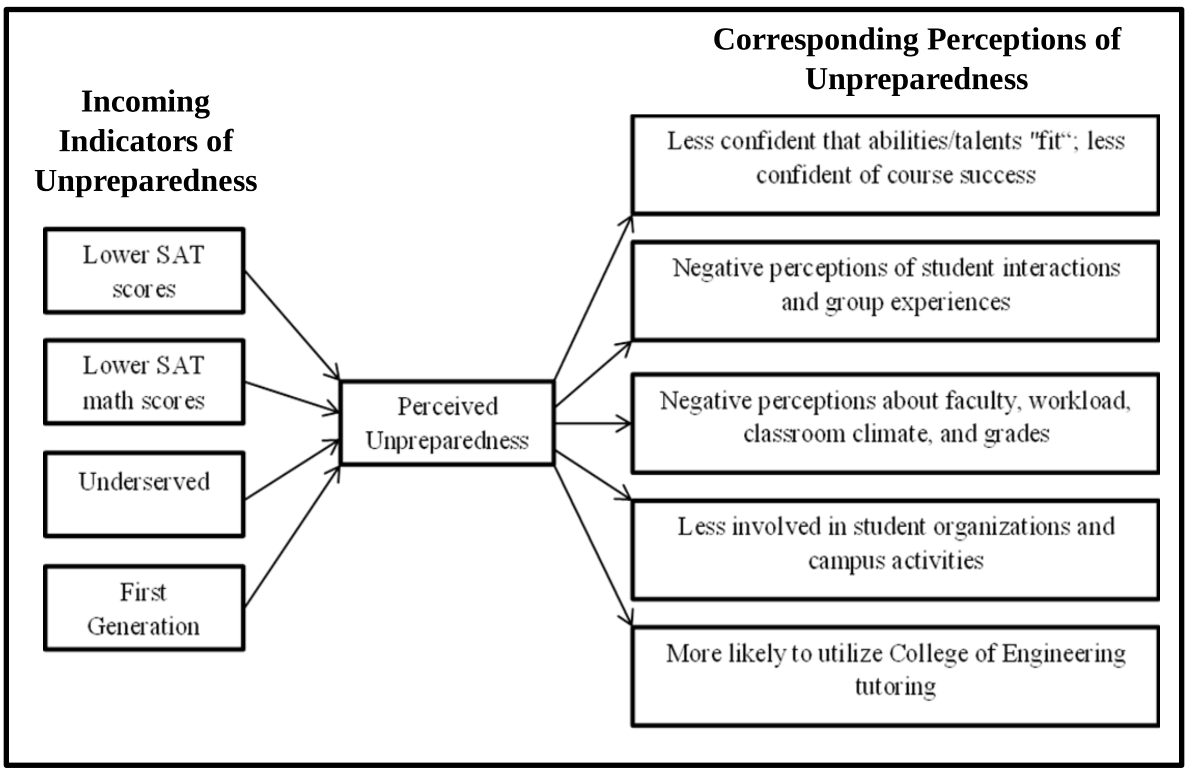

Figure 3.2. A model of inputs and outputs of perceived unpreparedness.

The attributes on the left side of the model show attributes related to the survey question that can serve as indicators of unprepared incoming students. These attributes include lower ACT/SAT overall scores, lower ACT/SAT math scores, first generation students, and underrepresented minorities. The attributes on the right side of the model are other student perceptions having a statistically significant relationship with the question on preparedness. These factors can be viewed as the perceptions of the college experience related to whether or not a student feels prepared entering college. This idea is further discussed in the "Discussion" section below.

3.6 Discussion

The direct results of the difference between BEETS participants and non-participants in 3^{rd} semester retention rates suggest that the previous summer bridge program was effective in increasing the retention rates for its participants. It is important to note the format of the assessed bridge program. It is likely that many factors contributed to the success of the program, yet this study does not assess the individual aspects of the program. Likely, one of the major components of the BEETS program that contributed to student retention was the offering of the tapered stipend and the regular follow-up conducted by an engineering faculty mentor. These results may not be generalizable across all engineering summer bridge programs, but since the driving purpose behind this study was to assess a specific case study bridge program, the results provide significant evidence of the program's success.

One underlying notion of the survey is that it pursues student perceptions, which gives us insight into the student experiences and opinions, but it must be noted that this is *perceived* data, not necessarily based on facts. For example, a student may *feel* that he or she was not well prepared by high school coursework, but that cannot necessarily equate to a factual statement that the high school coursework did not prepare the student for the engineering curriculum. Likewise, perceived quality of teaching cannot be assumed as actual quality of teaching, and so on. Although the survey results are specific to a single population of engineering students at one university, the survey questions were not program-specific, and the sample included students from various backgrounds across multiple engineering disciplines. Therefore, the results may be representative of the engineering student population, and could be tested and validated by conducting similar analyses at other institutions.

The model shown in Figure 3.2 provides valuable insight and yields many opportunities for future research to generalize, validate, and further explain the model. As depicted by the model, students with lower ACT scores—and specifically lower ACT math scores—are more likely to feel underprepared entering into the engineering curriculum. Likewise, underserved and first-generation students are also likely to feel underprepared for the engineering degree requirements. This finding offers a multitude of opportunities for program direction. The ultimate goal would be to go to the root cause—begin targeting the high schools and individual high school students to provide them with the tools needed to succeed during their high school years. For example, the level of math and science courses taken in high school were also correlated with preparedness according to the survey; this suggests there may be opportunity to encourage these courses at the high school level or increase the availability of these courses at the high school level. However, these options require intervention prior to the student enrolling in or committing to the university and therefore are less likely to be controllable or even identifiable by the university. Without affecting the high school experience, however, the finding that these four attributes have a relationship with perceived preparedness can still guide recruitment efforts. If the university chooses to reinstate the summer bridge program, this model suggests that underserved, first generation, and lower ACT scorers should be targeted to encourage participation in the program. An additional suggestion is that the College of Engineering should include a question on the initial enrollment survey to assess student perceived preparedness. If the question is asked at an earlier stage such as this, a negative response could serve as an indicator for academic advisers to promote specific programs such as tutoring within the College of Engineering, mentoring opportunities, or appropriate preparatory courses.

Ultimately, this model offers evidence to the high impact opportunity of a summer bridge program aimed at preparing students for the engineering curriculum. Just as unpreparedness has a negative impact on confidence, perceptions of student and faculty interactions and experiences, grade satisfaction, and involvement, the reverse is also true. If the university can offer a bridge program which better prepares students entering into the engineering program, those students will likely have higher confidence in their abilities, have better perceived interactions and experiences with faculty and other students, be more satisfied with their grades, and be more involved in student activities and campus organizations. Tinto's Longitudinal Model of Institutional Departure [65], shown in Figure B.1 of Appendix B, highlights the importance of academic and social integration in terms of student retention. Each of the positive outcomes of student preparedness as depicted by the model in Figure 3.3 is an aspect of academic or social integration. Based upon this deductive reasoning and the results of the direct comparison of percent retained for BEETS program participants vs non-participants, it is evident that a summer bridge program is a prime opportunity for high impact on engineering student retention.

3.7 Summary and Conclusions

This study provides tangible evidence that the BEETS summer bridge program had a positive impact on engineering student retention. Results from the college-wide engineering student survey further strengthen this conclusion and suggest that a summer bridge program has the potential for high impact on increased confidence and satisfaction with grades and interactions with other students and faculty. Therefore, it is suggested that this case study university seeks funding opportunities to reinstate the summer bridge program and focus on preparing students for academic success. The correlation analysis suggests that first generation and/or underserved students with low ACT scores—specifically in math—would be a good target population for bridge program recruitment because those students are more likely to enter the university feeling underprepared. It is also recommended that other institutions perform similar studies to test and validate the results of this study, particularly the model of inputs and outputs of perceived unpreparedness.

CHAPTER 4

DMAIC APPROACH TO UTILIZING ENGINEERING STUDENT PERCEPTIONS TO GUIDE RETENTION PROGRAM EFFORTS

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4.1 Abstract

Universities are working to reduce the attrition rate of students while increasing retention through strategic planning efforts. However, due to the nature of the problem involving multiple key factors influencing student satisfaction and, hence retention, there is no specific model-based retention technique to address the strategic plan and satisfy stakeholders. The purpose of this study is to provide a case study application of the DMAIC (Define, Measure, Analyze, Improve, and Control) method as an approach to strategic retention planning. The study utilizes a college-wide student survey to collect 136 variables for each respondent. The survey addresses a mixture of components, including demographics, pre-college academic performance, cumulative academic performance, and financial support, as well as self-reported variables such as incoming preparedness and confidence, campus involvement, and perceptions of faculty and student interactions. Several Six Sigma and statistical methods are used to analyze the data and identify relationships between student demographics, their experiences, and their perceptions. The study demonstrates how the DMAIC approach can help guide retention efforts at a case study university, utilizing an American Society of Engineering Education (ASEE) report on the best practices in engineering as a benchmarking tool and a college-wide survey to gather data and

information on student perceptions. Through the results of the Define, Measure, and Analyze phases, specific recommendations are made to Improve and Control retention strategic planning.

4.2 Introduction

Through the lens of Six Sigma, Tinto's Longitudinal Model of Institutional Departure may very well be viewed as a portion of a product life cycle (See Figure B.1 in Appendix B). Students enter the institution as an assembly would enter a production process. Just as products may vary by supplier or production batch, each student has initial individual characteristics and commitments, but those commitments are impacted by their experience within the academic system. Students are the highly valuable and highly variable product that passes through the system, but many students are lost in the process, and the supply of engineering graduates is not meeting current demand. Several factors impact student academic and social integration, and the more integrated students are into the College of Engineering—academically and socially—the higher the quality of their commitments and the greater their chance of persisting through degree completion. Graduation rate can be translated as throughput, and as with any production system with ever increasing demand, it is a value we want to increase. Therefore, it is in the college's best interest to increase integration and improve the academic system experience to increase the ultimate retention of engineering students. If engineering education is a process, and process improvement is the focal point of industrial engineering, it is a logical fit to apply industrial engineering techniques and principles to the subject of engineering student retention. The purpose of this study is to apply the Six Sigma DMAIC approach of quality improvement to the issue of engineering student retention at a case study university.

