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QUALITY MANAGEMET IN HIGHER EDUCATION: ENHANCING RETENTION AND GRADUATION RATES

BY

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ABSTRACT

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Title: Quality Management-Based Approach for Enhancing Academic Productivity in Higher Education

Supervisor of Thesis: Galal, M. Abdella.

Quality management and continuous improvement have become increasingly practiced in worldwide industries and organizations. Recently, the higher education sector has been gradually moving towards Quality Management as well. The academic success and retention of university students are major questions for universities worldwide, and many retention programs have been designed to remedy issues of students-at-risk and early dropouts since a university's academic productivity and efficiency are heavily linked to the institution's graduation and retention rates. In this way, it important for the university to find ways to identify students needing help and provide them with support. To that end, this research work aims to develop a framework through which the management can identify students-at- risk as early as possible, and to ensure that they are offered appropriate support in a timely manner. In addition, three machine learning-based prediction models have been proposed for predicting course difficulty level (CDL). The accuracy of the proposed prediction models is assessed by using a real dataset collected from the students of the college of engineering in Qatar University, Doha-Qatar.

DEDICATION

I dedicate this work to my beloved family whose unconditional encouragement and support made it possible for me to be at this stage today. And to my professors Qatar University, who have taught and supported me throughout this thesis.

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CHAPTER 1: INTRODUCTION

1.1 Background on the Research Topic

In order for businesses to thrive in today's market, they must seek out continuous improvement and development, as today's rapidly increasing competition does not allow for lagging behind. One way that an organization can ensure their business success is by applying quality management practices. In addition to placing customers at the center of processes and thereby ensuring their satisfaction, quality management also greatly improves the performance of a company, whether it be a product, service, or a process performance within the organization. In that way, quality management is a set of principles that are a means of achieving success for any organization, as it places high importance on customer satisfaction in a significant competitive manner. Furthermore, nowadays quality management is practiced in almost all types of businesses and industries. For instance, quality management can be seen now in accounting, healthcare, construction, public transportation and many more. The principles of quality management are such that they have the potential to be applied anywhere as long as the methodology is applied appropriately depending on the context.

Recently, the education sector has also heavily started leaning towards quality management as a way to remain competitive much like any other organization in today's market. Education is one of the most important sectors that society has, as it is the one to ensure the development and prosperity of that society. To that end, quality management is important not only from a market-competitive viewpoint but also from a social viewpoint as well. One of the main objectives of higher education institutes is to provide its students, who can be seen as the customers in this case, with a high-quality education. In order to do that, many techniques and methods are used to improve the quality of education, for instance, by enhancing the curriculum, the services provided, the support systems available, and so on.

One interesting field that integrates engineering research and education is Engineering Education. The systematic studies and research made to understand the different potential educational approaches and methods, result in a more efficient teaching environment. Rugarcia et al. (2000) stated that in recent years, engineering professors have been increasingly attending engineering education conferences, reading about it in literature, as well as attempting new methods and approaches in their own teaching. They went on to state that the primary value of engineering practice is functionality as well as profit. A process that was considered good was one that did what it was supposed to do in the most profitable manner possible. Engineering education should follow those values, and therefore applying quality management practices would be very beneficial to in order to achieve them.

Usually, when applying quality management in education, Higher Education Institutions (HEIs) will apply industrial quality models to their processes. Since that is the case, most of the time, quality management is seen in administration processes as it is more convenient to use industrial quality models in those areas. These processes might include student enrollment or class registration processes for example. This is because these type of processes are easy to define and break into tasks and activities. They are also easy to standardize, while processes such as teaching, for example, is not. According to Becket and Brookes (2008), the benefits of using quality models have mostly been achieved predominantly in administration and service functions in HEIs. In addition to that, they went on to state that a growing concern in HEI quality practices and approaches, is the lack of focus on the student learning experience and that industrial models in current quality management approaches fail to address the learning experience of a student body that is becoming increasingly more diverse.

Therefore, it is essential to focus on the improvement of the learning experience of students, as it is the core process of any educational institution. One major area that can be focused on in improving the student learning experience is the waste and how it can be eliminated or reduced. Waste here can be seen as students who fail a course, drop out of a course, or repeat a course. These types of waste can heavily affect students. For instance, they may be significantly delayed in graduating, or maybe demotivated enough to change majors, or they may leave the university altogether. One way of reducing this type of waste is by knowing beforehand whether a student will be struggling with a course and provide them with the appropriate support that will prevent them from doing poorly and failing or being discouraged enough to drop out. As such, these students are usually referred to as "At-Risk" students. Ultimately, quality management can be used here to reduce waste by monitoring student performance and detecting early whether students will be struggling and provide them with the support they need.

One principal direction that innovation in the improvement of student performance is headed is towards analyzing, understanding, and in turn, predicting student performance. This type of information can be beneficial to the management in education since it can potentially enable them to make certain decisions that will ensure that the student is given the right kind of support they need, at the time they need it, and in this way enhance the student experience. It also helps management in improving their graduation and dropout rates, which are significantly crucial to any educational institution.

To that end, it is essential that universities find ways to decrease their costs and improve their efficiency, especially when they are faced with a rapid increase in the number of graduates while having a limited budget, particularly for public universities where the costs may rise above their funding. According to Tinto (2006), student retention is recently viewed as a big business to researchers, educators, and entrepreneurs. There are now some consultant firms, journals, and conferences all dedicated to the improvement of retention rates. Additionally, Barefoot (2004) stated that many legislations are tying institutional funding to the graduation rate percentages of universities, which is considered especially tough on public universities where there are high rates of at-risk students. In addition to that, there is the reputation of a university, which also has to be taken into consideration. Increasing graduation rates can then improve the productivity of a university, satisfy the needs of employers in the market, and help their students get jobs or post-degree opportunities faster.

1.2 Research Statement

Quality Management philosophy can be used to enhance the student learning experience. Eliminating academic waste by detecting struggling students as early as possible and proactively providing them with the appropriate support increases the HEI's academic productivity. Early detection of struggling students can be done using machine learning techniques that predict student's perception of course difficulty. Knowing how students view the difficulty of courses will be further useful to the education management by enabling them to continuously assess and improve the curriculum they are providing.

1.3 Research Questions

- What is the current research trend under student at risk and student performance?
- What research has been done on course difficulty?
- What factors affect the course difficulty?
- What is an alternative of student perception as a way of measuring course difficulty?

1.4 Research Aim and Objectives

Research aim:

The research aim is to promote the research area of Quality Management philosophy used specifically for the student learning experience, and student performance development, for enhancing the academic productivity in higher education institutions.

Research objectives:

- Perform a deep literature review on quality management in education and student performance in order to thoroughly understand the current views on the topic
- Develop a framework for identifying students at risk and continuously providing them with early support when needed
- Develop statistical models for early detection of students in need of help by predicting their perception of difficulty for courses they are going to take

1.5 Research Scope

The scope of this thesis work involves undergraduate students. It involves students of the engineering college. However, it is believed that the methodology can be used for other curricula and colleges. Furthermore, the thesis work involves Multiple Regression Analysis rather than Structural Equation Modeling (SEM).

1.6 Research Methodology

In order to investigate and answer the aforementioned research questions, the following research methodology shown in Figure 1 was followed.

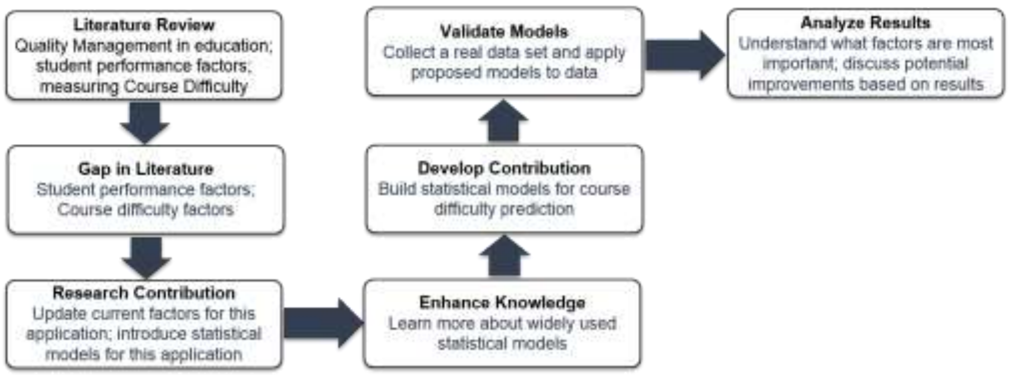

Figure 1: The Research Methodology Followed Throughout this Thesis

To begin with, a thorough literature review was conducted on the subject of quality management, quality management in education, quality management in student performance, student performance prediction, ongoing student performance prediction, and finally, course difficulty measurement. After that, some literature gaps were identified in order to contribute to the current research by updating the current factors that measure course difficulty and introduce the statistical prediction techniques to this area. In order to do that, knowledge in this particular area was enhanced through more research and reading. The contribution was then carried out by building three statistical models that predict the course difficulty level (CDL) of students using the updated course difficulty factors that are proposed. The models were then validated by collecting a real data set from the college of engineering at Qatar University, Qatar. The results of the models were then analyzed and discussed followed by recommendations, future work, and conclusion.

CHAPTER 2: LITERATURE REVIEW

2.1 Background on Quality Management

To begin with, Quality itself is a very subjective term, and it could mean different things depending on the situation, which is why it might be difficult to give it a meaning with no context. Shewfelt (1999) stated that despite there being many definitions of quality, there is little agreement on what it is, how it can be measured, and its relation to customer acceptability. Furthermore, quality will mean different things to different handlers across the distribution chain. According to them, quality can be seen as the absence of defects or the degree of excellence.

Therefore, when an organization wants to improve its quality, it is important to first understand quality from their perspective in order to have an appropriate plan in place. For example, Batalden and Davidoff (2007), proposed that quality improvement in healthcare be defined as the continuous efforts of everyone within the health care organization to make the changes that will result in better outcomes for the patient (in terms of their health), better system performance (in terms of patient care), and better professional development.

With today's rapidly growing and increasingly competitive market, organizations are more concerned with their quality practices in order to continuously improve and gain more market share. According to Cetindere, Duran, and Yetisen (2015), in order to gain more market shares and compete with other businesses, organizations have to revise their understanding of quality, decrease the error margin in their production of products or services, all to be able to survive, reach a level they aspire to, and maintain it. In that sense, these businesses have entered a “quality race” which brought light and importance to the Total Quality Management approach.

Total Quality Management (TQM) is consistently one of the most popular quality management systems. The TQM system can be defined as a holistic management philosophy that aims for continuous improvements in all functions of the organization. Furthermore, it can only be achieved if the concept of total quality is implemented from the input stage of the production or distribution chain, all the way to customer service after the sale, (Kaynak, 2003). According to Popa (2012) TQM is the integration of all functions of an organization in order to satisfy the customer and meet the organization’s objectives. Cetindere, Duran, and Yetisen (2015) defined it as the team work and participation of the management, to produce products that are free of defects that achieve customer satisfaction. They further added that it includes improving the performance of processes at all levels and activities within the organization.

Hackman and Wageman (1995) stated that the implementation of TQM has become similar to a social movement, in the sense that it has spread from its origins in industries, to a wide range of sectors such as healthcare, bureaucracies, non-profit organizations, and education. Samson and Terziovski (1999) mentioned how many well-known companies have had great improvement results after experiencing a decline in their fortunes and were able to restore their profitability based on the implementation of TQM. Kaynak (2003) stated that the improvements from implementing TQM should result in lower number of scrap and rework costs. In addition to that, TQM leads to more productivity and an enhanced lead-time performance.