4.3 Literature review

Although the number of engineering students graduating annually has been steadily increasing over the past decade, recent enrollment numbers indicate a slowing of growth [66] while the demand for engineers is still on the rise [1]. National statistics on engineering demand and engineering student retention provide strong evidence of the need for focus on engineering student recruitment and retention. Manpower Group's list of most difficult positions to fill in the U.S. has included the field of engineering for the past consecutive 9 years [1]. Yet the national average 5-year graduation rate is less than 50% for engineering colleges [3] despite the focus that has been placed on recruiting students into engineering majors and retention programs to keep those students in their engineering major [51,53,57–59,61]. It is necessary to work toward fulfilling the demand for engineers, not only for economic purposes, but also for the future of our nation and our world. The President's Council of Advisors on Science and Technology reported that "… the effectiveness of STEM education in the country will determine whether we are able to find solutions to many challenges, such as energy and health, and will ensure a better understanding of ourselves, our planet, and the universe" [2]. Engineering is not only a high-demand position, but it is position with opportunity for high impact. Therefore, we want to recruit students who will make the most of that opportunity. We also want to identify students who are motivated to do so, but may need an extra push if the odds are stacked against them.

Efforts have been made in varying degrees using a variety of techniques, methods, and programs to address the issue of engineering student drop-out or stop-out. Numerous studies have been conducted to identify student attributes that lead to attrition [15,19,23–25,42,45,67]. Utilizing these discovered student attributes, a variety of prediction models have been developed in an effort to identify students who are at-risk of attrition in order to intervene before students leave [17,21,47,55]. Prediction models have been compared and contrasted [23,55], and an abundance of retention programs have been created, implemented, and analyzed at various institutions [68–70]. Studies have been performed to measure and evaluate the effectiveness of those programs [71–74]. All of these efforts have been made toward the ultimate purpose of graduating more engineering students. However, the engagement and retention of students is still a longstanding issue in higher education as it interlocks several factors, of which many are specific at the individual and intuitional level [75].

We know that recruitment and retention are important and necessary for increasing the output of degreed engineers, but recruitment and retention come at a cost. According to a 2016 national report on college recruitment, the median cost to recruit a single undergraduate student at a four-year public institution was $578 [4]. On the other hand, the cost of losing a student to attrition is even higher—both to the individual student and to the institution losing that student. If a higher education institution had unlimited resources, every best practice recruitment and retention program could be implemented and sustained. However, there are obviously limits to resources available for recruitment and retention efforts. Therefore, the institution administration must be strategic in planning retention programs.

One strategic approach that has been proposed in recent years, but has had little visibility in the literature, is the Six Sigma DMAIC approach to quality improvement. DMAIC has proved successful in its application in the manufacturing industry [76–80]. More recently, DMAIC has found its way into service industry improvements [81–84]. Literature on the use of DMAIC in academia, however, is less common, and toward the specific application of student retention, the literature is sparse. However, a few studies have been conducted and will be discussed.

Jenicke et al. [85] provided a conceptual model of how a variety of Six Sigma tools—including DMAIC—could be used to understand, model, and improve student retention. Jenicke et al. [85] study focused on the purpose and examples of models and utilizing the tools such as fishbone diagram, FMEA (Failure, Modes, and Effects Analyis), and process maps in the context of college student retention. However, it did not discuss an actual case study approach with specific results or recommendations. Jenicke et al. [86] discussed the framework and related challenges to the application of Six Sigma methods to the academic environment. The only study found through the literature review to specifically apply DMAIC to guide student retention efforts was conducted by Chow and Downing [87]. In their study, the Define phase consisted primarily of the project charter, which included the problem-based objective of identifying causes for first-year STEM attrition and determine solutions to reduce first-year attrition to 10% or less. The team also used SIPOC (Suppliers-Inputs-Process-Outputs-Customers) analysis to help define the boundaries as part of the Define phase. For the Measure phase, the team looked at 10 cohorts of students and their corresponding attrition rates. The study used a P-chart, essentially using attrition rate as the proportion defective, and by setting control limits to measure system variation, it was concluded that the process was in-control with a slight upward trend in recent years [87]. For the Analyze phase, the study utilized Tinto's model to direct identification of possible factors for student attrition, and then used logistic regression and statistical analysis to evaluate student pre-college and first-year attributes in relationship to retention. The study additionally utilized qualitative data with a leaver's survey and focus group of seniors on academic probation. Quantitative analysis showed almost half of students who left among three of the cohorts did so due to falling behind in math. Quantitative analysis showed that academic performance and changes in interests were cited as reasons for leaving, while poor time management and study skills and difficulty adjusting to college life were the primary reasons for academic probation [87]. For the Improve and Control phase, Chow's team implemented an attrition risk identification process along with standard documented procedure and continual monitoring of students through the risk identification process [87].

4.4 DMAIC Approach

4.4.1 Define

The first phase of the DMAIC approach is Define the problem, scope, objective, and customers. The problem being addressed through this study is engineering student attrition. More specifically, the College of Engineering (CoE) for Wichita State University (WSU) would like to see an increase in student retention. The college does not have a measurable goal, but the current rate for retention into the third semester is 60.7%, so we suggest starting with a goal to increase third semester retention to 63% within the next two years. WSU is a large, public, urban, research-based state university in the Midwest of the United States. A useful tool for the Define phase of DMAIC is SIPOC (Suppliers-Inputs-Process-Outputs-Customers). The SIPOC method helps to define the complete system from suppliers, to inputs, to the internal process being addressed, to the outputs, and ultimately to the customers. Clearly, in a manufacturing environment, improvements to the process must take into consideration the prior sections of the supply chain. All stakeholders should be considered in steering decisions as well, and the customer is one of the major stakeholders. One major difference in the manufacturing setting versus the academic setting is that in academia, our students are both the “product” or “input” and the “customer”. For the SIPOC exercise we use the students as the input and consider the “end-user” of our graduated engineering students (e.g. industry) as the customer. Later in the study, we consider the student as the customer for considering the voice of the customer. Table 4.1 shows the results of the SIPOC exercise. The inputs are based on current College of

Engineering enrollment data, and the outputs are based on previous year's graduation numbers. We use results of the college-wide survey, discussed thoroughly in the Measure phase, to estimate figures to our supplier and customer.

TABLE 4.1. MODEL OF SIPOC EXERCISE

SUPPLIER	**INPUT**	**PROCESS**	**OUTPUT**	**CUSTOMER**
High Schools: 57% 2-year Colleges: 18% Industry: 10% 4-year Colleges: 8% Vocational/Technical school: 0.9% Military: 2.4% Other: 4.2%	Students seeking engineering degree: (Approx. 2,025) Freshmen: 13% Sophomores: 20% Juniors: 23% Seniors: 44% Returning Adult: 9% Transfer: 20% Male: 82% White: 47% International: 22% 1st Gen: 32% Military: 6%	• Enrollment • Curriculum Requirements • Faculty/Staff Interactions • Extracurricular Activities • Learning Objectives • Advising • Graduation	Individuals with an undergraduate engineering degree: Aerospace: 44 Biomedical: 23 Computer: 30 Computer Science: 24 Electrical: 54 Manufacturing: 2 Engr. Technology: 11 Industrial: 28 Mechanical: 99	Industry: 77.6% Grad School: 41.9% Personal Business: 26.2% College/University (Teach): 9.3% Professional School (med/law): 7.6% Military: 6.4% K-12 Schools (Teach): 2.3% Other: 5.2%

4.4.2 Measure

The second phase of DMAIC is to Measure the process performance. For this specific study, we need to measure current retention programs and their performances. This measurement was performed using two methods: (1) Benchmarking: Comparing current CoEretention programs to best practices, and (2) Voice of the Customer: Measuring current student satisfaction and related perceptions of experiences. The methods and results are discussed in the following subsections.

Benchmarking: Current CoE retention program and ASEE Best-Practices: In 2012, the American Society for Engineering Education (ASEE) published a report entitled "Going the Distance: Best Practices for Retaining Engineering, Engineering Technology and Computing Students" [51]. The report itself was the result of a much larger ASEE study consisting of an extensive literature review and documentation of over 60 effective strategies and practices for retaining engineering students. The report tabulated the retention programs practiced at engineering schools nationwide, categorized by the following seven types of programs: (1) Student learning through tutoring and mentoring; (2) Student programs and financial aid; (3) Student academic enrichment programs; (4) Student research/work experience; (5) Curriculum and class enhancements; (6) Institutional/ Educational research; and (7) Change in institutional/departmental policy and faculty development. As part of that study, ASEE requested engineering college deans and department chairs to provide evidence that those practices were effective, which resulted in almost 60 best-practice reports. From those reports, ASEE selected seven engineering school programs to represent the best practices for retaining engineering students. These seven best practice reports served as a benchmark for assessing the CoE's student retention programs and identifying possibilities for improvements. Table 4.1 was created as a side-by-side comparison of the reported best-practice programs and corresponding similar CoE retention program if available. Based on the side-by-side comparison, we found that the College of Engineering had retention programs that resembled five of the seven best practice programs. This process helped us document the current state of the College of Engineering with a comparative reference point. Additionally, it serves as a tool for the Measuring and Improvement phases in the DMAIC approach.

Voice of the Customer: Measuring Current Student Perceptions: As with any industry, whether manufacturing or service, the voice of the customer is a valuable input to guide and direct strategic decisions. When applying DMAIC to academia, the student is our primary customer, so understanding student needs and expectations is a necessary step in steering retention strategies. For this study we utilized a slightly tailored version of the Assessing Women and Men in Engineering (AWE) "Persisting in Engineering" survey [64]. We created the survey using Qualtrics software, and we sent the survey link to all undergraduate students (approximately 1700 students) in the College of Engineering via e-mail. After reminder e-mails and announcements in the weekly engineering newsletter, the effort resulted in a total of 344 completed surveys, offering insight into individual student perceptions and experiences. The survey collected 136 variables for each student respondent, including the student record data for demographics, pre-college academic performance, cumulative academic performance, and financial support, as well as self-reported variables such as incoming preparedness and confidence, campus involvement, and perceptions of faculty and student interactions.

Participants consisted of 344 engineering college students at a moderately sized research university in the Midwest U.S. The mean age of participants was 22.3 (SD = 5.5). A majority (78.8%) of participants were male. Just over half (53.8%) of the respondents were classified as white non-Hispanic, followed by International students (20.3%) Almost one-third (30.8%) of participants were first generation students. The majority of respondents were seniors (37.2%), followed by juniors (23.8%), sophomores (20.9%), and finally freshmen (18.0%). Most of the survey respondents were mechanical (27.6%) or aerospace engineering (21.8%), followed by biomedical (11.9%) and computer science (11.6%). Under 10% of the respondents fell into each of the remaining disciplines of engineering (Figure 4.1). The majority of the students were in high school immediately before entering this university (57%), while 18% came from a 2-year college. The remaining 25% were at a 4-year college, vocational or technical school, in the military, working, or other (Figure 4.2).

This survey was conducted to gather data and information on student perceptions to help the College of Engineering (CoE) at a case study university to identify areas of current excellence as well as opportunities for improvement in its retention strategies. Ultimately, the results of the study can help steer recruitment and retention efforts. The original scope of the study included students currently enrolled in the College of Engineering and students who had recently left the College of Engineering before degree completion. Results from the survey of non-persisting students would help identify reasons for why students left and therefore provide insight on what the college can do to prevent other students from leaving for these same reasons. Additionally, we can make comparisons between students who have persisted thus far and students who have left the College of Engineering, to assist in the identification of students at risk of attrition. Unfortunately, the response rate for non-persisting students was so low, that we were unable to make any statistical or generalizable conclusions on the results. However, the survey results of the students currently enrolled in the College of Engineering still provide important insight and feedback that can help guide future recruitment and retention efforts.

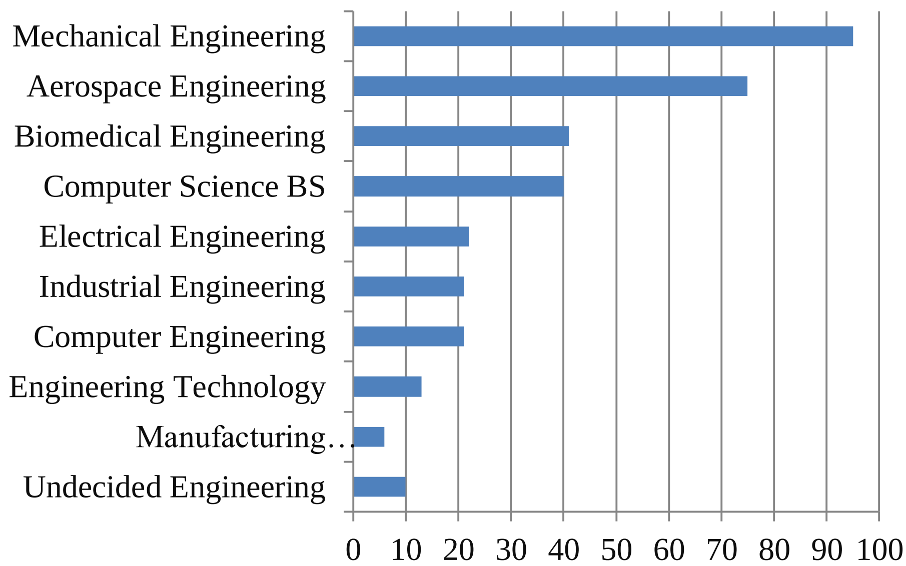

Figure 4.1. Percentage of survey respondents by major.

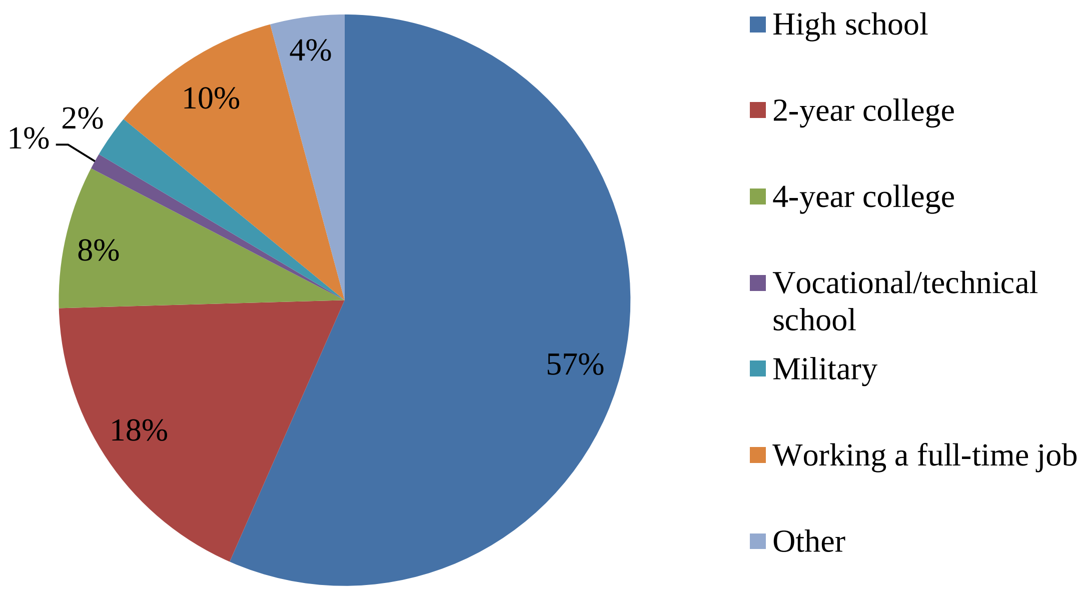

Figure 4.2. Background immediately before first semester at this university.

4.4.3 Analyze

After defining the problem and measuring the current state, the next phase in the DMAIC approach is to Analyze the process. We perform our analysis based on the measurements taken in the previous phase along with some additional Six Sigma tools and statistical methods including a cause and effect diagram, frequency tables and charts, Pareto chart, and bivariate correlation analysis.

Cause and Effect Diagram (Fishbone Diagram): The Cause and Effect Diagram aims to determine root cause. As numerous studies have been conducted on reasons for attrition, our fishbone diagram aims to tie together some of the well-documented reasons for leaving and the student attributes that serve as predictors for attrition. It should be noted that the fishbone diagram is used as a brainstorming technique, so the relationships shown are not necessarily validated by the data, but serve as a guide to *gather* data. Broad categories from review of the literature were used as the major causes of the fishbone diagram in place of the generally used manufacturing-based causes of measurements, materials, personnel, environment, methods, and machines. A previous study [56] identified student attributes that served as predictors for retention at this College of Engineering (Table 4.2). The same student attributes fill in the spines of the fishbone diagram. An interesting observation in the construction of the cause and effect diagram was the circular relationship among many of the student attributes within the major causes for attrition (Figure 4.3). For example, one major source for attrition may be "Student/Degree Match", meaning that either engineering is not a good fit for the student or that the student feels it is not a good fit. A student's cumulative GPA may be an *indicator* that engineering is not a good fit OR it may be the reason the student *perceives* that engineering is not a good fit. Likewise GPA may be an *indicator* of unpreparedness in the current and past curriculum, but it is also likely to be an *outcome* of unpreparedness for future coursework.

TABLE 4.2. ATTRIBUTES WITH STATISTICALLY SIGNIFICANT RELATIONSHIP TO RETENTION

1. CUM_GPA	Cumulative GPA at end of 1^{st} term
2. MATH_GPA	Math GPA at end of 1^{st} term
3. CUM_HRS	Cumulative earned hours end of 1^{st} term
4. INCS	Calculated score based on ACT/SAT and High School GPA
5. ACT_MATH	ACT Math score
6. FR_HRS	Freshman enrolled hours end of 1^{st} term
7. CRED	Total credits to student
8. MATH	Highest math course in first year
9. AGE	Age (20^{th} day)
10. COST_1^{ST}	Student net cost 1^{st} term
11. FINAID_AMT	Financial Aid semester award amount
12. FINAID_ACCPT	Financial Aid offer accepted (yes/no)
13. EFC	EFC income levels

Frequency Tables and Charts: We analyzed the results of the survey using IBM SPSS Software and Microsoft Excel. We summarized the results for each question on the survey, created appropriate charts and graphs to visualize the results, and then analyzed the results to identify any significant findings. For example, Table 4.3 shows the aggregate results of student perceptions of various factors related to the engineering program. The questions were based on a 5-point Likert scale for level of agreement, but were truncated into a 3-point scale for ease of analysis. Table 4.2 shows the results in increasing order of agreement such that the first item has the lowest level of agreement and therefore the most opportunity for improvement in terms of possible gain. Administration and college decision-makers must then balance those opportunities with the resources required to make those gains. For this case study, we may want to focus on the top 5 items as a start and consider what efforts can be, and are being, made to improve those areas. For example, if we look at the first item, which has the lowest level of agreement, we see that many students do not feel that they have the ability to find satisfactory co-ops and/or internships.

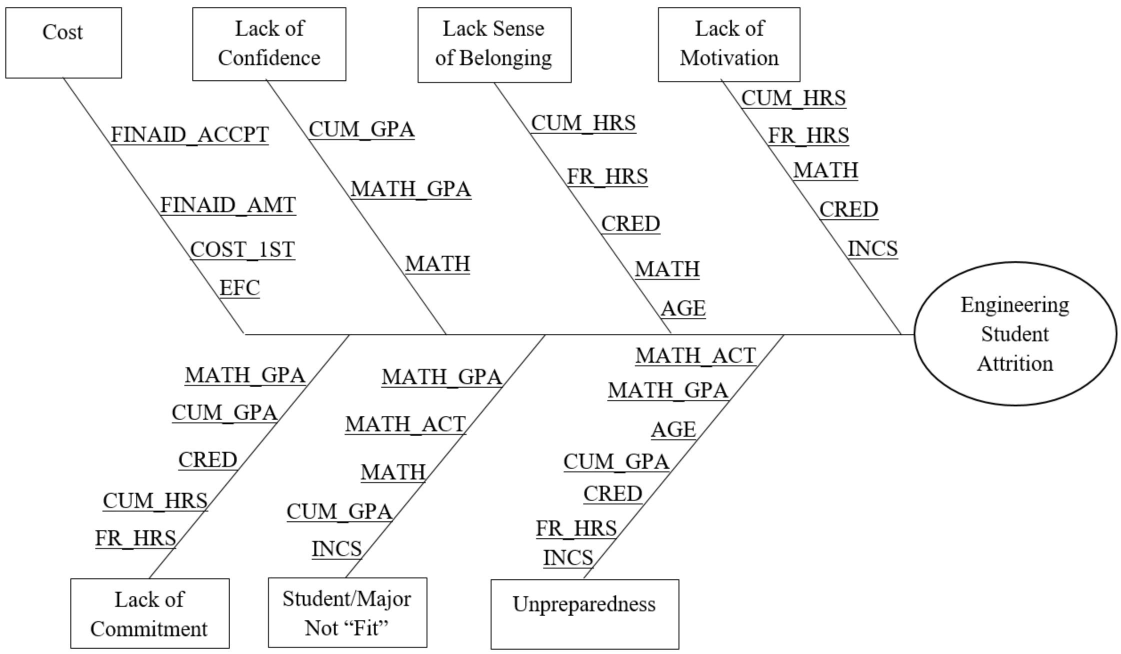

Figure 4.3. Cause and effect diagram.