2.2 Quality Management in Education

Clearly, today's many options and alternatives in higher education institutions, as well as the importance of a higher education institution's image, incites competition between those organizations and impels them to aim for development and excellence. Pushpa (2015) stated that Total Quality Management (TQM) has aided higher education institutions in providing education with excellence. Continuous improvement, trust, participation, teamwork, and quality-mindedness, are all aspects of the culture that is created by implementing TQM. In addition to that, Pushpa (2015) stated that TQM would give a competitive edge both locally and internationally to those HEIs that ensures a high quality service and satisfies the needs of their stakeholders. In order to achieve that, an in-depth understanding as well as key factors associated with quality performance practices, must be understood by HEIs to ultimately improve their efficiency and strengthen their growth and sustainability.

According to Papanthymou and Darra (2007), the key to distinguishing between competing HEIs, is by providing quality services in their institutions. In their review, they looked into the various quality models that were used in HEIs. Those models consisted of TQM, EFQM excellence model, Balanced Scorecard, Malcolm Baldridge Award, and ISO 9000 series. The one that is globally used the most is TQM, (Becket and Brookes, 2008, Papanthymou and Darra, 2007). Some more recent ones include FMEA, FMEA in Fuzzy Environment, AHP, QFD, and SERVQUAL amongst others. From looking at various applications of Quality Management models in HEIs, Papanthymou and Darra (2007) concluded that QM is appropriate to the purpose of HEIs and furthermore, it meets the expectations of HIE and the new roles within them. In addition to that, it has the potential to solve problems and propose appropriate solutions.

There are several meanings for quality in education as it depends mostly on perspective. Vlašić, Vale, and Puhar (2009) stated that education quality is a dynamic, multi-dimensional concept that refers to the educational model, the mission and goals of the institution, and the specific standards of the system, facility, program or event. They defined quality of education as the quality that is responsible for the product, which in this case, would be the student. In addition to that, Karapetrovic and Willborn (1997) defined quality as “the ability of a product to satisfy stated or implied requirements”. As the requirements are naturally set by the customer, Karapetrovic and Willborn (1997) viewed the product as the student and the customers that set out the requirements as the companies that the student will work for. They defined the product as more specifically the knowledge and experience that the student will gain during their studies. On the other hand, Lawrence and McCollough (2001) stated the student can be thought of in a number of ways when defining quality in the education system. A student may be viewed as the product-in-process, or as co-producers in the learning process. They may also be viewed as the customers of the service in some circumstances.

Applying TQM in the education setting might be viewed as difficult due to the complex nature of education. Lawrence and McCollough (2001) stated that one major obstacle to applying TQM in education, was the fact that there are a number of stakeholders that education is trying to serve, such as the students, their parents, their employers, taxpayers, as well as the society as a whole. Some believe that Quality Management may not be applicable, or only partially applicable, in education. However, it merely depends on how TQM is applied, as some tools cannot be taken exactly as they are and applied directly in education. According to Sohel-Uz-Zaman and Anjalin (2016), TQM is flexible and applicable to any organization because it can be adjusted to a given situation. With the aid of TQM, it is possible for an institution to develop its own definition of quality, benchmark, as well as its own practices for quality improvements based on its customers' requirements. They further stated that if TQM tools were to be selected at random, the techniques and concepts will not be able to provide any significant benefit. The wise thing to do, would be to appropriately select the tools and techniques that are consistent with a given academic situation.

Despite the idea that TQM is flexible and the context should be taken into consideration when applying it, many HEIs do not take that into consideration when applying it. This results in misconceptions about whether TQM can work in education. The quality methods practiced in industries might not lead to beneficial results in HEIs, as the requirements and definitions of quality and quality measures differ significantly. According to Becket and Brookes (2008), there is a growing concern that in current international HE quality management approaches, there is a lack of focus on the learning experience of students. They went on to state that the current approaches, where industrial models are used for academic situations, fail to address the learning experience of students, and might even be harmful in some cases where the quality of teaching might deteriorate as a result. Srikanthan and Dalrymple (2002) advised that implementing those quality models used in industries for all the operations in a university is flawed and does not fit with the core operation of a HEI, which is education.

In their review, Becket and Brookes (2008), observed that many HEIs rely heavily on industrial quality models, that they adopt directly or adapt them for certain uses in their institution. In terms of addressing both quality assurance and enhancement initiatives, the results were quite beneficial. However, the gained benefits of such models were seen predominantly in administrative and service functions. This is interesting as it seems most HEIs apply quality models in those areas, possibly because of its close compatibility with the popularly used models. Most models proposed are also applied at a macro level, such as applying TQM in the university as a whole, rather than any function in particular. For example, Pushpa (2015) proposed a model that could be applied in HEIs. In it they suggested steps that the university can follow, including understanding TQM, taking the decision to change, preparing for implementation of changes, training their faculty and employees, taking the initiative by starting projects and assignments, evaluating the performance of these activities, motivating faculty and employees, and finally, continuously improve. This looks at the institution as a whole, and not specifically the education function of a university.

On the other hand, some have looked at education, and more specifically, identified it as a “teaching process”. Sahney, Banwet, and Karunes (2004) have looked at education as a “transformation system” or a “production process”, in which there are inputs, processes, and outputs. The inputs in their model, included human resources, physical resources, and financial resources. Their processes included teaching, learning, researching, administrative activities, and so on. Finally, their outputs included value addition, tangible outcomes, and intangible outcomes. They viewed the student as being the customer of this system. They defined the customer as anyone who is being served, and depending on whether they are inside or outside of the organization, they could be internet or external customers. A student is an internal customer when they are participating in the learning system, and an external customer when they have graduated and left the university.

Karapetrovic, Rajamani, and Willborn (1999) also looked at education as a production process. Their main idea was that universities must use industrial quality techniques to remain competitive. Most of the quality definitions were therefore translated to fit the education sector. For example, if the product is a program or a course, then its customers here are the students, the suppliers are professional institutions, the process plan is the course outline, the production is the teaching, and many more. They also looked into what the production time, setup time, bottleneck resources, amongst others, are translated into when it comes to the education process. Furthermore, Karapetrovic, Rajamani, and Willborn (1999) discussed the concept of "zero-defect products of a university". Here, they referred to a student meeting all the specifications for their knowledge, experience, and skills, as a student who has reached the zero-defect objective. To achieve this goal, a university must have a systematic approach in place to improve quality in the education process.

2.3 Quality Management and Student Performance

Nowadays, many universities are heavily concerned with their retention and graduation rates, as these measures are very important to a university's image and ranking. More recently however, universities have growing concerns over their productivity and efficiency, as there is a growing number of students and limited funding, which ultimately signify the importance of improving graduation rates. Therefore there needs to be systematic improvements made that lead to higher graduation and retention rates of students. Goldberg and Cole (2002) stated that schools that approach change from a systems perspective, are those that ultimately learn and improve. How systematic the change is, affects the changes in behavior, culture and structure within an institution, and makes the changes even more lasting. Educators must challenge their current teaching processes and methods in order to arrive at the desired results. Goldberg and Cole (2002) further stated that the impact of quality is the greatest when focus is given to instructional processes and student learning. Therefore, looking at student performance, and applying quality management philosophy in the classroom, might be very beneficial.

When looking at student performance specifically, it may be interesting to look at the concept of "zero defects" as a way of improving efficiency and academic productivity. According to Harvey and Knight (1996), the absence of defects is where excellences becomes 'perfection'. However, the zero defect philosophy is not only about conforming to specifications. Rather, it encompasses a philosophy of prevention and not inspection. (Peters and Waterman, 1982, Harvey and Knight, 1996). The "zero-defect" concept, and whether it can be applied to students, was discussed by Karapetrovic and Willborn (1997), who stated that techniques used for decades in the industry to improve quality and approach the "zero-defect" ideal, can also be applied to create the "zero-defect student". Examples of the techniques mentioned were from quality control tools, including check sheets and Pareto diagrams, which follow student reports and assignments, where common errors are recorded and appropriate support is given by the teacher to prevent students from making similar mistakes in the future.

In addition to that, looking at waste in the classroom might be very useful, as it allows for a more efficient and productive educational process. Pavlović et al. (2014)

attempted to apply Lean Six Sigma method in an educational setting. For each of the seven basic types of waste, they identified the equivalent type of waste in the educational process, and developed a table with corresponding methods for waste elimination. For example, a defect in this situation, is what they consider as a wrong teaching plan, failed exams, withdrawing from exams, as well as incomplete or incorrect provided information. To eliminate this waste, they suggested creating a check list to define what is considered good in the curriculum, identify student requirements, follow the current application of modern curriculum, amongst other suggestions. They did this with the other types of waste, including buffers, motion, waiting, transportation, over processing, and over production wastes.

Even though identifying these types of waste might be beneficial in some ways, the fact is that every class is different, every instructor is different, and every student may have very different needs. In addition to that, educational processes, unlike industrial processes, may be very difficult to standardize. Therefore, trying to translate every industrial type of waste may not be very meaningful overall. However, there are some wastes that are more relevant in the educational process. Graduating late, dropping out from a program, or the university, failing courses, repeating courses, withdrawing from courses, are all relevant wastes that are more applicable to the higher education institution.

Aina and Casalone (2011) stated that the delay in graduation is a waste of resources at both the individual as well as the collective level, which in turn affects the investment returns in higher education. The rate of return decreases for a college at the individual level because of the opportunity cost increase of graduation. At the collective level on the other hand, when education is highly subsidized, delayed graduation can mean misallocation of resources, meaning classrooms, libraries, instructor times and many other resources will be shared by a larger number of students causing congestions in university areas. Finally, Aina and Casalone (2011) mentioned how delayed graduation means the economic system is deprived of new up-to-date competencies in the labor market.

These types of waste are more in line with the nature of the higher education process, and eliminating those wastes will improve the institution's quality of education. A possible way of doing that is by identifying students "At-Risk" and providing them with support they need to prevent those wastes from occurring. In this case, students "At-Risk" are those that will be graduating late, failing a course, withdrawing from a course, and so on. Sweeney et al. (2016) stated that the valuable information obtained from predicting future student performance could significantly help in aiding the students, advisors, and educators in achieving better student retention. They went on to state that the identification of students who need help (students at-risk) is a key method of preventing them from potentially dropping out due to discouragement. To that end, focusing on the improvement of graduation and retention rates is way of improving the academic productivity of a higher education institution.

2.4 Typical Factors in Predicting Student Performance

Usually, certain known factors are used to analyze and predict student performance. These factors could be cognitive and non-cognitive and include factors such as a student's past grades, their age, gender, socioeconomic status, parent's academic history, as well as psychological and mental health factors like motivation, depression, and stress levels. One common factor that is used in almost every model is the student grade point average (GPA) since it indicates academically how well a student is doing. According to Shahiri, Husain, and Rashid (2015), in most of the researches done on this topic, the cumulative grade point average (CGPA) and internal assessments have been widely used for developing the prediction models. Kumar, Singh, and Handa (2017) also reported that CGPA along with internal marks obtained by the students are both very important attributes for the results for predicting the future performance of the student. Additionally, Iqbal, Mian, and Kamiran (2017) reported that Higher Secondary School Certificate (HSSC) and the entry tests of students are the most important and significant factors in predicting student performance in their freshman year at the university.