There may be two main sources for disagreement with this statement: (1) There is dissatisfaction due to a lack of co-op/internship opportunities, or (2) Students are not aware of the co-op/internship opportunities. Some background knowledge and intuition can help guide the analysis further. The case study city is a hub for the industry of aircraft manufacturing. As such, some large companies, which provide co-ops and internships to our students, also have military agreements and therefore, require the employees and even student workers to be U.S. citizens. Since the case study university has a large international student population within the College of Engineering, we looked at this specific question at the residency level to see if the dissatisfaction was primarily among international students. However, as can be seen in Table

4.3, this was not the case. As mentioned, another possibility of dissatisfaction is that students are simply unaware of the opportunities that exist. Since the university's Career Development Center is responsible for coordinating with local industry and making co-ops and internships available to students, this result can and will be passed along to the College of Engineering representative within the organization to determine what they can do to help increase awareness and satisfaction with co-op and internship opportunities. The second item on the list for least agreement is "Faculty help me understand what practicing engineers do." One of the current efforts within the College of Engineering is to train faculty on promoting an entrepreneurial mindset. The college has recently sent many of their faculty members to conferences and training specifically focused on incorporating collaborative learning and project-based-learning (PBL) into the classroom and encouraging curiosity, connections, and value creation. These are principles of the Kern Entrepreneurial Engineering Network (KEEN). The second and fifth items in Table 4.3 provide evidence of the importance for faculty training on promoting applied and collaborative learning.

Many of the findings were positive, providing evidence of the success and effectiveness of the college's current efforts. For example, the results in Table 4.5 reveal that over 87% of the students who took the survey are at least fairly confident that they will complete an engineering degree at this university. However, it is important to remember that only 18% of the survey respondents were freshmen, so most of the students in this sample had already passed the first-year threshold for retention.

TABLE 4.3. LEVEL OF AGREEMENT WITH STATEMENTS

The following are statements related to your engineering education experience. For each statement, please select your level agreement.	**Agree**	**Neutral**	**Disagree**
I have the ability to find satisfactory co-ops and/or internships	44.7%	33.1%	22.2%
Faculty help me understand what practicing engineers do	45.4%	22.8%	31.8%
I've had sufficient opportunities for financial aid or scholarships	51.3%	18.9%	29.8%
Engineering faculty/departmental personnel show an interest in me	54.6%	22.2%	23.2%
Overall, I have had positive experiences in design teams or other collaborative learning experiences in engineering	55.0%	32.1%	12.9%
The workload of the engineering classes is reasonable	56.6%	18.2%	25.2%
Academic advising by engineering faculty or advisers is effective	61.3%	16.9%	21.9%
The engineering faculty, instructors, or graduate assistants provide good teaching	63.9%	18.2%	17.9%
My engineering coursework grades are satisfactory	65.2%	17.5%	17.2%
The climate in engineering classes is friendly	66.9%	22.5%	10.6%
I am confident of succeeding in engineering future classes	80.8%	12.9%	6.3%
My personal abilities/talents "fit" the requirements in engineering	82.5%	14.2%	3.3%
Overall, I have had positive interactions with other engineering students	84.8%	10.9%	4.3%

TABLE 4.4. CO-OP/INTERNSHIP AVAILABILITY SATISFACTION BY RESIDENCY

I have the ability to find satisfactory co-ops and/or internships	Agree	Neutral	Disagree
International Student	38.2%	32.7%	29.1%
Out-of-State Student	58.8%	26.5%	14.7%
In-State Student	44.1%	34.3%	21.6%

TABLE 4.5. CONFIDENT IN ENGINEERING DEGREE COMPLETION AT THIS UNIVERSITY

At the present time, how confident are you that you will complete an engineering degree at this university?	Valid Percent
Not very confident; it is highly likely I will not complete an engineering degree at this university	3.1%
There is about a 50% chance that I will complete an engineering degree at this university	9.8%
I am fairly confident (greater than 50%) that I will complete an engineering degree at this university	29.2%
I am very confident that I will complete an engineering degree at this university	57.8%

From the frequency tables, we created charts to serve as visual representations of the data. One of the significant findings from this process was the number of students who were either "unaware" or "aware, but did not participate in" various activities within the college. Figure 4.4 shows the results for the following survey question: "The following is a list of engineering activities (co-curricular and academic). For each activity indicate your level of involvement during the current academic year (e.g., August to May)." The College of Engineering offers a variety of programs, student organizations, and activities to engage students and promote social and academic integration within the college. However, it is alarming that "unfamiliar activity" and "aware of activity, but not involved" were the top two responses for seven of the nine listed opportunities. This is a significant finding that can help direct retention efforts. If we develop and implement high-quality retention programs, but the students are not aware those programs exist, we cannot get our return on investment. Additionally, if students are aware of activities and programs, but are not involved in them, we are not reaping the benefits of our invested efforts and resources to create and run those programs and activities. This finding suggests that we need to improve the "marketing" of the resources and programs available to our students.

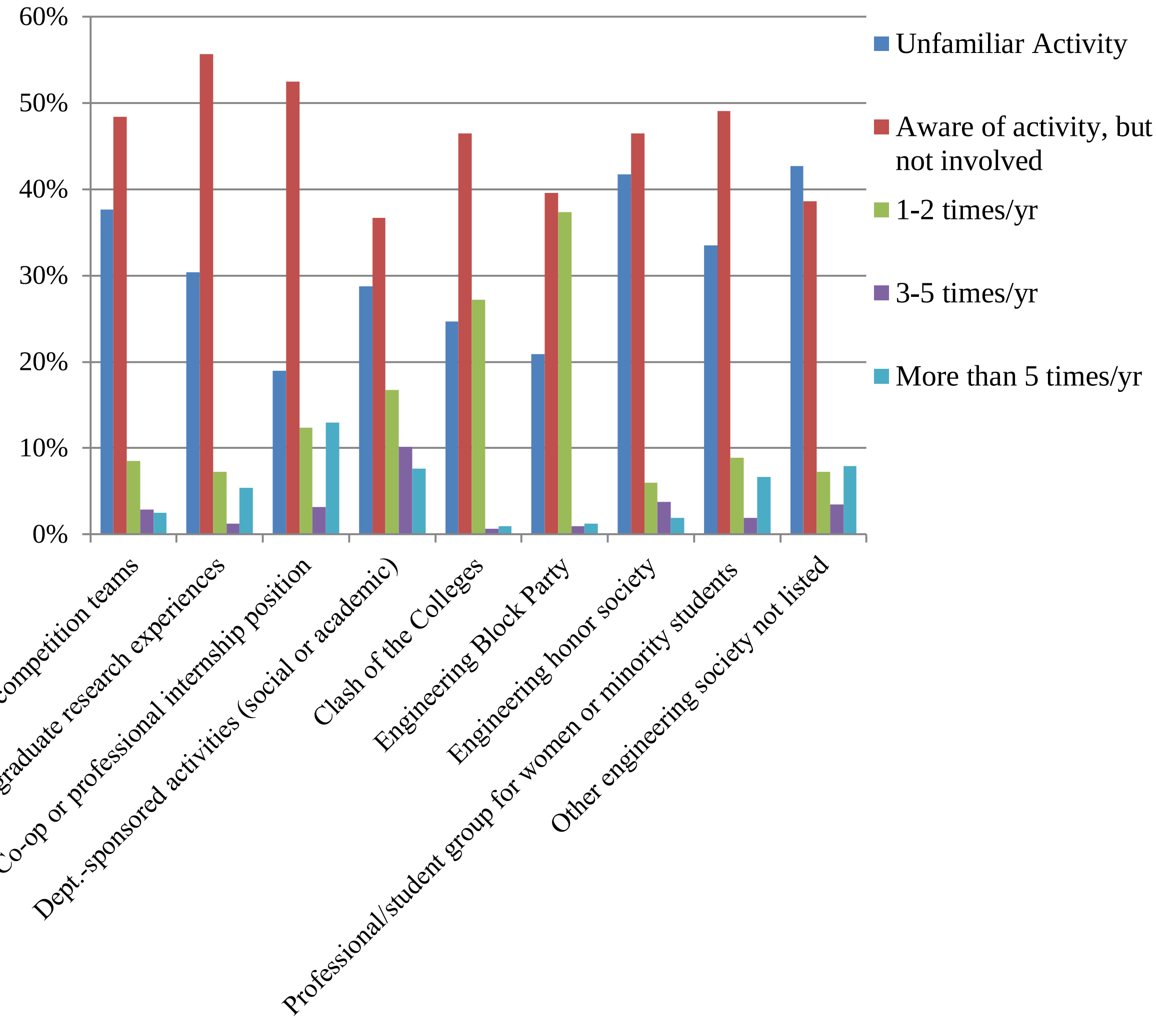

Figure 4.4. Responses to indication of level of involvement during current academic year.

***Department Comparisons*:** Additionally, we created frequency tables by department for questions that related to department faculty or advising in order to determine if there were differences between departments. Some examples of questions that may vary by department are as follows: The following are statements related to your engineering education experience. For each statement, please select your level of agreement (from “strongly agree” to “strongly disagree”).

1. Engineering faculty/ departmental personnel show an interest in me
2. Faculty help me understand what practicing engineers do
3. The engineering faculty, instructors, or graduate assistants provide good teaching
4. Academic advising by engineering faculty or advisers is effective

Differences by department can lead to identification of areas for improvement. For example if one department was rated high for the questions above, we can look into what specifically that department may be doing differently that helps students understand what practicing engineers do or how the teaching styles/department atmospheres promote and demonstrate interest in the students. A separate root cause analysis for departments scoring lower on these types of questions could lead to significant findings, which could be addressed and have opportunity for impact on student retention.

Compilation of Responses to Open-Ended Questions: There were two main open-ended questions aimed at gaining insight into student perceptions related to retention. The questions were as follows: (1) “What is the one biggest factor that helps you persist in your study of engineering?” and (2) “What could the College of Engineering or your engineering department do to make the study of engineering more enjoyable or satisfying?” Results of each question are discussed in the subsections below.

Analysis: What is the one biggest factor that helps you persist in your study of engineering?

Of the 344 survey participants, 224 provided a response to this question. Upon evaluation of the responses, we observed thirteen major categories that encapsulated all of the responses. The results are summarized verbally in this paragraph and visibly through Figure 4.5.

The top factor, for which 19.8% of the respondents attributed to being the biggest factor in their persistence in engineering, was intrinsic motivation. We only included responses in this category that specifically stated determination, tenacity, motivation, stubbornness or drive to succeed in and of itself, without the source of that determination or motivation being attributed to another factor (e.g. one of the other twelve categories). The second highest response category, holding 15.8% of the responses, included reasons related to persistence toward a future career and/or the financial security that the career would bring. The third highest source of persistence related to a general interest in the field of engineering or specific engineering discipline, and College of Engineering student respondents was the idea that the student was too far in with their investment of time and/or money to not finish the engineering degree. This idea of having *too much invested to quit now* was the strongest contributing factor to degree persistence for 10.1% of the question's respondents. The next four highest frequency responses were having a support group, the desire to make an impact, the degree in and of itself, and family, with percentages of 7.9, 5.7, 5.7, and 5.3, respectively. The category of support group included having the support of family, faculty, friends, or classmates, whereas the category of family captured the responses related to not wanting to let family down or providing financial support for family. Figure 4.5 shows the remaining five categories, which included less than 5% of the responses each. These results can help guide specific strategies for the "Improve" phase of DMAIC. As shown in the Measure phase, 82% of the survey respondents were either sophomores, juniors, or seniors. Therefore, the vast majority of the responses are from the students who have persisted past the threshold of 3rd semester enrollment. The analysis of these results should then revolve around how we can increase these factors among the students who have not persisted.

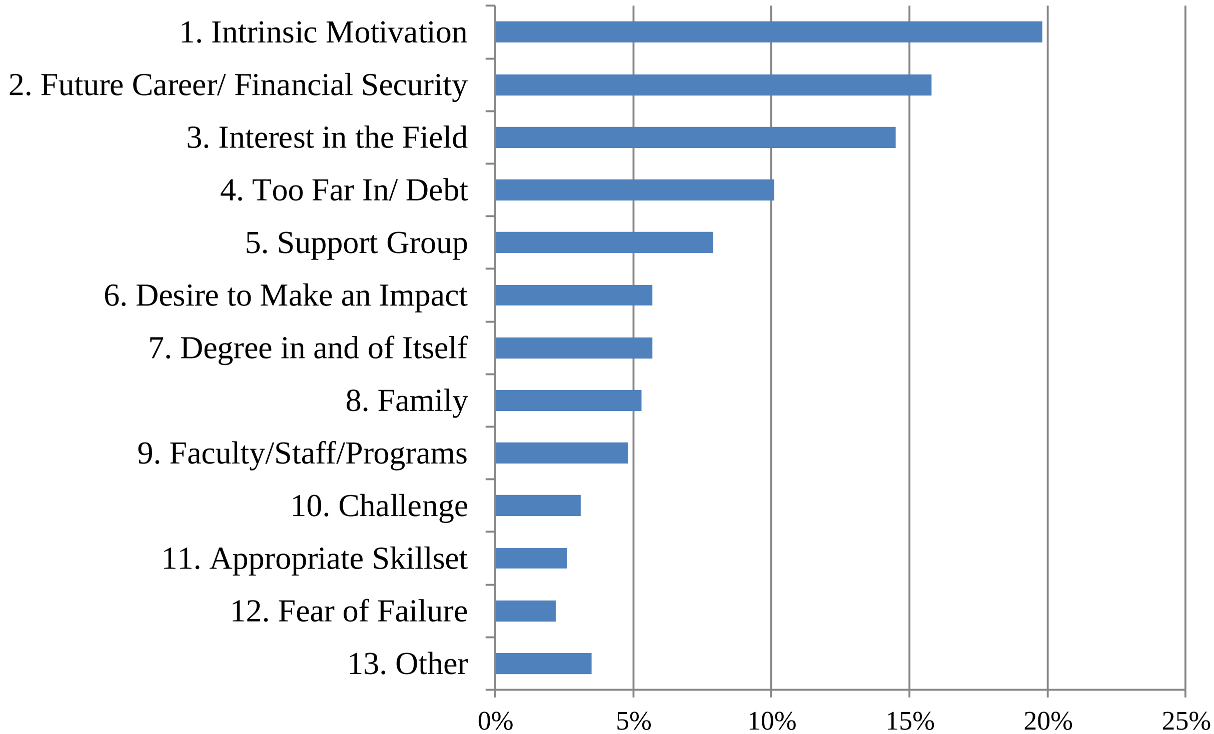

Figure 4.5. Biggest factor in engineering degree persistence according to responses from open-ended survey question.

Based on this sample, the primary reason for persisting in the engineering program was most frequently reported as intrinsic motivation. We must ask ourselves then, can we as the College of Engineering, increase student intrinsic motivation? If so, how? This question, in and of itself, could lead to an entirely new literature review and future study. Clearly, one of the greatest opportunities that falls directly under the college's control is the ninth item on the list. Faculty, staff, and programs have made the list as being one of the biggest factors in engineering degree persistence. In fact, 4.8% of the students who responded to the question stated that the single biggest factor in persisting in engineering was either faculty, staff, or programs offered. By analyzing individual responses, we can get a better idea of specifically what is working well—for example college tutoring, online resource, and encouragement of faculty and advisers.

Specific recommendations for improvement utilizing this analysis will be made in the Improve phase.

Analysis: What could the College of Engineering or your engineering department do to make the study of engineering more enjoyable or satisfying?

This was the last question on the survey and allowed for anywhere from a one-word statement to an essay-type response. Of the 344 survey participants, 197 provided a response to this question. The responses were analyzed similar to the process for the previous open-ended question, resulting in twelve major categories. The number one opportunity for improvement (25.9%) was in the area of faculty and staff. Individual answers range in content as most responses mention teaching ability or quality, but some mentioned advising quality, some mention faculty availability, and some mention relational skills. The second opportunity for improvement as voiced by the students (12.7%) was inclusion of hands-on application opportunities. The third highest response were answers that specifically stated "nothing" or "everything is good" (12.2%). It should be noted that non-responses were not included in totals described here. The fourth highest category of response was course/degree requirements (9.6%), followed by cost/financial assistance (7.1%), resources (6.6%), course structure/content (5.6%), non-traditional student support (5.1%), social activities (4.6%), Engineer of 2020 program (3.0%) and guidance (1.5%). An additional 12 responses fell into the "other" category (6.1%.). Some of these responses were too vague to interpret the meaning or they were simply a single response falling into a category of their own. The responses should still be viewed be considered for analysis, but are not reported here at the aggregate level.

Clearly, the most frequently mentioned opportunity for improvement in this group of responses was faculty and staff. It had more than double the amount of the second most mentioned improvement opportunity. The third most frequent response was that nothing could make the study of engineering more enjoyable or satisfying, and the remaining responses were broadly spread across the other categories with less than 10% of the responses falling into each category. To guide prioritization for later recommendations in the Improve phase, a Pareto chart was created to show the top frequency responses and the cumulative percentages when addressing each topic from the highest rank to the lowest rank. The result is shown in Figure 4.7. Generally, the top 80% of the data will fall within the first 20% of the categories, meaning that if we address the top 20% of the categories, we can address 80% of the issues. Clearly, the most frequently mentioned opportunity for improvement in this group of responses was faculty and staff. It had more than double the amount of the second most mentioned improvement opportunity. The third most frequent response was that nothing could make the study of engineering more enjoyable or satisfying, and the remaining responses were broadly spread across the other categories with less than 10% of the responses falling into each category. Therefore, if we wanted to address 80% of the issues, we would have to impact the first seven categories. That may not be feasible in a first-step plan. However, by addressing just the top three issues, we can address just over half (50.8%) of the responses. Moreover, since the third highest category requires no action, we can address over half of the responses by considering faculty/staff and hands-on/application. This finding will guide recommendations for the Improve phase.

Bivariate Correlation: As another step toward the analysis of the survey results, we created a bivariate correlation table across all 136 variables and analyzed the Pearson correlation coefficients where applicable. One of the significant findings of that analysis was the number of variables that had a relationship with the following question: "My high school coursework adequately prepared me to be successful in an engineering curriculum (strongly agree; somewhat agree; neither agree nor disagree; somewhat disagree; strongly disagree)". A concurrent study addresses the implications of this result.

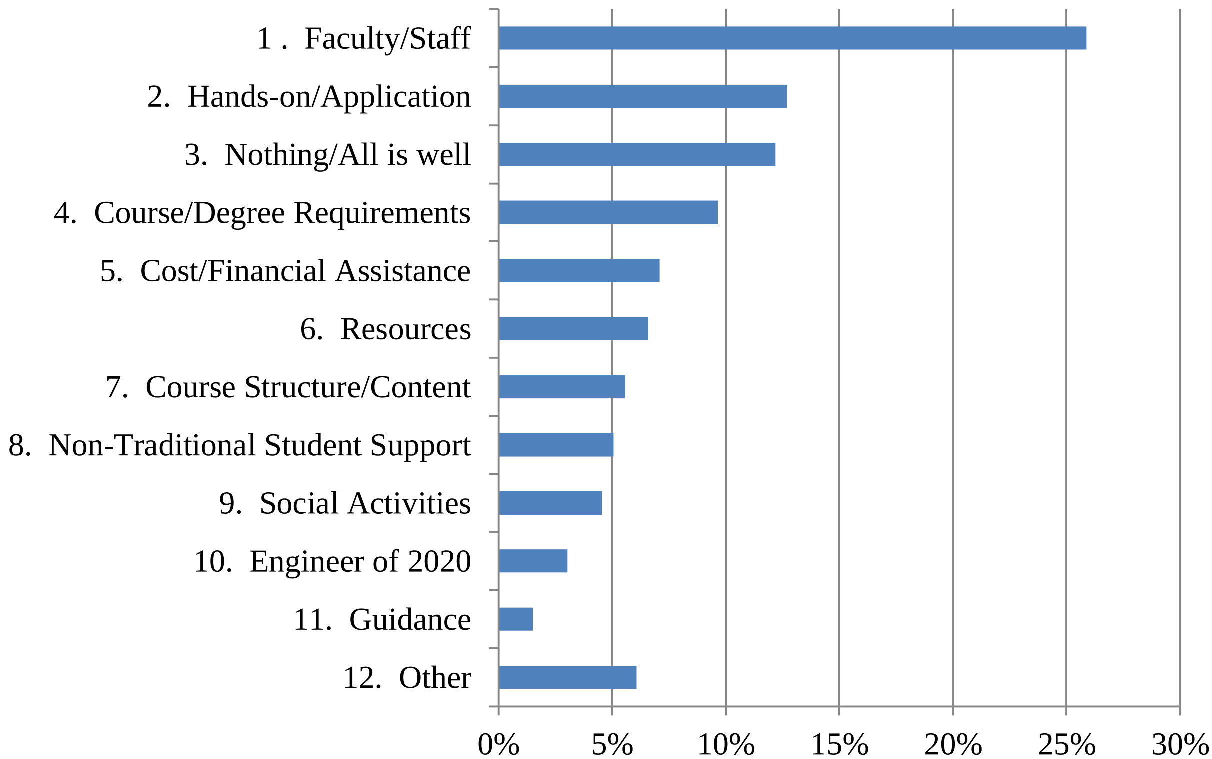

Figure 4.6. What CoE could do to make study of engineering more enjoyable or satisfying.

4.4.4 Improve

Utilizing the results from the Measure and Analyze phase, we can recommend some recommendations for improvement, more specifically, toward the increase in engineering student retention. First, we go back to the original benchmarking process in the Measure phase. The College of Engineering was missing two of the seven best practices in engineering student retention. One of two missing programs was an engineering summer bridge program. The concurrent study provides details on the bivariate correlation analysis of the survey results and specific student attributes, attitudes, perceptions, and experience related to unpreparedness. Based on that analysis, it is recommended that a summer bridge program be prioritized as a retention effort if funding can be obtained.