All these factors can be very helpful in predicting student performance in the first few semesters in university. In fact, most prediction models are used to predict the first year GPA, which is especially important for the admissions department for instance. Iqbal et al. (2017) stated that the first year at the university is very important regarding dropout rates, which tend to occur more at this stage, and therefore many prediction models aim to predict freshman GPA. Wilson (1983) stated that in almost every prediction model, the freshman GPA was the selected prediction measure, and that investigation on predicting post-freshman performance, such as junior or senior year, based on the most common factors (admission data and freshman GPA), are rarely investigated. However, it is also very important that the university is actively monitoring and ensuring that the students are getting the help they need with each passing semester, rather than only focus on the first year. Xu, Moon, and Schaar (2017) have stated that using the students' ongoing academic records to predict their future performance is crucial for carrying out the right type of interventions and helping them to graduate on time as well as ensuring their satisfaction.

In this way, using the GPA, along with historical academic data from the time the student was in school, may not always help, and in fact might not be relevant in the future semesters as the student progresses through their degree. These factors do not consider the student's current situation, it only considers past information, which might not be enough to give a real indication of their possible future performance, especially if the students' way of thinking and skills are changing with each passing semester. Schuh (2000) found that the persistence of students is not related to the high school GPA and standardized tests. Therefore, even though past research has shown them to be the best predictors of student performance, they might not be able to indicate how the student will perform in the years following the first. Wilson (1983) found that the best predictor of any given semester was the CGPA and the second best predictor was the immediate previous GPA to the one being predicted. He went on to state that using the freshman GPA and the students' admission data (such as high school grades) has a declining correlation with the student performance with each passing semester, with the freshman GPA being consistently better than the admission's data.

Therefore, there needs to be a way that allows management to predict a student's performance in any semester, at any point during their academic degree path, without relying on only the CGPA or the previous GPA alone as a way of indicating how well or bad the student will perform in the following semester. Sweeney et al. (2016) stated that while current prediction models find factors that assist with predicting overall student success, semester-to-semester support is not fully realized as of yet. In that way, new factors for student performance prediction are required as the situation the student faces is constantly changing. Xu et al. (2017) reported several reasons for using ongoing academic data. These include the fact that students' backgrounds and selected courses differ tremendously from one another and the courses they are enrolled in are different enough that predictions may not be as accurate. Moreover, using student performance based on all previous courses can introduce noise in the prediction models, and the evolving progress of the students needs to be incorporated into the prediction model to increase its accuracy. In order to use new relevant information that will result in a better understanding of the status of the student at a given time, the current situation that the student is facing needs to be taken into account. One factor that should be considered to accomplish this is the current courses that are registered by the student for the next semester.

2.5 Ongoing Prediction of Student Performance

Some research has already been conducted on looking at the predicted future performance by looking at specifically the courses that are to be taken by students in the following semester. According to Sweeney et al. (2016), incorporating grade predictions in early-warning systems may significantly improve the retention rates as it helps identify the students in need of help more correctly. Their goal was to predict the grades of each student in the next term. They trained one model per academic term in their dataset and used it to predict grades only for the "current term" in order to achieve fair and effective evaluation of the methods they proposed. In their experiments, they found that Factorization Machines (FM), Random Forests (RF), and the Personalized Multi-Linear Regression model resulted in the least prediction error. They went on to state that a hybrid FM-RF method was the best in terms of accuracy for new or returning students. On the other hand, Iqbal et al. (2017) used Collaborative Filtering (CF), Matrix Factorization (MF), and Restricted Blotzmann Machines (RBM) techniques in order to analyze their dataset. After conducting their experiments, they found that the RBM method was the best in predicting the grades of the student for a particular course. Using this method they were able to develop a feedback model that calculates the student's knowledge in a particular course domain, and in that way the instructor is informed about courses in which a student was considered weak.

Additionally, Polyzou and Karypis (2016) developed a model called course-specific regression (CSR) for predicting future grades specific to each course or student-course tuple, based on sparse linear models and low-rank matrix factorizations. The performance achieved by a student in a subset of earlier courses is used to predict their performance in future courses. However, since the prior courses could be taken by students from very flexible degree programs, a single linear model may not be enough to capture the prior combinations of various courses. A different method was then developed to address that limitation called the student-specific regression (SSR). This method combined course-specific as well as student-specific linear regression models. In another study, Hu et al. (2017) also proposed a course-specific regression model that was enriched with student, courses and instructor features. They developed two methods based on this model: Course-Specific Regression with Prior Courses and Course-Specific Regression with Content Features. They mentioned how the first method may not be helpful if a student has not taken a sufficient number of prior courses, so content features were added to the second method. Their results indicated that the model is generalizable and that adding content features to the model increased it accuracy.

One model that was developed for predicting ongoing performance of students was proposed by Xu et al. (2017). Their method adopted a bilayered structure, one layer being the base predictor layer and the other being an ensemble predictor layer. The base layer was comprised of multiple base predictors which make local predictions based on the student's performance in the current semester. The ensemble layer predicts the future performance of the student by synthesizing the results of the local predictions and the results of the previous term ensemble prediction. They concluded by stating that this model provides valuable information for academic advisors in order for them to support the students. Ren, Ning, and Rangwala (2017) also considered that the knowledge of a student is continuously developing as they progress through their courses. To that end, they presented a novel approach called the Matrix Factorization with Temporal Course-wise Influence (MFTCI) model that predicts the grades of a given student in the next term. This model takes into account that the grade of a student is determined by two components. The first component consists of the competency of the student with the course's topics, contents and requirements. The second component is the performance of the student over other courses.

All these models were attempting to predict the student's final grade, as a way of predicting their performance. On the other hand, some have tried to identify the students "At-Risk" through looking at certain behaviors and performance indications as the student progressed through the semester, rather than attempt to predict the student's grades. Bainbridge et al. (2015) used data generated by an online program that the students were taking, to predict whether students would be classified "At-Risk". They classified their variables as static and dynamic variables. Where static variabl.es were ones such as the student's age and gender. Furthermore, they considered the class size, the student's full time/part time status, as well as their cumulative GPA, as static variable at the time of taking the class. As this was an online program, the dynamic variables considered were the number of times the student has logged into the course, scores from contributions to the final grade submitted by the instructor, the number of times a student reads content from the lessons, and the number for times the student participates in forums.

2.6 Implications of Typically Used Factors

Through this literature review, it is apparent that in order to predict the performance of students while incorporating courses into the prediction model, most papers predicted the grades of the courses. Taking into consideration how the students will perform in their future courses along with other typical factors, like their current CGPA, makes the prediction model more accurate. In addition to that, as Xu et al. (2017) have stated, the majority of the work on student performance prediction treats it as a one-time task, ignoring the fact that students develop as they progress through their studies. However, methods that rely on previous grades to predict future grades alone, may have some pitfalls due to certain aspects about grades that do not reveal how the student really performed in a course, or illustrate the actual capability of a student. Mundfrom (1991) stated that it is necessary to remember that an achievement, from a measurement perspective, represents only a sample of an individual's ability since it is based on a test or another suitable method of measurement. Therefore, it is more of an estimate than an accurate measurement of the student's ability.

Moreover, research that looked at behaviors and contributions the student made throughout the course they are taking, as means to assess the risk status of the student, may also have some pitfalls as well. Using ongoing data that can only be measured as the student is taking the course, means that the corrective action taken is possibly a little late, while better support and direction might have been given to the student before they started the course. In a sense, waiting to collect data from an ongoing class means that an error might have already occurred and is not known yet. Predicting whether a student will perform poorly before a class has begun is therefore very important and can give very useful information on what kind of support would the student require.

2.7 Course Difficulty as an Indicator of Future Performance

In a way, a grade may be an imperfect measure of how the student really performed in that course, and perhaps their performance needs to be linked with a measurement that shows their true capability. One other approach could be to look at course difficulty and how it can impact the performance of a student in a course. The difficulty of courses is rarely taken into consideration or included in prediction models of student performance. However, in literature, some have looked at defining or estimating course difficulty for a variety of reasons, such as its effect on a student's success, mental health, and retention. Some have also looked at its effect on a teacher's or a course's evaluation by students. Usually, the definition of course difficulty in past literature is very similar and can be categorized into three groups: student average perceptions, student average grades, and course type. These factors are summarized in Table 1.

Student average perceptions of the course, seems to be a frequent factor in finding the difficulty of a course. Mundfrom (1991) acknowledged that there are clearly differences in the difficulty level of courses offered by a university, even within the same department and even at the same level (sophomore courses, junior courses, etc.). Their main question was what made some courses more difficult than others. To that end, they determined several possible criteria in order to assess the difficulty level of a course. They included the perception of difficulty and the perception of workload into their course difficulty estimation. Centra (2013) stated that the difficulty of a course is usually measured by student ratings of the course difficulty, the workload, and the pace of the course. Furthermore, Marsh (1991) also used the difficulty rating, workload rating, pace rating and the hours of work outside of class as the factors for determining the difficulty level of a course. Additionally, Tucker et al. (2006) investigated the sources of stress in physiotherapy students and found that the perceived difficulty of a course was significantly correlated with academic sources of stress. They used a questionnaire to get the student ratings of the perceived difficulty of a course.

Another factor frequently considered in the course difficulty value, are the student average past performance in the course. Mundfrom (1991) added the average grade of the course to their estimation of course difficulty. They stated that their view on considering it was that courses that have a lower mean grade value will be rated as more difficult than courses with a higher grade mean value. Szafran (2001) defined the difficulty of a course by using the percentage of students with grades below C for that course. Caulkins, Larkey, and Wei (2001) mentioned that the difficulty index of a course, can be calculated based on the relative grading standard. For example, if a course's average grade is below the average GPA of the students in the course, then it is considered to have a higher difficulty index since it has a stricter grading standard. Hu et al. (2017) used the GPA of the course from the previous term to represent the course difficulty. Wigdahl (2013) considered the average failure rate of a course in their "difficulty metric" to calculate the difficulty of all individual courses in a degree. They then added all difficulty values of the courses in the degree to assess the difficulty of the entire curriculum of a given program.

Lastly, the type of course is also another common factor looked into when finding the course difficulty. Mundfrom (1991) mentioned how the courses that are designed for freshmen and sophomores are usually considered less difficult than ones designed for junior or senior students. Wladis, Wladis, and Hachey (2014) considered the level of course as a part of the course difficulty. Whether a course is to be taken in the first year, second, third or fourth will mean an increase in difficulty level of a course. Their reasoning behind that was, lower courses (100-level courses) do not have prerequisites, and those that are 200-level and above require prerequisites. Wigdahl (2013) also took into account the position of the course in the curriculum to define the difficulty of the course. In this case, they looked at the path length to reach the course, as well as the number of prerequisites required for that course. Joyce (2017) measured class difficulty using three variables: number of in class activities, number of homework assignments, and number of tests.