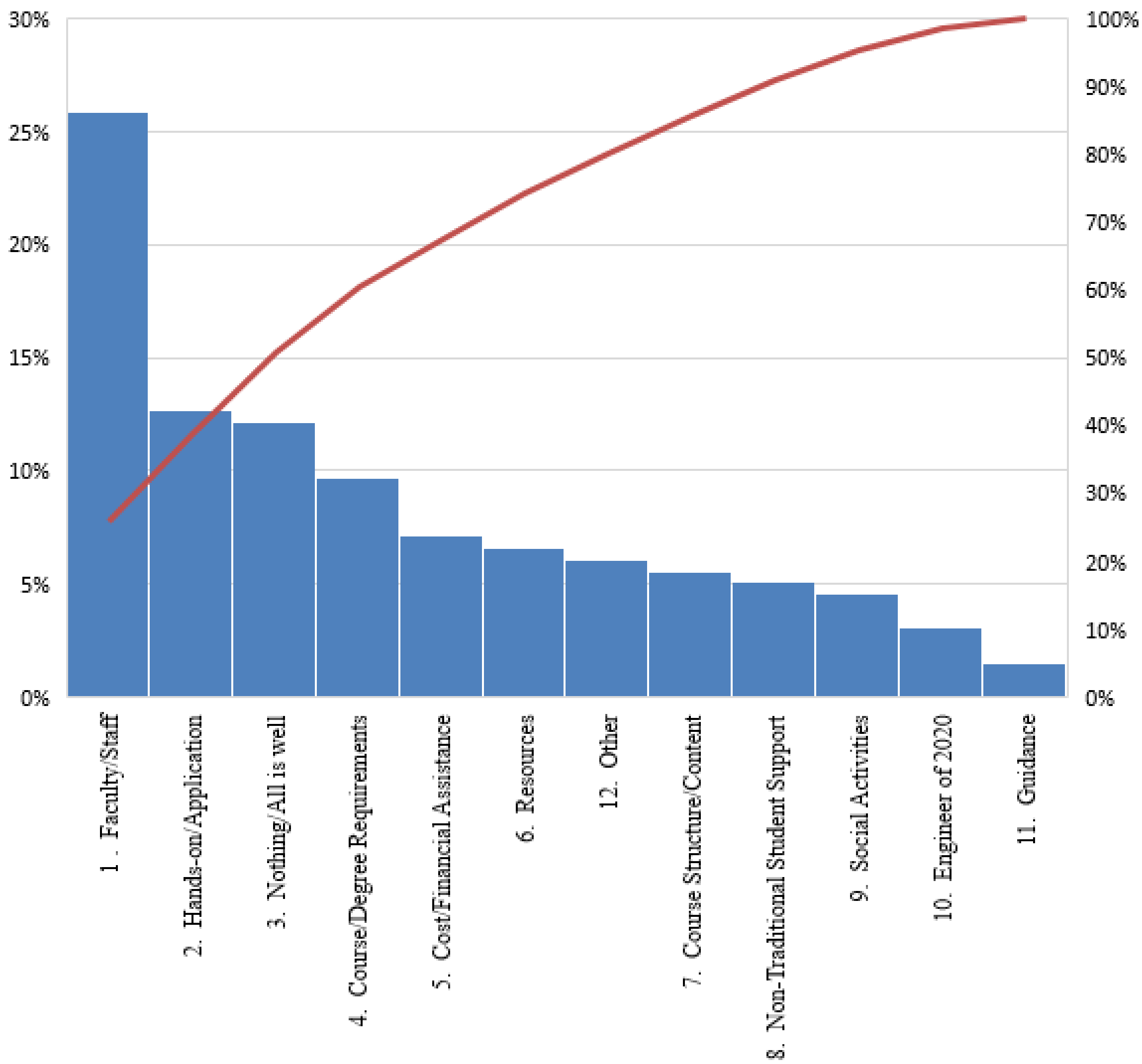

Figure 4.7. Pareto chart of what CoE could do to make study of engineering more enjoyable or satisfying.

The other best practice retention program that the College of Engineering does not have is the strategic placement of select faculty members as instructors for first and second year courses. The benchmark for this type of program was the “Keystone Program” at the University of Maryland. The idea of the program is to strategically place key faculty members in the role of the first and second year fundamental courses of engineering. Faculty members are selected based on their teaching abilities, rapport with students, and specific interest in undergraduate students and the corresponding course material. Data from the Analyze phase provides evidence of the possible high impact of implementing such a program. As Figure 4.6 shows, the top recommendation for making the study of engineering more enjoyable or satisfying involves faculty and staff. In fact, focusing on faculty and staff would address over one-fourth (25.9%) of the responses to the corresponding question. Additionally, from Table 3 in the Analyze phase, two of the top four statements that had the least level of agreement were “Faculty help me understand what practicing engineers do” and “Engineering faculty/departmental personnel show an interest in me.” In fact, “Faculty help me understand what practicing engineers do” had the highest level of disagreement. It is important to remember that the survey respondents are primarily those students who have persisted, so if those students are suggesting faculty/staff as a primary area for improvement, it is likely that faculty/staff may have been a factor in student departure from engineering. Placing key instructors early in the engineering curriculum has the potential to have a positive impact on getting students past that first-year threshold of high attrition. This gives students time to integrate academically and socially into the College of Engineering and decrease risk of attrition. However, we must also improve the quality of instruction, the hands-on applications, and the student/faculty relationships beyond just the first two years. As mentioned in the Analyze phase along with the discussion of Table 4.3 results, the

College of Engineering has recently placed focus on encouraging an entrepreneurial mindset, curiosity, connections, and creating value, and implementing project-based learning (PBL) as promoted by the Kern Entrepreneurial Engineering Network. When asked about plans for the future, over one-fourth of the survey participants (26.2%) selected "participate in business start-up or start my own business," which offers further evidence of the value of the entrepreneurial mindset. These efforts should continue and seek to extend to faculty across all departments at all course levels.

Although the results of the survey provide evidence of the possible high impact of implementing the two missing best practices programs, we must consider the impact of our existing programs. These best practice programs were at seven different universities. It would be quite rare to find a school with each type of retention program, and if found, it likely that not all programs would be to the quality and effectiveness of these best practice examples. The final improvement recommendation, therefore, addresses the existing retention programs at the College of Engineering. As observed in Figure 4.4 of the Analyze phase, it is surprising to see the percentage of students who are either unaware of college activities and programs, or are aware but did not participate. The first recommendation, therefore, is to improve the marketing and visibility of the programs and activities currently available. How to improve the marketing and visibility is another project and topic of research on its own, but the topic should be addressed to ensure opportunity for a return on the investment of existing programs. Two of the highest attended activities according to the survey were Clash of the Colleges and Engineering Block Party. This may be a good starting point to investigate how those events are announced and publicized. Almost 40% of the respondents reported involvement with the Engineering Block Party, and almost 30% reported involvement with the Clash of the Colleges.

The second recommendation related to the improvement of existing programs, which will also be necessary for the Control phase, is the development of a program assessment strategy. A standard method for evaluating program effectiveness should be implemented and maintained. Program participants should be tracked systematically. It may also be valuable to conduct pre- and post-program surveys. If a new retention program is implemented, consideration of its assessment criteria and assessment method should be considered and included into the overall retention assessment strategy.

4.4.5 Control

The final phase in the DMAIC process is Control. After improvements have been made, there must be a system in place to control the process, ensuring that the gains are not made in a single stride and then left to slide back to the pre-DMAIC state. There should be opportunity for continuous improvement. If retention rates, for example, are increased based on process improvements, we must ensure we have procedures in place to control that level of retention and ultimately increase further.

The last set of recommendations in the Improve phase focus on creating a program assessment strategy. This idea is critical to efficiently control the retention process. We need to understand our process in order to control it. If we do not have an objective method to assess the programs we currently have or create in the future, overall student retention may decrease or increase, but we will not have a way to determine what is causing that fluctuation.

4.5 Conclusions

This study contributes to the literature in three major aspects. First, it demonstrates the application of DMAIC to a case study student retention effort. This application of DMAIC is rare in the current literature. Second, the study exhibits the use of ASEE's report of best practices in engineering student retention as a benchmarking tool for individual institution retention programs. Last, it displays the use of the Assessing Women and Men in Engineering (AWE) "Persisting in Engineering" survey as a source for collecting valuable student data to guide retention strategies. The AWE program, made possible by a National Science Foundation (NSF) grant, created a "Persisting in Engineering" survey and "Leaving Engineering" survey to gather information on why students persist in engineering and why students leave engineering (AWE, © 2007). The surveys are presented in standard format so that engineering colleges nationwide can use them as-is, and if results are shared, data can be combined, compared, and contrasted. The current work demonstrates how the application of three standard tools—DMAIC, ASEE best-practices report, and AWE "Persisting in Engineering" and "Leaving Engineering" surveys—can help steer engineering student retention efforts. Utilizing these three methods, we were able to Define the problem and associated objectives and scope, Measure the current state, Analyze the current retention programs and voice of the customers (students), offer recommendations to Improve the retention efforts at a case study university, and recommend a strategy to Control the process once improvements are made.

CHAPTER 5

RESULTS AND CONCLUSIONS

Each of the three studies of this dissertation served their own individual objectives to address different aspects of engineering student retention. Though hundreds of studies have been conducted on various pieces of the puzzle of engineering student retention, this dissertation, as a whole, aimed to pull those various pieces together at a single case study university. The following discussion is an amalgamation of the overall results and conclusions derived upon through the course of the three studies.

The study in Chapter 2 introduced the probabilistic neural network to the application of engineering student attrition prediction. This study first identified 14 variables predictive of student attrition and utilized those variables to create three different prediction models—logistic regression (LR), a multi-layer perceptron (MLP), and a probabilistic neural network (PNN). Results showed that the multi-layer perceptron had the highest accuracy in predictability and also the greatest specificity (probability of correctly detecting a retained student). However, the probabilistic neural network had the highest sensitivity (probability of correctly detecting a non-retained student). The study contributed to the literature by introducing the use of a probabilistic neural network for predicting student attrition. Although the accuracy and sensitivity of the PNN were not as high as the MLP or LR, the PNN had the highest level of sensitivity. Therefore, the PNN should be considered for future use and refinement in the application of attrition prediction.

Chapter 3 provided an objective mixed model approach to the assessment of a case study retention program. The study evaluated effectiveness of a summer bridge program quantitatively by comparing the bridge program participant population to a stratified random sample of non-participants from respective cohorts. The overall percentage of bridge participants retained into their third semester was compared to percentage of the stratified sample of non-participants retained into their third semester. Results showed that the bridge students were retained at a statistically significant higher rate than their non-participant counterparts. The Chapter 3 study also utilized qualitative data from a student survey to provide further evidence of the possible impacts of a summer bridge program on engineering student retention. The combined qualitative and quantitative results suggest that the case study summer bridge program was effective in its objective of increasing engineering student retention.

Chapter 4 applied the Six Sigma DMAIC approach to address engineering student retention for the case study College of Engineering. The study provided a model by which three standardized tools can be used for strategic engineering student retention planning. The three tools were DMAIC, ASEE's best practices in engineering retention report [49], and AWE's "Persisting in Engineering" and "Leaving Engineering" surveys [62]. The study went through each phase of DMAIC utilizing the actual data collected through benchmarking with the best practices report and through the college-wide survey. Based on the Define, Measure, and Analyze phases of the DMAIC process, practical recommendations for Improve and Control were made.

Some of the major observations and inferences made through the completion of this dissertation are not necessarily in the reported conclusions of each study. One of the most difficult aspects of the topic of student retention is that the problem itself is dynamic and ever-changing. Literature reviews can serve as a source for ideas of what other researchers have found, and may serve as a baseline for the identification of student attributes predictive of attrition, for creation of prediction models, for development of retention programs, and for assessment of retention programs. However, as populations of students are different, results from other studies can serve as a guide, but must be tailored to the specific population of students. Even within a given student population, the variables and constraints are dynamic, and as soon as a snapshot in time is taken of the population, those variables begin changing. GPA will change from semester to semester. Students will graduate, students will drop out, students will change majors or transfer out of the college; in the meantime, other students are entering, some are coming in as freshmen, while others are transferring in from other colleges. Even the students remaining in the college are changing; they are aging, having children, getting married or divorced, moving, getting jobs, losing jobs. There are administration changes, faculty changes, and curriculum changes. Any system to measure students and student attributes must be as dynamic as the student population itself. A low-risk student this semester may be a high-risk student next semester due to the volatility of the population itself. There are circular relationships among many of the predictive attributes of students. For example, a student who enters the college unprepared for the rigors of the engineering curriculum may not be prepared to get through calculus. If the student struggles through calculus, he or she may continue the subsequent courses unprepared. There is interconnectivity among the student attributes. The unprepared student described here will likely lose confidence and may begin feeling that engineering is not a good fit. Meanwhile, GPA is dropping, reinforcing the feelings of lack of fit and lack of confidence, and reducing the sense of belonging.

Systems for identifying at-risk students must consider numerous student factors and must be fluid enough to change as the students change. The system must be updated at nearly real-time increments as attrition risk can change that quickly as well. Methods for assessment must also be standardized and performed on a routine basis in order to ensure accurate evaluation of the program and its effectiveness. Student needs and expectations should be considered and utilized to guide retention programs and efforts. It should be noted that the case study university itself has made great strides toward this effort of creating a dynamic real-time system for monitoring risk. As described with the DMAIC process, we just need to make sure that we utilize the measurements provided to properly intervene in a timely manner in order to ensure improvement, and those actions must become part of our routine procedures in order to control and make continuous improvements. Efforts being made at the university level must trickle down to the individual colleges and departments, and there should be consistency among the departments. New faculty and staff should be trained on how to effectively utilize the systems that have been put in place.

Although systems for attrition risk identification are necessary, and well-planned, highly structured retention programs can have a high impact on student persistence, there is much that can be done at the individual faculty and staff level with minimal effort and no cost. As faculty, I can make a connection with my individual students. I can remember my students' names, and make an effort to help them understand what engineers do and how their coursework can be utilized in the real world. I can promote academic and social integration by offering opportunities for collaboration in my classroom, encouraging participation in student activities and organizations. I can make connections between industry and academia that are beneficial to both entities. Through the course of this dissertation, I have discovered student factors that are related to attrition and some signs that those factors may be present. I have learned about the various retention programs that have been implemented and proven effective across the country. Ultimately, my knowledge of engineering student retention has expanded, and I take away from this study, practical ways in which I can make an effort to impact *my* world of engineering students.

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APPENDIXES

APPENDIXES

Appendix A

TABLE A.1. COEFFICIENTS & VARIABLES FOR LOGISTIC REGRESSION EQUATION

Variables		β values	
X_1	age	β_1	-0.183
X_2	poverty	β_2	1.181
X_3	efc_grp1	β_3	-0.498
X_4	efc_grp2	β_4	0.125
X_5	efc_grp3	β_5	0.948
X_6	efc_grp4	β_6	0.516
X_7	efc_grp5	β_7	-0.976
X_8	efc_grp6	β_8	0.190
X_9	efc_grp7	β_9	1.380
X_{10}	mcg_divl2	β_{10}	1.093
X_{11}	mcg_divl3	β_{11}	-20.317
X_{12}	mcg_divl4	β_{12}	-0.513
X_{13}	mcg_divl5	β_{13}	0.625
X_{14}	mcg_divl6	β_{14}	0.522
X_{15}	mcg_divl7	β_{15}	-0.623
X_{16}	mcg_divl8	β_{16}	2.166
X_{17}	mcg_divl9	β_{17}	1.791
X_{18}	ACTsatmathimp	β_{18}	0.059
X_{19}	INCSR100	β_{19}	-0.034
X_{20}	fhrse	β_{20}	0.253
X_{21}	cgpaef	β_{21}	1.701
X_{22}	cehrsef	β_{22}	0.021
X_{23}	finaidf	β_{23}	-0.703
X_{24}	finaidamtf	β_{24}	0.000
X_{25}	SARDnetcost	β_{25}	0.000
X_{26}	SARDcredits	β_{26}	0.000
X_{27}	MATHcrs1	β_{27}	0.162
X_{28}	MATHcrs2	β_{28}	0.171
X_{29}	MATHcrs3	β_{29}	1.213
X_{30}	MATHcrs4	β_{30}	1.113
X_{31}	MATHcrs5	β_{31}	19.168
X_{32}	MATHgpaadj	β_{32}	0.028

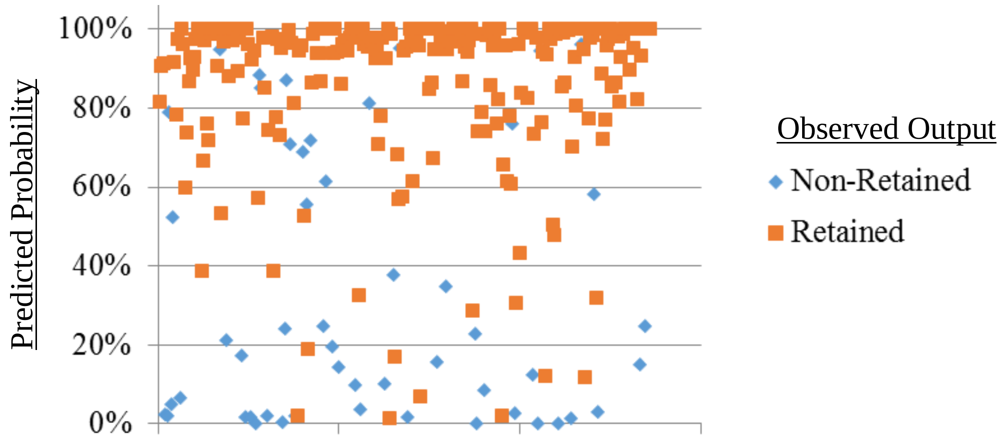

Figure A.1. Logistic regression scatter plot.

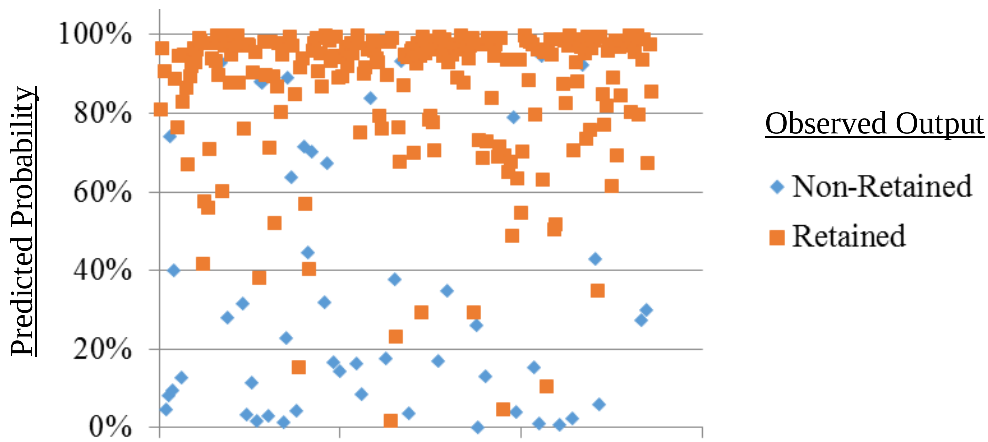

Figure A.2. Multi-layer perceptron scatter plot.

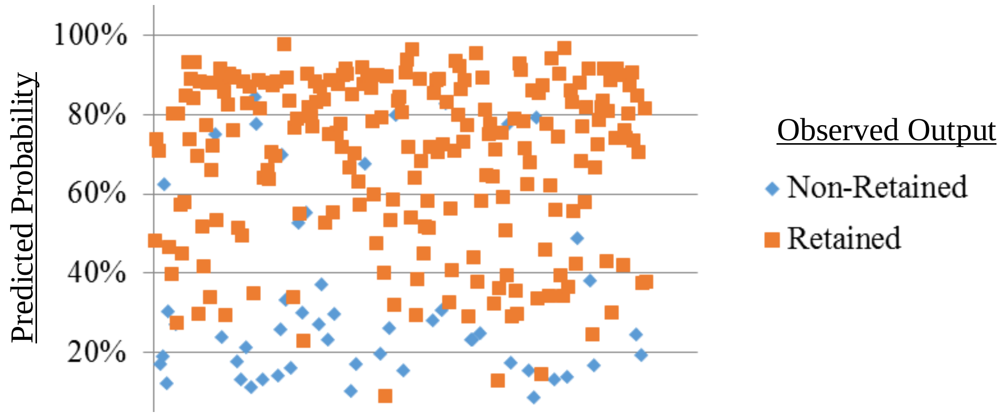

Figure A.3. Probabilistic neural network scatter plot.