Table 1: Summary of Course Difficulty Factors used in Literature

	Average Perceptions	Average Performance	Course Type
Tucker et al. (2006)	Perception of difficulty		,
Centra (2013)	Ratings of course difficulty, workload, and pace		
Marsh (1991)	Difficulty rating, workload rating, pace rating and hours of work outside of class		
Mundfrom (1991)	Perception of difficulty and workload	Average grade of the course	Freshmen and sophomore classes are less difficult
Wigdal (2013)		Average failure rate	Position of the course in the curriculum
Szafran		Percentage of students with grades below C for that course	
Caulkins, Larkey, and Wei (2001)		Relative grading standard (compare course average GPA with students' enrolled average GPA)	
Hu et al. (2017)		GPA of the course from the previous term	
Wladis, Wladis, and Hachey (2014)			Level of the course is part of the course difficulty
Joyce (2017)			Number of classes, number of assignments, and number of tests

CHAPTER 3: FRAMEWORK FOR IDENTIFYING STUDENTS AT RISK

The retention and graduation rate has recently become a focal concern for higher education institutions worldwide. The early prediction of academic student performance provides the management valuable insights on the effectiveness of the current educational strategies and practices. In addition to that, it gives the management a change to proactively provide support to students who are in need of support to make sure students maintain a positive performance level. In turn, this will enhance the graduation and retention rates which will greatly contribute in reducing educational costs and improve academic efficiency. There are many costs that are associated with the loss of a student (Fusch, 2017). These losses are:

- Tuition revenue
- Auxiliary revenues
- Revenue from future alumni philanthropy
- Additional cost of recruiting and enrolling the students who will fill the voided places of those who transferred or academically dismissed.

3.1 General framework for Identifying Students at Risk

To begin with, it is necessary to have a record of students' relevant data that will enable the education management to detect whether a student might be struggling. As universities grow and their student body grows very rapidly, there is a large amount of data and storing it in an efficient manner that enables the management to quickly retrieve and study it, would be very beneficial to a higher education institution. There is a lot of potential in the large amount of data that a university keeps for record, which can be tracked or pulled from previous years very easily, that enables the management to clearly identify issues or patterns that need their attention. Having a database for this function, can also mean very fast detection of students at risk, since the data can be pulled and processed very fast with today's technology.

The next step would be to use the data stored. It is important to study and analyze the data to get information from it. This can be done by applying statistical models to see patterns, issues where the management can interfere and solve problems, or areas of interest where there are opportunities for improvement. After performing statistical analysis on the data, it is also important to present it in a meaningful way so that the support unit can easily utilize the models in a fast and efficient manner.

Having the data, and from it the needed information, the next step is to determine what kind of support the student requires. First, the results of the statistical models should interpreted in meaningful way, after that the education management can identify the weaknesses the student has in order to focus on those. The final step would be to provide the student with the method of support selected, whether it be extra sessions, tutorial, assignments, workshops, etc. It is also important to monitor the student afterwards to make sure their performance is improved and that they are encouraged to further improve and seek out help when they need it. This framework is illustrated in Figure 2.

3.2 Continuous Improvement

Once the student is provided with the support they need, their performance is monitored and the new data can be again used to detect whether they will be at risk in order to provide them with support, and so on. In a way, this framework is very similar to the popular concept of continuous improvement in Quality Management and closely resembles the PDCA (Plan, Do, Check, Act) cycle made popular by W. Edwards Deming, which is why it is also called the Deming Cycle.

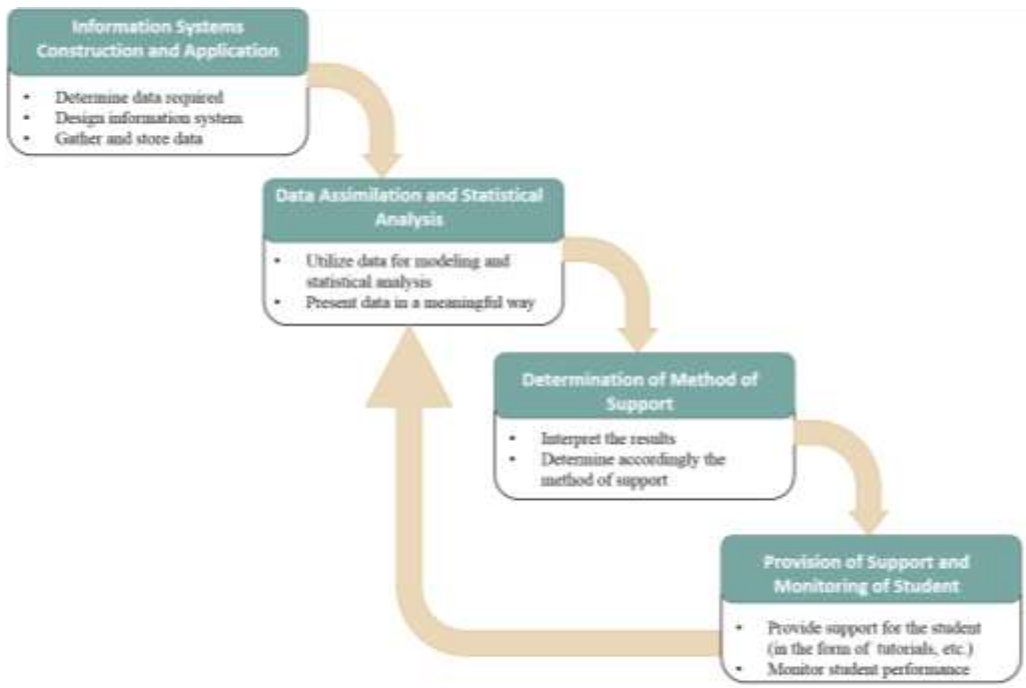

Figure 2: Framework for Identifying and Providing Support for At-Risk Students

The "Plan" step is done when the stored data is used in statistical analysis to identify the weaknesses of the student. The "Do" step is figuring out what type of support the student requires and providing them with the selected method of support. Checking is made when the student is monitored and their performances is assessed. The "Act" step is to maintain this system and continuously utilize the statistical models to detect struggling students, provide them with support, and monitor their performance. Throughout the course of the thesis work, the concentration will be primarily on the statistical analysis stage of the framework.

CHAPTER 4: COURSE DIFFICULTY FACTORS AND PREDICTION TECHNIQUES

There are clearly differences in the difficulties of courses between different curricula and in between the same level in a curriculum as well. Students are aware of this themselves and take that into consideration when applying for a program, courses within a program, or when discussing and evaluating courses. This information might be very helpful to the management in education, and did in fact had many uses in literature. Some examples include adjusting the calculated GPA value by taking the difficulty of a course into consideration, comparing between different curricula design, and understanding how students evaluate courses and professors. In addition to that, the difficulty of a course can be used as a way to make predictions of students “at risk”, or student performance in general, more accurate.

Several main factors determine the difficulty of a course according to past literature. These factors were categorized into Student Average Perceptions, Student Average Grades, and Course Type shown in Table 1. Student Average Perceptions are those factors that involve how students felt about a course they already took, in terms of the difficulty, pace, and workload. Student Average Grades are those factors that are related to students’ past performance in this course, which can be in terms of alphabetical grades, GPA, or pass/failure rates. Finally, the Course Type factors are those related to the course, which can be about the level of the course (100-, 200-, 300-level, etc), the number of prerequisites of the course, or the workload of the course like the number of assignments and exams for instance.

Applying statistical models to find the course difficulty level would be very useful for predicting the academic student performance in early stages and during a student's degree path. Most of the previous relevant studies have shown a lot of concentration on average historical data, which can be helpful to a limited extent. The course difficulty for one particular student has not been considered, as most of the studies were focused on finding the average difficulty of the course. To find the average difficulty, they mostly looked at the average perceptions of students, usually by distributing a survey asking the students to rate how difficult the course was. That meant that these students had already taken the course, and these results were therefore dependent on the historical average perception of difficulty. This is also applied to the average perceptions of workload and pace. In addition to this, they looked at average historical performance, using grades or GPA as the input. Lastly, some looked at the number of prerequisites or course level.

4.1 Factors Affecting Course Difficulty

As the aim here is not to measure the average difficulty, but to predict it in advance, there are some disadvantages of using the same factors to predict the difficulty of a course for a particular student. First of all, knowing the average perception of course difficulty, workload, or pace, might lead to some very inaccurate results for some students, as each incoming batch could be very different from one another, and it overlooks the variation between students within each batch. Taking the past average performance is also helpful, but in the same way, does not take into account the individual performance of the student. Lastly, taking the number of prerequisites alone is also quite insufficient. Not all prerequisites are the same, in the sense that, some of them have a greater impact on the difficulty of a course than others. For example, a prerequisite that is taken one semester away will have a different impact than a prerequisite course taken three semesters away. In addition to that, a prerequisite a student performed well on will have a different impact than a prerequisite a student performed poorly in. Therefore, the factors have to be centered more about the student themselves rather than only average values based on historical data. The information used have to also involve the ever changing capabilities and progress of the student themselves. In that way, some specific information about the student will result in more accurate results on how difficult a course might be for them.

The model proposed ultimately predicts the difficulty of a course for a given student. Therefore, in this model the independent variable is the perceived difficulty of the student. In that way, the perceived difficulty is not a factor, but a result, of the model. The factors on the other hand, are more centered on the student, in order to find an accurate result for their perceived difficulty in a particular course. These factors are summarized in Figure 3.

To begin with, the first factor to be considered will be the Student Applied Effort. In this case, this factor will be measured by looking at specific student behavior related to the course. Here, the student's attendance and participation in class are very important, as it shows their engagement within each class session and therefore will impact the difficulty they face in the course. In addition to that, the studying hours they spend outside of class, as well as their office hour visits, will also impact the difficulty of the course, as it is related to how much content the student is keeping up with and whether they make sure to revise for the course regularly.

The second factor to be taken into consideration, is the Student Capability. Some courses rely on some skills that the student has, or that the student should have learnt and built upon, in order to do well in the course. In this instance, some very important skills in engineering for almost all courses, are teamwork skills, math and science skills, as well as independent learning skills. These skills were selected because of how common and generally useful they are to courses in engineering.

Finally, the last factor to be considered is the Student Relevant Performance. Here, the prerequisites are taken into consideration. However, not only is the number of prerequisites taken into account, but the grade they received in that course, the knowledge relevance of the prerequisite to the course being taken, and the time gap between the prerequisite and the course. All of them are important in determining the impact of a prerequisite on the difficulty of the course. The grade is important as doing poorly in a prerequisite might mean the student will face greater difficulty in the course. Conversely, a course a student did poorly on but has little knowledge relevance to the course to be taken, might not impact the difficulty. The same can be said about the time as well. A student who did well in a prerequisite might still struggle if the prerequisite was taken a few semesters away, rather than one semester away.

The prerequisite in this model will be measured by the following equation:

$$\frac{knowledge \times grade}{time\ gap} = prerequisite\ score \qquad (1)$$

The prerequisite increases when the knowledge and grade values increase, and decreases when the time gap (semesters between prerequisite and course) increases.

Some assumptions were made for this model. The first assumption is that all courses are homogeneous in what affects their difficulty, in other words, all the factors seen in Figure 3 affect the difficulty of any given course in the engineering curricula. The second assumption that was made, is that all instructors for all courses have the same syllabus and therefore teach the same content, and that they do not differ in their grading style or workload amount.