Appendix B

TABLE B.1. CORRELATIONS WITH PREPAREDNESS (STUDENT RECORDS)

My high school coursework adequately prepared me to be successful in an engineering curriculum	**Pearson's R**
enrolled hours	-.206**
full time student	-.137*
cumulative GPA	-.296**
institute GPA	-.324**
transfer GPA	-.216**
transfer earned hours	.122*
history of undergraduate probation	.235**
ACT score	-.270**
Math ACT score	-.335**
INCS score	-.320**
max APAP sortest	.233**
remedial need	.183**
age at time of 20th day	.190**
race ethnicity reporting	-.204**
underserved student	.214**
first generation student	.185**
region	-.210**

**Correlation is significant at the 0.01 level * Correlation is significant at the 0.05 level

TABLE B.2. CORRELATIONS WITH PREPAREDNESS (PRE-COLLEGE)

My high school coursework adequately prepared me to be successful in an engineering curriculum	**Pearson's R**
Where were you immediately before your first semester/term at this university? (check one)	.176**
Is your current major the same major you had your first semester of college?	.109*
Check whether you completed a general section of the course, an advanced section of the course, or did not take the course in High School:-Algebra	-.302**
Check whether you completed a general section of the course, an advanced section of the course, or did not take the course in High School:-Computer Science	-.165**
Check whether you completed a general section of the course, an advanced section of the course, or did not take the course in High School:-Pre-Calculus	-.384**
Check whether you completed a general section of the course, an advanced section of the course, or did not take the course in High School:-Calculus	-.331**
Check whether you completed a general section of the course, an advanced section of the course, or did not take the course in High School:-Chemistry	-.220**
Check whether you completed a general section of the course, an advanced section of the course, or did not take the course in High School:-English	-.123*
Check whether you completed a general section of the course, an advanced section of the course, or did not take the course in High School:-Geometry	-.277**
Check whether you completed a general section of the course, an advanced section of the course, or did not take the course in High School:-Physics	-.332**
Check whether you completed a general section of the course, an advanced section of the course, or did not take the course in High School:-Trigonometry	-.298**

**Correlation is significant at the 0.01 level * Correlation is significant at the 0.05 level

TABLE B.3. CORRELATIONS WITH PREPAREDNESS (COLLEGE EXPERIENCE)

My high school coursework adequately prepared me to be successful in an engineering curriculum	**Pearson's R**
When you began your engineering degree, how confident were you that you would complete it?	-.283**
At the present time, how confident are you that you will complete an engineering degree at this university	-.257**
Indicate your level of involvement during this academic year- A professional or student group for women or minority students (e.g. SWE, NSBE, SHPE)	-.176**
Indicate your level of involvement during this academic year- Other engineering society not included above	-.156**
Indicate your level of involvement during this academic year-Activities (social or academic) sponsored by your department or major	-.199**
Indicate your level of involvement during this academic year-Clash of the Colleges	-.111*
Indicate your level of involvement during this academic year-Design competition teams	-.141*
Indicate your level of involvement during this academic year-Undergraduate research experiences	-.241**
Which best describes your level of involvement with GEEKS (Tutoring within the College of Engineering)	.184**
Which best describes your level of involvement with university tutoring (outside of the College of Engineering)	.125*
Do you currently participate in any college/university athletic activities (intramural or official)?	.140*
The following are statements related to your engineering education experience. For each statement, please select your level of agreement-Engineering faculty/departmental personnel show an interest in me	.232**
Select your level of agreement -The workload of the engineering classes is reasonable	.295**
Select your level of agreement -The climate in engineering classes is friendly	.188**
Select your level of agreement -My engineering coursework grades are satisfactory	.370**
Select your level of agreement -Faculty help me understand what practicing engineers do	.252**
Select your level of agreement -The engineering faculty, instructors, or graduate assistants provide good teaching	.204**
Select your level of agreement -I have the ability to find satisfactory co-ops and/or internships	.165**
Select your level of agreement -My personal abilities/talents "fit" the requirements in engineering	.186**
Select your level of agreement -I am confident of succeeding in engineering future classes	.320**
Select your level of agreement -Overall, I have had positive interactions with other engineering students	.150**
Select your level of agreement -Overall, I have had positive experiences in design teams or other collaborative learning experiences in engineering	.303**
How supportive is your family in your decision to study engineering?	.203**

**Correlation is significant at the 0.01 level * Correlation is significant at the 0.05 level

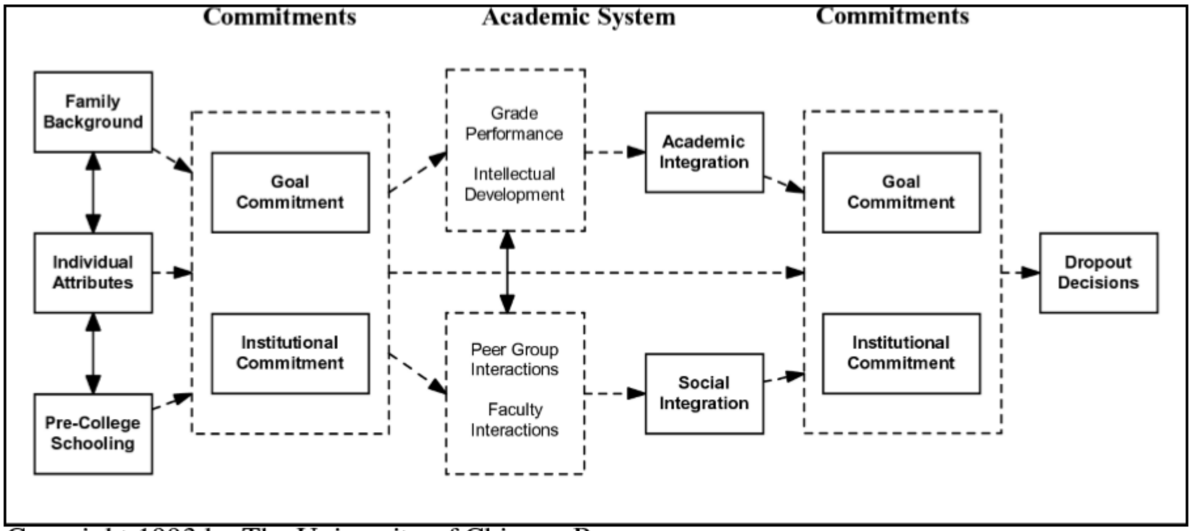

Figure B.1. Tinto's longitudinal model of institutional departure

Appendix C

TABLE C.1. COMPARISON OF COE'S RETENTION PROGRAMS TO ASEE'S BEST PRACTICES

Best Practice Program	**CoE Program**
University of Colorado – Boulder: Quadrangle Engineering and Sciences Living and Learning Community (the "Quad") • Optional shared living environment: • On-site supplementary calculus work groups • Engineering computer lab • Free drop-in tutoring • Late-night breakfasts before midterms • Workshops	***Engineering Living and Learning Community*** • Optional shared living environment: • On-site supplementary calculus work groups • Engineering computer lab • Free drop-in tutoring • Late-night breakfasts before midterms • Workshops

University of Southern California: University-wide Retention Initiative
• Tutoring
    • Early detection of performance problems
    • Free one-on-one & group tutoring sessions
• Pre-Enrollment Efforts
    • 4-week pre-enrollment summer session for incoming freshmen from underrepresented groups
    • Relentless monitoring and advising of freshmen
• First Year Excellence Program
    • New student welcome
    • First-year advising
    • ENGR 102 required
    • Academic workshops & programs
	College of Engineering Student Support and Retention Initiatives
	• GEEKS Tutoring
	    • Early detection of performance problems
	    • Free one-on-one & group tutoring sessions
	• Pre-Enrollment Efforts
	    • BEETS*
	    • Relentless monitoring and advising of freshmen
	• Freshman Year Opportunities
	    • Engineering Open House
	    • First-year advising
	    • ENGR 101 recommended
	    • Academic workshops & programs
	* BEETS was recently discontinued due to loss of funding

Washington University in St. Louis: Retention Strategies Based on Students' Reasons for Leaving
• Academic Support
    • Tutoring, Calculus Help Room, Problem-solving teams, Progress counseling
• Freshman Engineering Seminar
    • Weekly hands-on course taught primarily by upperclassmen
• Pre-orientation Engineering Program
	College of Engineering Student Support and Retention Initiatives
	• Academic Support
	    • GEEKS tutoring, Engineering Student Success Workshops, Mentor UPP
	• Freshman Engineering Seminar
	    • Monthly Engineering Student Success Workshops, Engineering lunch and learns, Mentor UPP
	• BEETS*
	• Experience Abroad Opportunities
	• Mentor UPP

• Experience Abroad
• Mentoring of Student Groups
• Strategic Admissions
    • School chooses most academically prepared students with apparent genuine engineering interest
• Four-Year Advising
    • Adviser sticks with student throughout duration of enrollment
	• Strategic Admissions (N/A)
	• Four-Year Advising
	
	* BEETS was recently discontinued due to loss of funding

West Virginia University: Integrated Student Support and Enrichment Paradigm
• Focus on recruitment, appropriate course placement, and academic support
• Freshmen required to spend at least 2 hours in the free tutoring center
• "Out of Class Experiences": teaches study and time management skills, career preparation, study abroad opportunities
• EngineerFEST: Student organization fair early in the fall with outreach and recruiting activities, promoting early engagement
• Mentoring Programs:
    • Grad Students volunteer to mentor 2-3 freshmen
    • Resident Assistants in engineering dorm halls
	Integrated Student Support and Enrichment
	• Focus on recruitment, appropriate course placement, and academic support
	• GEEKS Tutoring (although not required)
	• Engineering student success workshops, lunch & learns, ENGR101, study abroad opportunities
	• Engineering Block Party, Clash of the Colleges, Engineering Open House
	• Mentor UPP: Freshman students mentored by upper classmen

Bucknell University: Engineering Success Alliance (ESA) • Partners with the Posse Foundation to recruit students with strong leadership potential from under-resourced high schools • Selection indicators include SAT scores, high school coursework, and underrepresented status in engineering • Students enter as a supportive cohort and are provided additional academic support	***GEEKS Scholarship*** • Offered to students with strong leadership potential from under-resourced high schools • Selection indicators include SAT scores, high school coursework, and underrepresented status in engineering • Students enter as a supportive cohort and are provided additional academic support
Purdue University: Minority Engineering Program Academic Boot Camp (ABC) • Designed to identify, evaluate and resolve bottlenecks in the academic process • Targets minority students to assist them in adjusting to a new social climate and fast-paced academic environment • Students live on campus	***Bridge for Engineering and Engineering Technology Students (BEETS)**** • Designed to identify, evaluate and resolve bottlenecks in the academic process • Targets under-represented students to assist them in adjusting to a new social climate and fast-paced academic environment • Students live on campus

	* BEETS was recently discontinued due to loss of funding

University of Maryland: Keystone Program
• Revamped fundamental engineering courses (first and second year courses) to be taught by the school's best teaching faculty; selected based on qualification and rapport
• "Keystone Professor"
    • Renewable three-year appointment
    • Supplemental funds to support teaching
    • Classroom support personnel
    • 2% base salary increase
	Currently no similar program exists at CoE