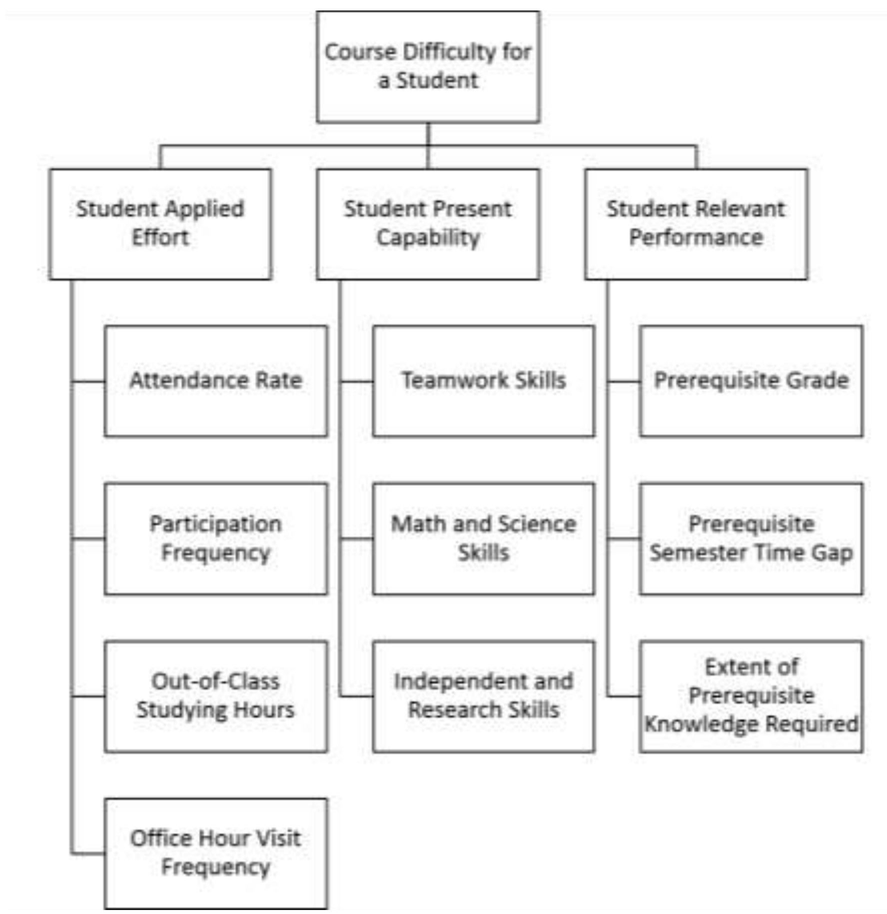

Figure 3: Student Specific Factors that Affect Course Difficulty

As stated in the research objectives, statistical models will be developed and proposed to predict the course difficulty for a student using the factors seen in Figure 3. The result of the model will one of three categories: High Difficulty, Medium Difficulty, or Low Difficulty. As this is the case, multinomial type statistical models will be used.

4.2 Multinomial Logistic Regression

Multinomial logistic—or logit regression—is a standard tool for modeling effect and interactions when the dependent variable is categorical with multi-levels. The multinomial logistic regression is sometimes considered an extension of standard or binary logistic regression to allow for a dependent variable with more than two class categories. The multinomial logistic regression is used when the likelihood of the occurrence of the outcomes are modeled as a linear combination of the explanatory – or predictor variables. The applications of multinomial regression is very wide to include several of industrial and service sectors such as manufacturing production systems, business economics, education, healthcare, and social science studies. It is widely applied for that it is insensitive to the data's violation of the normality, linearity, and homoscedasticity assumptions. The sample size guidelines reported by Schwab (2002) for multinomial logistic regression have shown that the minimum of ten cases per each explanatory variable.

4.3 Penalized Regression Techniques

The relationship between a set of predictor variables and a response (outcome) variable, could be investigated by multiple regression which can then be used to estimate a model that predicts future responses. Meulman and Kooij (2016) mentioned that over the years, many methods for regularized regression were developed. Some of the ones they mentioned were Ridge Regression, Lasso Regression, Elastic Net Regression, amongst others.

These penalization-based regression techniques are widely known for their efficiency in preventing the overfitting issue that may arise due to the large numbers of predictors involved in the model. The penalized regression techniques, in general, minimize the error by using a penalty on the regression coefficients of the GzLM. This penalty causes the regression coefficients to shrink towards zero and possibly setting the regression coefficients of some performance predictors exactly to zero. Both of the ridge and Lasso penalty functions can shrink the regression coefficients towards zero values, but only the Lasso can shrink the regression coefficients to exact zeros. For further reading about these penalization regression techniques, see Verweij and Van Houwelingen (1994), and Tibshirani (1996). The Lasso is an acronym for "least absolute shrinkage and selection operator" (Tibshirani, 1996). This acronym comes from its functionality that it does not only shrink coefficients towards zero but it also provides a selection of the significant covariates.

The penalized regression techniques are often preferred for their robustness to the multicollinearity phenomena; see Hasti et al. (2001). The penalized maximum likelihood estimation (PMLE) is the typical method usually applied to estimate the regression coefficients in the linear combination shown in Equation (2). The PMLE is simply formed by adding a penalty function to the GzLM estimates in the standard maximum likelihood function. The PMLE method provides a good fit of the regression coefficients given that the data has been collected. Given that that $\boldsymbol{\beta} = (\beta_1, \beta_2 \ldots \beta_P) \in \mathbb{R}^P$, the solution of the PMLE can be written as follows (see Park, and T. Hastie 2007, Friedman, Hastie, and Tibshirani, 2010):

$$\hat{\boldsymbol{\beta}}_\lambda = \arg \min_{\boldsymbol{\beta}} \left\{ - \sum_{i=1}^{n} \log L(\boldsymbol{\beta} \backslash y_1, y_2, \ldots, y_n) + \lambda(.) \right\} \qquad (2)$$

where $\lambda \geq 0$ is a pre-determined fixed-tuning- or shrinkage parameter, and the term (.) is the penalty function. The shrinkage parameter is selected to maintain a certain penalty strength. Let $\hat{\boldsymbol{\beta}}_\lambda$ be the solution of the penalized log-maximum likelihood problem in Equation (2) then the following two properties are true:

- Property 1: As As $\lambda \longrightarrow 0$, $\hat{\boldsymbol{\beta}}_\lambda \longrightarrow \hat{\boldsymbol{\beta}}$, where $\hat{\boldsymbol{\beta}}$ is the solution of the classical GzLM
- Property 2: As $\lambda \longrightarrow \infty$, $\hat{\boldsymbol{\beta}}_\lambda \longrightarrow \mathbf{0}$

These methodologies will be illustrated in the following chapter using real data in order to assess and evaluate them.

CHAPTER 5: STATISICAL MODELS FOR PREDECTION—THE CASE STUDY OF QATAR UNIVERSITY

In order to demonstrate the methodologies proposed, the research instrument, participants, procedures and the overall data will be described first. The data will then be used as an example to assess and validate the methodologies.

5.1 Research Instrument

In order to evaluate the methodologies, a real data set was collected using both online and paper survey. For each factor that affects course difficulty, the student was asked to give a rating from 1 to 5 with a description of each rating value. For example, the student is asked to rate their attendance from 1 (Attend Rarely) to 5 (Attend Always). At the end of the survey, the student is asked to select their perception of difficulty level for that course, whether it is Low, Medium, or High Difficulty with values from 1 to 3 respectively. The survey was made for four courses from the Industrial and Systems Engineering curricula at Qatar University, Qatar. The first survey was for Computer Simulation System, which has two prerequisites: Probability and Statistics for Engineers and Computer Programming. The second was for Production Planning and Inventory Control, which has three prerequisites: Probability and Statistics for Engineers, Operations Research, and Engineering Economics. The third was for Statistical Quality Control which has one prerequisite: Probability and Statistics for Engineers. Finally, the fourth was for Advanced Operations Research which has one prerequisite: Operations Research. The survey distributed for the Advanced Operations Research course can be viewed in Appendix A. Samples of responses from the four surveys can be seen in Appendix B and C.

5.2 Participants

The participants for this study were undergraduate female Industrial and Systems Engineering students from the engineering college at Qatar University, Qatar. Those students were taking or had taken the four courses.

5.3 Data Collection Procedures

The data was collected through online survey links sent to the students via their student email addresses sent by the college, as well as through on-paper survey distribution in classes.

5.4 Data Description

The number of student who had participated in the surveys are shown in Table 2.

Table 2: Data Description of Data Collected

`	Course				
	PPIC	CSS	SQC	AOR	Total
Answered Online	23	14	0	0	37
Answered on Paper	0	13	49	19	81
Total	23	27	49	19	118

The average results for factors from the surveys are shown below in Table 3.

Table 3: Data Description of Data Collected

	Average Combined Result	Stdev
Attendance	4.09	0.96
Participation	3.46	1.04
Instructor Hours	2.88	0.94
Outside hours	3.27	1.08
Teamwork skill	3.91	0.86
Research skill	3.86	0.78
Math/Science skill	3.96	0.81
Prerequisite Score	6.82	5.25

5.5 Data Standardization

Before applying the proposed methodologies, the data was first standardized since one factor (prerequisite factor) had a different range than the other factors. The purpose of standardization is to scale all the values so that they are in the same range. The data set was rescaled so that it had a mean of 0 and standard deviation of 1. According to Frost (2017) standardizing the independent variables is very important when they might have multicollinearity (independent variables that are correlated). As a result, statistical significance of model terms might be obscured, or the model might produce imprecise coefficients making it difficult to choose between the prediction models. The data used in the proposed multinomial regression models and its applications are discussed below.

5.6 Data Collinearity Test

In addition to standardizing the results, the data was tested for multicollinearity, the results can be seen in Table 4. These results indicate that the factors have little correlation with each other.

Table 4: Multicollinearity Test of the Data Collected

	X1	X2	X3	X4	X5	X6	X7	X8
X1	1.000	.409	.351	.181	.353	.419	.400	.061
X2	.409	1.000	.403	.260	.172	.283	.276	-.118
X3	.351	.403	1.000	.358	.314	.326	.228	-.016
X4	.181	.260	.358	1.000	.248	.260	.286	-.145
X5	.353	.172	.314	.248	1.000	.545	.388	-.039
X6	.419	.283	.326	.260	.545	1.000	.629	.045
X7	.400	.276	.228	.286	.388	.629	1.000	.088
X8	.061	-.118	-.016	-.145	-.039	.045	.088	1.000

5.5 Data Reliability

The reliability of the data collected from the surveys was tested using Cronbach's alpha, which measures the internal consistency of the data set and shown in Table 5. This result indicates an acceptable level of internal consistency of the data.

Table 5: Data reliability using Cronbach's Alpha

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.770	.781	7

5.7 Ridge Multinomial Logistic Regression for Predicting Course Difficulty

The ridge regression proposed by Hoerl and Kennard (1970) shrinks the coefficient estimates of the GzLM towards zeros, but will never become exactly zeros. The ridge regression estimates the coefficients of the GzLM by replacing the term (.) in Equation (2) by an L_2 Norm− or Euclidean norm. Hence, the solution of the ridge penalization-based MLE is written as follows:

$$\hat{\boldsymbol{\beta}}_{\lambda}^{\text{Ridge}} = \arg\min_{\boldsymbol{\beta}} \left\{ -\sum_{i=1}^{n} \log L\left(\boldsymbol{\beta} \backslash y_1, y_2, \ldots, y_n\right) + \lambda \|\boldsymbol{\beta}\|_2^2 \right\} \qquad (3)$$

where $\lambda\|\boldsymbol{\beta}\|_2^2 = \lambda \sum_{j=1}^{p} \beta_j^2$ is the ridge penalty function. The penalization in Equation (3) is often called as quadratic penalization. This method is a kind of trade-off between the bias and the variance of the coefficient estimates of the GzLM. In this method, the coefficients of the GzLM are firstly estimated over a wide range of λ, and then one value is selected from the sub-range in which the changes in the GzLM are insignificant. The procedures followed in his paper are explained below:

Step 1: Define $\emptyset = \{X_1, X_2 \ldots, X_p\}$ as a subset of the course difficulty factors or predictors.

Step 2: Specify *k* values of the tuning parameter λ.

Step 3: Solve the Ridge model in Equation 3 and find $\mathbf{B}^{\mathrm{Ridge}} = \left[\boldsymbol{\beta}_{\lambda_1}^{(1)} \quad \boldsymbol{\beta}_{\lambda_2}^{(2)} \quad \cdots \quad \boldsymbol{\beta}_{\lambda_k}^{(k)}\right]$, where $\boldsymbol{\beta}_{\lambda_i}^{(i)}$ is a column vector containing the preliminary estimates of the GzLM at λ_i. This step is repeated for all categories.

Step 4: Use the results in Step 3 to predict the student difficulty level

Step 5: Calculate the ratio of matching and the Absolute Deviation as follows:

Ratio of Matching:

$$\mathrm{MR\%} = \frac{\text{Number of Matching}}{\text{Total Number of Trails}} \times 100 \qquad (4)$$

Absolute Deviation:

$$\mathrm{AD} = \left|\mathrm{P}(\mathrm{Y} = \mathrm{Y}^{\mathrm{Actual}} \backslash \mathbf{X}) - \mathrm{P}(\mathrm{Y}^{\mathrm{Esimated}} \backslash \mathbf{X})\right| \qquad (5)$$

where **X** is the vector of magnitudes of the course difficulty factors. The terms $Y = Y^{actual}$ and $Y = Y^{Estimated}$ are the probability of actual level and predicted level. Note that the probability of the course difficulty level is estimated as below:

$$P(Y = r \backslash \mathbf{X}) = \frac{e^{(\mathbf{X}^T \boldsymbol{\beta}_r)}}{1 + \sum_{all\ r} e^{(\mathbf{X}^T \boldsymbol{\beta}_r)}} \qquad \nabla r \qquad (5)$$

where *r* is the course difficulty level (category) and $\boldsymbol{\beta}_r^T = (\beta_{10}, \beta_{21}, \dots, \beta_{rp})$

Step 6: Define $\lambda_{\mathrm{opt}}^{\mathrm{Ridge}}$ at the β_{rp} associated with the minimum AD

Step 7: Set the selected $\boldsymbol{\beta}_r^T$ as the optimal solution for the category *r*.

The above methodology will now be validated using the data described above.

Step 1: The factors used for the model are the factors that were discussed in Chapter 4 and were illustrated in Figure 3, the factors are listed in Table 6 below.

Table 6: List of Course Difficulty Factors

Symbol	Description
X1	Class Attendance
X2	Class Participation
X3	Out-of-Class Studying Hours
X4	Office Hour Visits
X5	Teamwork Skill
X6	Math and Science Skill
X7	Independent and Research Skill
X8	Prerequisite Score

Step 2: An initial study has been done using training data to find the optimum range of λ^{Ridge}. The range that provided an acceptable stability in the coefficients of all categories, was found to be from 0.005 to 0.025. Accordingly, five values of λ have been selected, including the extremes, to illustrate the rest of the methodology.

Step 3: The estimated coefficients of the three categories are listed in the following Tables.

Table 7: Ridge Regression Coefficient Estimates for the "Low" Category

Coefficients, $\hat{\beta}_i$	Tuning Parameter, λ				
	0.005	0.010	0.015	0.020	0.025
$\hat{\beta}_0$	0.895	0.774	0.702	0.654	0.618
$\hat{\beta}_1$	0.585	0.560	0.537	0.518	0.500
$\hat{\beta}_2$	0.621	0.541	0.491	0.454	0.426
$\hat{\beta}_3$	0.349	0.312	0.290	0.273	0.261
$\hat{\beta}_4$	0.047	0.082	0.102	0.114	0.121
$\hat{\beta}_5$	0.589	0.533	0.495	0.466	0.443
$\hat{\beta}_6$	0.454	0.457	0.451	0.443	0.433
$\hat{\beta}_7$	0.197	0.154	0.133	0.120	0.112
$\hat{\beta}_8$	-0.043	-0.026	-0.018	-0.013	-0.010

Table 8: Ridge Regression Coefficient Estimates for the "Medium" Category

Coefficients, $\hat{\beta}_i$	Tuning Parameter, λ				
	0.005	0.010	0.015	0.020	0.025
$\hat{\beta}_0$	1.603	1.463	1.375	1.311	1.262
$\hat{\beta}_1$	-0.192	-0.183	-0.175	-0.166	-0.158
$\hat{\beta}_2$	0.407	0.333	0.288	0.255	0.230
$\hat{\beta}_3$	0.255	0.215	0.190	0.171	0.156
$\hat{\beta}_4$	-0.316	-0.270	-0.240	-0.218	-0.201
$\hat{\beta}_5$	0.215	0.174	0.149	0.132	0.118
$\hat{\beta}_6$	-0.217	-0.194	-0.179	-0.169	-0.161
$\hat{\beta}_7$	0.438	0.382	0.348	0.324	0.305
$\hat{\beta}_8$	0.004	0.018	0.023	0.026	0.027

Table 9: Ridge Regression Coefficient Estimates for the “High” Category

Coefficients, $\hat{\beta}_i$	Tuning Parameter, λ				
	0.005	0.010	0.015	0.020	0.025
$\hat{\beta}_0$	-2.499	-2.237	-2.077	-1.965	-1.880
$\hat{\beta}_1$	-0.394	-0.376	-0.363	-0.352	-0.342
$\hat{\beta}_2$	-1.028	-0.875	-0.778	-0.709	-0.656
$\hat{\beta}_3$	-0.604	-0.527	-0.479	-0.444	-0.416
$\hat{\beta}_4$	0.269	0.188	0.138	0.104	0.079
$\hat{\beta}_5$	-0.803	-0.707	-0.644	-0.598	-0.561
$\hat{\beta}_6$	-0.237	-0.264	-0.272	-0.274	-0.272
$\hat{\beta}_7$	-0.635	-0.537	-0.481	-0.444	-0.418
$\hat{\beta}_8$	0.039	0.008	-0.006	-0.013	-0.017

Step 4: The R-studio code was used to predict the course difficulty level for all the students.

At each lambda, the predicted value was compared with the actual value and the number of times the values matched were added up. This is can be seen in Table 10 below.

Table 10: Ridge Regression Number of Matching Predicted and Actual Values

	Predicted Level at each Lambda				
	$\lambda_1 = 0.005$	$\lambda_1 = 0.010$	$\lambda_1 = 0.015$	$\lambda_1 = 0.020$	$\lambda_1 = 0.025$
Number Matching	85	85	84	83	81

Step 5: The ratio of matching (MR%) and the absolute deviation (AD) were calculated at all proposed values of $\boldsymbol{\lambda}$ and reported in Table 11 below.

Table 11: Ridge Regression MR% and AD for the Proposed Range of λ

Criterion	Tuning Parameter, λ				
	0.005	0.010	0.015	0.020	0.025
MR%	72.03%	72.03%	71.19%	70.34%	68.64%
AD	9.70	9.51	9.38	9.28	9.20

It is interesting to note that the ratio of matching (MR%) criteria alone is not enough. Some of the data observations had the same number of matching values (predicted with actual values). The absolute deviation (AD) criteria on the other hand was much more accurate in terms of evaluating the error, since it compared the probability of predicted with the actual probability value at each lambda in order to see how close the model was at predicting the actual value for each student. The optimal value was therefore selected based on the Ratio of Matching along with the AD criteria.

Step 6: With the support of Table 11 above, the $\lambda_{\text{opt}}^{\text{Ridge}}$ is found to be 0.010.

Step 7: In accordance, the optimum coefficients estimates of the three course difficulty levels are as shown in Table 12 below.

Table 12: Ridge Regression Optimum Coefficients of Course Difficulty Levels

Coefficients, $\hat{\beta}_i$	Course Difficulty Level		
	Low	Medium	High
$\hat{\beta}_0$	0.774	1.463	-2.237
$\hat{\beta}_1$	0.560	-0.183	-0.376
$\hat{\beta}_2$	0.541	0.333	-0.875
$\hat{\beta}_3$	0.312	0.215	-0.527
$\hat{\beta}_4$	0.082	-0.270	0.188
$\hat{\beta}_5$	0.533	0.174	-0.707
$\hat{\beta}_6$	0.457	-0.194	-0.264
$\hat{\beta}_7$	0.154	0.382	-0.537
$\hat{\beta}_8$	-0.026	0.018	0.008

5.8 Lasso-Based Multinomial Logistic Regression for Predicting Course Difficulty

To form the Lasso version of the optimization problem in Equation (2), we incorporate the L_2 norm constraint from Park and Hastie (2007) as follows:

$$\hat{\beta}_{\lambda}^{\text{Lasso}} = \arg\min_{\beta} \left\{ \sum_{i=1}^{n} \log L\left(\beta \backslash y_1, y_2, \ldots, y_n\right) + \lambda_1 \|\beta\|_1 \right\} \qquad (6)$$

Here, the same steps used previously, are followed for the Lasso-Based multinomial regression method.

Step 1: The factors used for this model are the same ones used for the Ridge Regression model and can be seen in Table 6.

Step 2: A different range from that of the λ^{Ridge} range provided an acceptable stability in the coefficients of all categories for the Lasso-Based Regression, and was found to be from

0.001 to 0.005. Accordingly, these five values of λ have been selected, including the extremes, to illustrate the rest of the methodology

Step 3: The Lasso-based logistic regression was applied and the estimated coefficients of the three categories are listed in the following Tables.

Table 13: Lasso-Based Regression Coefficient Estimates for the "Low" Category

Coefficients, $\hat{\beta}_i$	Tuning Parameter, λ				
	0.001	0.002	0.003	0.004	0.005
$\hat{\beta}_0$	1.094	1.000	0.932	0.876	0.826
$\hat{\beta}_1$	0.800	0.788	0.775	0.762	0.750
$\hat{\beta}_2$	0.223	0.220	0.218	0.216	0.213
$\hat{\beta}_3$	0.091	0.088	0.085	0.082	0.080
$\hat{\beta}_4$	-	-	-	-	-
$\hat{\beta}_5$	0.389	0.384	0.377	0.371	0.365
$\hat{\beta}_6$	0.615	0.660	0.655	0.645	0.634
$\hat{\beta}_7$	-	-	-	-	-
$\hat{\beta}_8$	-0.045	-0.039	-0.031	-0.023	-0.008

Table 14: Lasso-Based Regression Coefficient Estimates for the “Medium” Category

Coefficients, $\hat{\beta}_i$	Tuning Parameter, λ				
	0.001	0.002	0.003	0.004	0.005
$\hat{\beta}_0$	1.816	1.716	1.641	1.641	1.520
$\hat{\beta}_1$	-	-	-	-	-
$\hat{\beta}_2$	-	-	-	-	-
$\hat{\beta}_3$	-	-	-	-	-
$\hat{\beta}_4$	-0.369	-0.368	-0.367	-0.367	-0.364
$\hat{\beta}_5$	-	-	-	-	-
$\hat{\beta}_6$	-0.063	-0.003	-	-	-
$\hat{\beta}_7$	0.243	0.234	0.228	0.228	0.213
$\hat{\beta}_8$	-	-	-	-	0.009

Table 15: Lasso-Based Regression Coefficient Estimates for the “High” Category

Coefficients, $\hat{\beta}_i$	Tuning Parameter, λ				
	0.001	0.002	0.003	0.004	0.005
$\hat{\beta}_0$	-2.911	-2.716	-2.573	-2.452	-2.346
$\hat{\beta}_1$	-0.201	-0.176	-0.167	-0.159	-0.151
$\hat{\beta}_2$	-1.784	-1.637	-1.538	-1.452	-1.374
$\hat{\beta}_3$	-1.016	-0.915	-0.840	-0.776	-0.719
$\hat{\beta}_4$	0.384	0.276	0.197	0.129	0.065
$\hat{\beta}_5$	-1.227	-1.147	-1.090	-1.041	-0.998
$\hat{\beta}_6$	-	-	-	-	-
$\hat{\beta}_7$	-1.054	-0.918	-0.851	-0.797	-0.745
$\hat{\beta}_8$	0.085	-	-	-	-

Step 4: Using R-Studio code, the number of times the predicted and actual values matched were added up at each lambda. This is can be seen in Table 16 below.

Table 16: Lasso-Based Regression Number of Matching Predicted and Actual Values

	Predicted Level at each Lambda				
	$\lambda_1 = 0.001$	$\lambda_1 = 0.002$	$\lambda_1 = 0.003$	$\lambda_1 = 0.004$	$\lambda_1 = 0.005$
Number Matching	84	85	85	84	83

Step 5: The ratio of matching (MR%) and the absolute deviation (AD) were calculated at all proposed values of $\boldsymbol{\lambda}$ and reported in Table 17 below.

Table 17: Lasso-Based Regression MR% and AD for the Proposed Range of λ

Criterion	Tuning Parameter, λ				
	0.001	0.002	0.003	0.004	0.005
MR%	71.19%	72.03%	72.03%	71.19%	70.34%
AD	9.84	9.69	9.61	9.53	9.48

Step 6: With the support of Table 14 above, the $\lambda_{\text{opt}}^{\text{Lasso}}$ is found to be 0.003.

Step 7: Table 18 shows the optimum coefficients estimates of the course difficulty levels.

Table 18: Lasso-Based Regression Optimum Coefficients of Course Difficulty Levels

Coefficients, $\hat{\beta}_i$	Course Difficulty Level		
	Low	Medium	High
$\hat{\beta}_0$	0.932	1.641	-2.573
$\hat{\beta}_1$	0.775	-	-0.167
$\hat{\beta}_2$	0.218	-	-1.538
$\hat{\beta}_3$	0.085	-	-0.840
$\hat{\beta}_4$	-	-0.367	0.197
$\hat{\beta}_5$	0.377	-	-1.090
$\hat{\beta}_6$	0.655	-	-
$\hat{\beta}_7$	-	0.228	-0.851
$\hat{\beta}_8$	-0.031	-	-

5.9 Elastic net Lasso-based logistic regression for predicting course difficulty

The elastic net is a regularized regression method that linearly combines the L_2 and L_1 penalties of the Lasso and Ridge methods. This done by adding the value α to both penalties being added, this can be seen in Equation 7 below.

$$\hat{\boldsymbol{\beta}}_{\lambda}^{\text{Elastic}} = \arg\min_{\boldsymbol{\beta}} \left\{ \sum_{i=1}^{n} \log L(\boldsymbol{\beta} \backslash y_1, y_2, \ldots, y_n) + \alpha \|\boldsymbol{\beta}\|^2 + (1-\alpha)\|\boldsymbol{\beta}\|_1 \right\} \qquad (7)$$

Where:

$$\alpha = \frac{\lambda_2}{\lambda_2 + \lambda_1}$$

Here, the same steps used previously, are followed for the Elastic Lasso-Based multinomial regression method.

Step 1: The factors used for this model are the same ones used for the Ridge Regression model and can be seen in Table 6.

Step 2: The range for the Elastic Lasso-based logistic regression where there was the most stability in the coefficients of all categories was the same one the Lasso-Based regression had—from 0.001 to 0.003.

Step 3: The Elastic net Lasso-based logistic regression was applied and the estimated coefficients of the three categories are listed in the following Tables.

Table 19: Elastic Lasso-Based Regression Coefficient Estimates for the “Low” Category

Coefficients, $\hat{\beta}_i$	Tuning Parameter, λ				
	0.001	0.002	0.003	0.004	0.005
$\hat{\beta}_0$	1.089	1.000	0.933	0.882	0.838
$\hat{\beta}_1$	0.801	0.788	0.776	0.764	0.752
$\hat{\beta}_2$	0.406	0.358	0.321	0.293	0.268
$\hat{\beta}_3$	0.093	0.093	0.093	0.092	0.092
$\hat{\beta}_4$	-	-	-	-	-
$\hat{\beta}_5$	0.391	0.388	0.385	0.381	0.377
$\hat{\beta}_6$	0.609	0.634	0.656	0.656	0.648
$\hat{\beta}_7$	-	-	-	-	-
$\hat{\beta}_8$	-0.047	-0.043	-0.039	-0.034	-0.029

Table 20: Elastic Lasso-Based Regression Coefficient Estimates for the "Medium" Category

Coefficients, $\hat{\beta}_i$	Tuning Parameter, λ				
	0.001	0.002	0.003	0.004	0.005
$\hat{\beta}_0$	1.812	1.717	1.645	1.587	1.537
$\hat{\beta}_1$	-	-	-	-	-
$\hat{\beta}_2$	0.181	0.134	0.097	0.069	0.044
$\hat{\beta}_3$	-	-	-	-	-
$\hat{\beta}_4$	-0.369	-0.366	-0.363	-0.360	-0.357
$\hat{\beta}_5$	-	-	-	-	-
$\hat{\beta}_6$	-0.074	-0.038	-0.007	-	-
$\hat{\beta}_7$	0.249	0.244	0.239	0.236	0.232
$\hat{\beta}_8$	-	-	-	-	-

Table 21: Elastic Lasso-Based Regression Coefficient Estimates for the "High" Category

Coefficients, $\hat{\beta}_i$	Tuning Parameter, λ				
	0.001	0.002	0.003	0.004	0.005
$\hat{\beta}_0$	-2.901	-2.717	-2.578	-2.469	-2.376
$\hat{\beta}_1$	-0.216	-0.203	-0.195	-0.194	-0.193
$\hat{\beta}_2$	-1.592	-1.496	-1.422	-1.366	-1.316
$\hat{\beta}_3$	-1.018	-0.930	-0.862	-0.810	-0.766
$\hat{\beta}_4$	0.393	0.303	0.233	0.180	0.134
$\hat{\beta}_5$	-1.217	-1.141	-1.079	-1.029	-0.985
$\hat{\beta}_6$	-	-	-	-	-0.007
$\hat{\beta}_7$	-1.059	-0.946	-0.859	-0.805	-0.761
$\hat{\beta}_8$	0.108	0.045	-	-	-

Step 4: The R-studio code was used to predict the course difficulty level for all the students.

At each lambda, the predicted value was compared with the actual value and the number of times the values matched were added up. This is can be seen in Table 22 below.

Table 22: Elastic Lasso-Based Regression Number of Matching Predicted and Actual Values

	Predicted Level at each Lambda				
	$\lambda_1 = 0.001$	$\lambda_1 = 0.002$	$\lambda_1 = 0.003$	$\lambda_1 = 0.004$	$\lambda_1 = 0.005$
Number Matching	84	83	84	84	83

Step 5: The ratio of matching (MR%) and the absolute deviation (AD) were calculated at all proposed values of $\boldsymbol{\lambda}$ and reported in Table 23 below.

Table 23: Elastic Lasso-Based Regression MR% and AD for the Proposed Range of λ

Criterion	Tuning Parameter, λ				
	0.001	0.002	0.003	0.004	0.005
MR%	71.19%	70.34%	71.19%	71.19%	70.34%
AD	9.89	9.78	9.70	9.65	9.59

Step 6: With the support of Table 23 above, the $\lambda_{\text{opt}}^{\text{Elastic}}$ is found to be 0.004.

Step 7: In accordance, the optimum coefficients estimates of the three course difficulty levels are as shown in Table 24 below.

Table 24: Elastic Lasso-Based Optimum Coefficients of the Course Difficulty Levels

Coefficients, $\hat{\beta}_i$	Course Difficulty Level		
	Low	Medium	High
$\hat{\beta}_0$	0.882	1.587	-2.469
$\hat{\beta}_1$	0.764	-	-0.194
$\hat{\beta}_2$	0.293	0.069	-1.366
$\hat{\beta}_3$	0.092	-	-0.810
$\hat{\beta}_4$	-	-0.360	0.180
$\hat{\beta}_5$	0.381	-	-1.029
$\hat{\beta}_6$	0.656	-	-
$\hat{\beta}_7$	-	0.236	-0.805
$\hat{\beta}_8$	-0.034	-	-

CHAPTER 6: DISCUSSION AND FUTURE WORK

6.1 Case Study Results Discussion

Looking at the results, the most accurate method of predicting the difficulty of a course for a student, in terms of both ratio of matching numbers as well as absolute deviance, was the Ridge Regression method. Taking a closer look at the values of the coefficients, it is observed that the factors that have the most effect on the course difficulty levels, were Attendance, Participation, and Teamwork Skills. These factors are related to the student's engagement and interaction within classes. Research and Independent Skills, and Instructor Hours were also important, and those are related to how much the student will attempt to learn even more outside of class.

On the other hand, the factors that had the least effect on the course difficulty level, were Out-of-Class studying hours and Prerequisite Score. This is very interesting, as it seems to relate to the nature of the engineering curricula, which usually focuses on the practical aspects of studying and learning, meaning, the student is more likely to get more use out of class learning rather than studying at home. The students who attend, engage, and participate more in classes, are more likely to not find the course highly difficult. While studying outside of class had little effect on whether the student is likely to find the course highly difficult. In addition to that, how the student performed in their prerequisite courses had little effect on their present perception of difficulty.

This highly implies that for the engineering curricula, it is important for the management to consider putting significance on student participation, group work and incentivizing students to attend classes more regularly. Revising the curricula, and placing more activities that engage the students and allows them to interact more, are ways to improve the student's perception of course difficulty, and therefore their learning experience and satisfaction. Furthermore, using this information, the student support unit can know what kind of support the student needs help with and specifically what areas or skills the student is currently weak in and needs tutorials or extra workshops that help them improve them.

In terms of the course difficulty perception data, it was expected that as the factors' mean value increased, the perception of difficulty decreases. However that was not the case. The correlation of the mean values of the mean values of the factors and the perception of difficulty was 0.61. This is possibly because at this current time the student has not experienced the class activities that required those skills, such as their assignments so far or their exams. In addition to this, the student might be basing of their perception of difficulty on some results they might have achieved so far. For instance, if the student achieved a very low result in one of their assignments they might perceive the course as highly difficult even though that is not really how they feel, however, the low grade instance changed their perception.

Regarding the statistical results, it was observed that the Ridge Regression was the best in terms of its accuracy in predicting the course difficulty. This implies that all variables were very important in the model, and that cutting some of them off like in the Lasso-based and Elastic Net Lasso-based Regression models, reduced the accuracy of the models. Looking at the accuracy results, between the three proposed methods, Ridge Regression and Lasso-Based Regression both achieved at maximum 85 out of 118 matching values with the actual value. While the Elastic Lasso-Based Regression achieved at maximum 84 matching numbers, making it in this case, the worse of the three. In terms of absolute deviation criterion, Ridge Regression performed better than Lasso-Based Regression. It is interesting to note here that the number of matching values between what was predicted and the actual value was not very sensitive to the change in λ. Absolute deviation provided further error comparison within each method. When comparing the three methods however, it is important to take both into account at the same time. Ridge and Lasso-Based Regression both had 85 matching values, however the Absolute Deviance was smaller for the Ridge Regression. Moreover, when the number of matching value started to decrease, absolute deviation does not become necessary in differentiating the results afterwards, since the matching number result is already worse. Therefore, using both criteria is very useful for comparison, especially when the matching numbers are not sensitive to change.

The highest accuracy in all three methods, was 72.03%, which means that when applying these models around 72% of the students could be provided with the correct type of support that they need.

6.2 Recommendations

To begin with, the correlation of the mean of the factors and the course difficulty perception was low. It was discussed that this may have been because the student is basing their perception of difficulty on certain instances that occurred during the semester such as a low grade for an assignment. This can be avoided by interviewing the student about how they perceive the difficulty of a course rather than asking them through a survey, and in that way a better explanation of what the perception of difficulty means could be explained to the student. In addition to that, another way to improve this could be to design a standard way of measuring the course difficulty perception, such a standardized course-specific course difficulty perception test.

Moreover, the student could also be provided with more than three categories of difficulties. The reason behind that is that sometimes the student might be unsure of whether they want to select one of two categories and end up choosing the one that does not capture how they really feel, such as choosing the medium over the high difficulty when they feel it is somewhere in between. The challenge in doing so would be the larger number data observation requirement. All categories must be observed a sufficient number of times for the models to be acceptable.

Regarding the survey reliability, the data has an acceptable level of internal consistency. However, it can be improved further. Some of the questions in the survey were perhaps difficult for the student to understand which might have resulted in some of the actual data not being fully captured. To improve this, the direct interviews can be replaced with the surveys as the research instrument for this study.

Finally, the number of observations for this study can be improved further by collecting more data to increase the overall accuracy of the models. The observations can also be collected from courses that belong to different engineering curricula as well.

6.3 Conclusion and Future Work

Continuous improvement is a key goal for many organizations worldwide, as today's rapidly expanding and ever evolving market is very competitive indeed. The education sector should also strive for development and improvement, since the education of any society is extremely important for its development and its prestige as well. The philosophy of Quality Management has a great potential to help institutions achieve this goal. One major area Quality Management could be very useful in, is where an institution's academic productivity lies.

The academic productivity of an institution could be seen from various perspectives, in this thesis work, the academic productivity of a university was explored in terms of graduation and retention rates of students. These aspects of a university are very important and quite relevant in today's improvement issues surrounding higher education institutions. The loss of students due to dropping out or transferring, are major losses to the college or university. Therefore, it is very important to ensure the students are on track and provide them with the support they need.

In the course of the thesis work, the early prediction of course difficulty for a student was proposed in order to allow the education management a chance to remedy the situation by providing the student with necessary support throughout the semester in which they have registered for that course. The most important factor found to affect the difficulty of the course difficulty were Attendance, Participation, and Teamwork Skills. Implying that the management needs to concentrate on those skills for the engineering curricula. In addition to that, knowing which courses are considered very difficult to the students can be further helpful to the education management as it allows them to reconsider and reevaluate the current curriculum design the students are following.

The course difficulty prediction models were developed by using data collected from four courses. It would be interesting to further investigate the models by collecting data from the entire college of engineering. It might be also interesting to see how the models behave when applied to different colleges. Moreover, the models can be applied to each specific course individually rather than have a combined courses model in order to further find the skills required for each individual course and therefore increase the accuracy of the model. One useful benefit of these models can be explored more by adding it to prediction of students “at risk” models, by combining it with other useful factors such as a student’s CGPA, registered number of credit hours, motivation, and many other factors used in literature as well.

From the course of this work, it is strongly believed that it is very important to consider the difficulty of courses in a student’s performance other than their CGPA alone in predicting and classifying students as “at risk”. Detecting the difficulty of a course for a student before they start the course is very beneficial and will save a lot of time for the student and the institute as well. Not only will it allow management to know that a student is facing a difficulty and needs help, but also where the focus of help should be in. Ultimately, figuring out when a student is struggling very early, can lead to better academic productivity by tackling the retention and graduation rates issue, and will also ensure better and more personalized learning experience for the students.

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APPENDIX A: COURSE DIFFICULTY SURVEY FOR ADVANCED OPERATION RESEARCH COURSE

College of Engineering
Engineering Management

This survey is for a thesis work that aims to enhance the student learning experience and improve student retention and graduation rates. Thank you in advance for answering the survey.

The researcher requests your consent for participating in a study about a thesis study titled: Quality Management-Based Approach for Enhancing Academic Productivity in Higher Education

Here are some important information to read first:

- Purpose and Nature: thesis study
- Description: identifying students in need of help in a course as early as possible.
- Risks/harms: no risks or harms are involved in the study, only your time inconvenience
- Task: answer the survey, it might take you only about 5 min to answer this survey
- Participation: it is voluntary for you to participate, you may skip any question or withdraw at any time
- Results: the results will be used only for the thesis and will not be shared with anyone
- Data gathered: will be stored in a computer for the thesis work only.
- Contact:
    - My name: Wassen Mohammad
    - Reach me on this cell phone: 30030103
- Approval: conducting this survey has been approved by Qatar University Review Board

<u>I have understood the above and I agree to participate</u>

Signature of the Participant: Date:

Name and Signature of the Researcher: Date:

PART 1: General Attributes

The following are some general attributes about **<u>yourself</u>**. Please mark how you feel about each attribute.

1. **How often do you attend classes this class?**

1 ☐	Attend rarely (75%-80%)	2 ☐	Attend occasionally (85%-80%)	3 ☐	Attend usually (90%-95%)	4 ☐	Attend very frequently (95-100%)	5 ☐	Attend always (100%)

1. **How often do you participate in this class?**

1 ☐	Participate rarely	2 ☐	Participate occasionally	3 ☐	Participate usually	4 ☐	Participate very frequently	5 ☐	Participate always

2. **For this course, how often do you meet your instructor during office hours?**

1 ☐	Rarely	2 ☐	Occasionally	3 ☐	Usually	4 ☐	Very frequently	5 ☐	Always

3. **For this 3 credit hour course, how many hours do you study outside of class per week?**

1 ☐	1-2	2 ☐	2-3	3 ☐	3-4	4 ☐	4-5	5 ☐	5-6

4. **How do you feel about your teamwork skills?**

1 ☐	Poor	2 ☐	Fair	3 ☐	Good	4 ☐	Very good	5 ☐	Excellent

5. How do you feel about your independent learning and research skills?

1	Poor	2	Fair	3	Good	4	Very good	5	Excellent

6. How do you feel about your math and science skills?

1	Poor	2	Fair	3	Good	4	Very good	5	Excellent

PART 2: Prerequisite Operations Research

The following are some specific attributes about the **prerequisite** of the course Advanced Operations Research.

Prerequisite	How far away did you take this prerequisite from Advanced Operations Research? (e.g. 2 semesters away)		How relevant and helpful was this prerequisite in terms of the knowledge applied in Advanced Operations?		What academic grade did you get for this prerequisite	
Operations Research IENG 331	1	1 semester away	1	Barely helpful <20%	1	<D
	2	2 semesters away	2	Slightly helpful (20%-40%) relevance	2	D
	3	3 semesters away	3	Somewhat helpful (40%-60%) relevance	3	C
	4	4 semester away	4	Very helpful (60%-80%) relevance	4	B
	5	>5 semesters	5	Extremely helpful (80%-100%) relevance	5	A

PART 3: Course Difficulty of Advanced Operations Research

The following is a specific question about the **difficulty** of the course Advanced Operations Research.

1. **How difficult do you feel Advanced Operations Research is?**

1 ☐	Low Difficulty	2 ☐	Medium Difficulty	3 ☐	High Difficulty

Thank you for filling this survey out.

APPENDIX B: COURSE DIFFICULTY RESPONSE FOR COMPUTER SIMULATION SYSTEMS

Course Difficulty Survey for Computer Simulation Systems (CSS) SurveyMonkey

#18

COMPLETE

Collector:	Web Link 4 (Web Link)
Started:	Monday, April 16, 2018 7:00:23 AM
Last Modified:	Monday, April 16, 2018 7:02:11 AM
Time Spent:	00:01:48
IP Address:	86.36.66.129

Page 2: PART I: General Attributes

Q1 How often do you attend this class?	**Attend always (100%)**
Q2 How often do you participate in this class?	**Participate usually**
Q3 For this course, how often do you meet your instructor during office hours?	**Sometimes**
Q4 For this 3 credit hour course, how many hours do you study outside of class per week?	**2-3 hours**
Q5 How do you feel about your teamwork skills?	**Very good**
Q6 How do you feel about your independent learning and research skills?	**Excellent**
Q7 How do you feel about your math and science skills?	**Excellent**

Page 3: PART II: Prerequisite GENG 200 for Computer Simulation Systems

Q8 How far away did you take GENG 200 from CSS?	**1 semester away**
Q9 How relevant and helpful was GENG 200 in terms of the knowledge applied in CSS?	**Somewhat helpful (40%-60%) relevance**
Q10 What academic grade did you get for GENG 200	**A**

1 / 2

Page 4: PART III: Prerequisite GENG 106 for Computer Simulation Systems

Q11 How far away did you take GENG 106 from CSS?	**3 semesters away**
Q12 How relevant and helpful was GENG 106 in terms of the knowledge applied in CSS?	**Barely helpful (<20%) relevance**
Q13 What academic grade did you get for GENG 106?	**A**

Page 5: PART IV: Computer Simulation Systems Difficulty

Q14 How difficult do you feel Computer Simulation System was?	**Medium Difficulty**

APPENDIX C: COURSE DIFFICULTY RESPONSE FOR PRODUCTION PLANNING AND INVENTORY CONTROL

#31

COMPLETE

Collector:	Web Link 1 (Web Link)
Started:	Sunday, April 15, 2018 10:14:17 AM
Last Modified:	Sunday, April 15, 2018 9:24:29 PM
Time Spent:	11:10:12
IP Address:	185.37.110.10

Page 2: PART I: General Attributes

Q1 How often do you attend this class?	**Attend occasionally (85%-80%)**
Q2 How often do you participate in this class?	**Participate rarely**
Q3 For this course, how often do you meet your instructor during office hours?	**Sometimes**
Q4 For this 3 credit hour course, how many hours do you study outside of class per week?	**5-6 hours or more**
Q5 How do you feel about your teamwork skills?	**Excellent**
Q6 How do you feel about your independent learning and research skills?	**Excellent**
Q7 How do you feel about your math and science skills?	**Very good**

Page 3: PART II: Prerequisite IENG 330 for Computer Simulation Systems

Q8 How far away did you take IENG 330 from Production Planning?	**1 semester away**
Q9 How relevant and helpful was IENG 330 in terms of the knowledge applied in Production Planning?	**Slightly helpful (20%-40%) relevance**
Q10 What academic grade did you get for IENG 330?	**C**

Page 4: PART III: Prerequisite GENG 200 for Production Planning and Inventory Control

Q11 How far away did you take GENG 200 from Production Planning? — **3 semesters away**

Q12 How relevant and helpful was GENG 200 in terms of the knowledge applied in Production Planning? — **Somewhat helpful (40%-60%) relevance**

Q13 What academic grade did you get for GENG 200? — **C**

Page 5: Part IV: Prerequisite GENG 360 for Production Planning and Inventory Control

Q14 How far away did you take GENG 360 from Production Planning? — **2 semesters away**

Q15 How relevant and helpful was GENG 360 in terms of the knowledge applied in Production Planning? — **Barely helpful (<20%) relevance**

Q16 What academic grade did you get for GENG 360 — **B**

Page 6: PART V: Production Planning and Inventory Control Difficulty

Q17 How difficult do you feel Production Planning was? — **Low Difficulty**